STUTTGARTER BEITRÄGE ZUR PRODUKTIONSFORSCHUNG

Max Weeber

»Simulation-Based Assessment of Energy Use in Factories«

Fraunhofer IPA

Universität Stuttgart

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»Simulation-Based Assessment of Energy Use in Factories«

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Kurzzusammenfassung

Das zunehmende Bewusstsein über die begrenzten Ressourcen unseres Planeten verlangt von den Industrieunternehmen ihre Ressourceneffizienz zu steigern. In diesem Zusammenhang ist die Verbesserung des Energieeinsatzes in Fabriken Gegenstand laufender Forschung. In jüngster Zeit wurden Fabriksimulationsmodelle vorgeschlagen, um die gegenseitigen Abhängigkeiten des Energieeinsatzes in den verschiedenen Peripherien eines Fabriksystems besser zu verstehen. Die Komplexität der vorgeschlagenen Modelle und ihre Unfähigkeit, mehrere energiebezogene Leistungskennzahlen gemeinsam zu bewerten, haben ihre Anwendung in der Praxis jedoch bisher eingeschränkt. Diese Arbeit erweitert bestehender Fabriksimulationsmodelle mit einem besonderen Schwerpunkt auf Vor-Ort-Energieversorgungssysteme und ergänzt konventionellen Energieleistungskennzahlen um nicht-energetische Vorteile. Die Arbeit präsentiert außerdem einen neuen Bewertungsprozess um Fabriksimulationsmodelle strukturiert auf Maßnahmen zur Verbesserung des Energieeinsatzes hin zu untersuchen. Die Ergebnisse zeigen, dass die Kombination aus Fabrikmodell und Simulationsexperimenten den Umfang der erforderlichen Simulationsläufe und die Verallgemeinerbarkeit der erzielten Simulationsergebnisse verbessern kann. Die Ergebnisse zeigen, dass durch die Anwendung der vorgeschlagenen Methodik Energieeinsparpotenziale von 38% für das Fabrikgebäude und seine technischen Gebäudeanlagen erreicht werden können. Gleichzeitig können nicht-energetische Vorteil wie bspw. im Bereich der Arbeitssicherheit um 40% ermittelt werden. Ausgehend hiervon sind weitere Verbesserungen im Hinblick auf den Aufbau des Energieversorgungssystems möglich. Mithilfe des Bewertungsprozesses können verschiedene Energiekennzahlen der Fabrik weiter verbessert werden, darunter Energiekosten (-10 %), Energiebedarf (-7 %) und CO_2-Emissionen (-11 %). Darüber hinaus wurde der Anteil der erneuerbaren Energien an der Energieversorgung um 16 % und die Energieflexibilität um 31 % erhöht. Die Ergebnisse dieser Arbeit sollen das Verständnis für die Zusammenhänge des Energieeinsatzes in Fabriken fördern und den Übergang der Fabriksimulationsmodelle und der damit verbundenen Bewertungsprozesse in die Planungspraxis beschleunigen.

Abstract

The increasing awareness of the limited resources of our planet, coupled with a growing number of climate protection regulations, is demanding that industrial companies improve the sustainability of their business strategies and urging decision-makers to adopt environmentally friendly manufacturing practices. In this respect, identifying ways to improve energy use in factories is subject to ongoing research. Recently, factory simulation models have been proposed to better understand the interdependencies of energy use in the different peripheries of a factory system. However, the complexity of the proposed factory simulation models and their inability to jointly evaluate multiple energy-related performance metrics has so far limited their application in practice. This work extends the scope of existing factory simulation models with a particular focus on on-site energy supply systems and extends conventional energy performance metrics to include non-energy benefits. It also improves upon the prevailing trial-and-error approaches currently used to evaluate improvement measures within these models. The findings show that an assessment procedure that combines a multi-peripheral factory model with a comprehensive evaluation process using design of simulation experiments can improve both the comprehensiveness and generalizability of the obtained simulation results. The results show that by applying the proposed methodology, combined energy-saving potentials of 38% can be achieved for the factory building and its technical building systems. At the same time, the non-energy benefits in terms of improved occupational safety can be increased by 40%. Starting from this baseline, further improvements are possible with regard to the energy supply system setup. Using the proposed evaluation process, it is possible to further improve various energy performance metrics of the factory, including energy costs (-10%), energy demand (-7%), and CO_2 emissions (-11%). In addition, the share of renewables on the energy supplied was increased by 16% and energy flexibility by 31%. The results of this work should promote the understanding of the complex interdependencies of energy use in factories and advance the transition of the corresponding factory simulation models and related evaluation processes into planning practice.

Table of Acronyms

ABS	Agent-Based Simulation
AHP	Analytical Hierarchy Process
BCVTP	Building Controls Virtual Test Bed
BSS	Battery Storage System
CCS	Carbon Capture and Storage
CCHP	Combined Cooling Heat and Power
CHP	Combined Heat and Power
CNC	Computerized Numerical Control
COP	Coefficient of Performance
DAE	Differential-Algebraic Equations
DES	Discrete Event Simulation
DSS	Dynamic System Simulation
EES	Energy Supply Systems
EnMS	Energy Management Systems
EU	European Union
GA	Genetic Algorithm
HVAC	Heating Ventilation and Air-conditioning
IEA	International Energy Agency
LCA	Life Cycle Assessment
LUT	Look-Up Table
MAC	Maximum Allowable Concentration
MCDA	Multi-Criteria Decision Analysis

MCS	Monte Carlo Simulation
MES	Manufacturing Executing Systems
MET	Metabolic Equivalent of Task
MILP	Mixed-Integer Linear Programming
NMF	Neutral Model Format
NPV	Net-Present Value
ODE	Ordinary Differential Equations
OO	Ordinary Optimization
PCR	Power Control Reserve
SDS	System-Dynamics Simulation
SPS	Samples per Second
TBS	Technical Building Systems
VSM	Value Stream Mapping

1 Introduction

1.1 Motivation and Background

In an era of "The Great Acceleration", improved strategies are needed to minimize the impact that economic activities have on planet Earth. Socio-economic trends such as the growth of the world's population (9.8 billion by 2050 - 7.6 billion in 2017) and the alignment of consumption patterns between developing and industrialized countries intensify the continuous depletion of natural resources worldwide. (Steffen et al. 2015, p. 88 ff., UN 2017, p. 2, UNEP 2011, p. 1). In this context, the world energy demand is expected to grow by 30% by 2040, which from today's perspective is equivalent to adding another China and India (IEA 2017, p. 23) (ref. Figure 1-1). Although renewables already account for two-thirds of the annual growth in installed electricity capacities, the scenarios developed by the International Energy Agency (IEA) assume that in 2040 more than 75% of the global primary energy demand will still be met by fossil fuels (81% in 2017) (IEA 2017, p. 298; 80). Between 1970 and 2010, CO_2 emissions from fossil fuel combustion and industrial processes increased and contributed 80% to the increase in greenhouse gas emissions (IPCC 2014, p. 5). Today, research can provide evidence that the increase in average global surface temperature from 1970 to the present is consistent with the increase in global greenhouse gas emissions. Moreover, half of the temperature increase is considered to be anthropogenic (WMO and GAW 2017, p. 1, IPCC 2014, p. 44 ff.). As a result, and despite various mitigation policies, the climate protection goals of the Paris Agreement, especially the goal of limiting global warming to 2 °C (or even 1.5 °C) above pre-industrial levels, remain under severe pressure (UN 2015, p. 3, IPCC 2014, p. 57 ff.).

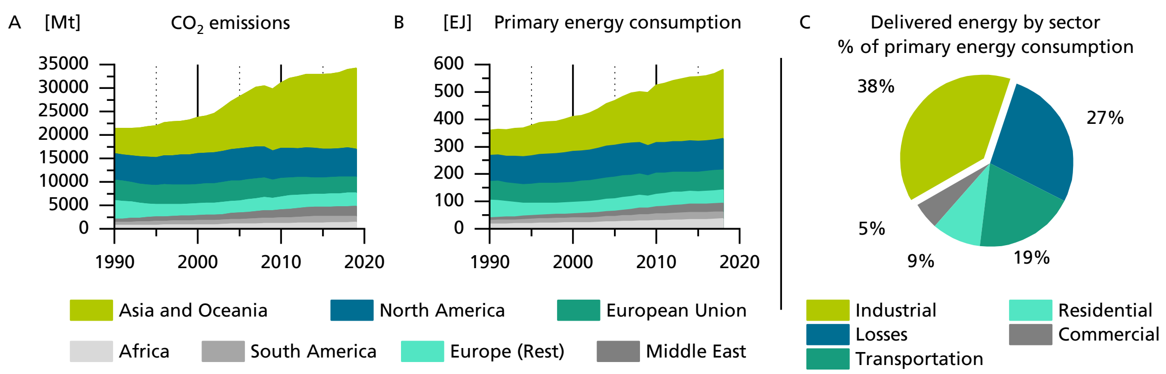

Figure 1-1 Development of CO_2 emissions (world) (A) and primary energy consumption (world) (B). (C) Share of delivered energy consumption by end-use sector (world) (A, B - own representation based on BMWi 2019, Table 12 and Table 31, EIA 2019, p. 40, BP 2020 and C - EIA 2019 Table F1)

Apart from households and transportation, industry, including manufacturing, is the single highest energy end-user, accounting for 53% (38% when electricity-related losses are taken into account) of the total energy supplied worldwide (EIA 2019 Table F1). Although energy productivity is increasing, especially in OECD countries, the growth rate for total energy demand in the industry sector is still projected to increase by 1.2% per year until 2040 (EIA 2016, p. 114).

With the "Green Deal", the European Union (EU) raised its reduction target for greenhouse gas emissions from 40% to 55% by 2030. What is more, the EU aims to become the first climate-neutral continent and establish a European economy with net-zero greenhouse gas emissions by 2050 (EU 2019, p. 4). These ambitions are also reflected in the targets to improve energy efficiency and increase the use of renewables energies sources. Currently, the energy efficiency reduction target is set to 32.5% by 2030 (relative to modeling projections for 2030 made in 2007) for both final and primary energy consumption (EU 2018a, p. 211). The target for the overall share of renewable sources on the EU's total energy needs is set to 32% by 2030 (EU 2018b, p. 83). In line with EU targets, Germany has developed a national energy policy that aims to ensure a secure, economical, and environmentally compatible energy supply (BMWi 2016, pp. 7-9). Although positive trends can be observed, the projections also show that efforts need to be intensified in order to achieve the national targets within the envisaged time frame (ref. Figure 1-2) (BMWi 2021a, pp. 4-5).

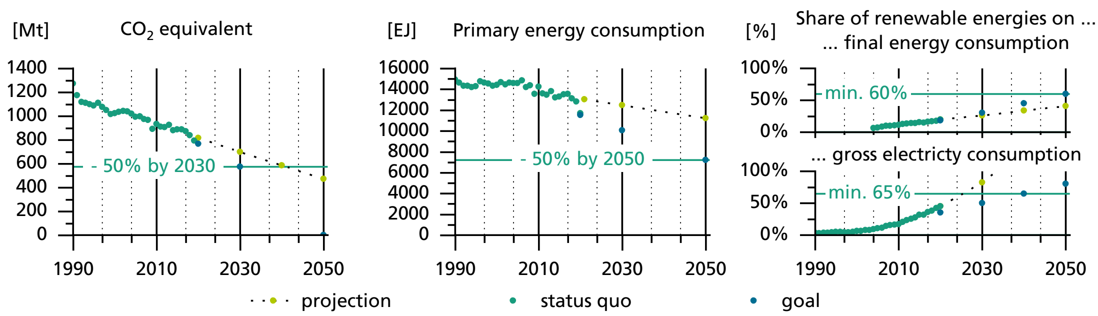

Figure 1-2 Selected goals of the German "Energiewende" status quo and development trend (own representation based on BMWi 2021a, AGEE-Stat 2021, and BMWi 2019)

Energy efficiency is considered a cost-effective means of reducing specific energy consumption and mitigating greenhouse gas emissions in all industries (Worrell 2010, pp. 3,12). At a national level, primary and final energy productivities are the efficiency indicators used to monitor the decoupling of economic growth and energy consumption. However, according to Figure 1-3, current trends are lagging behind the long-term objectives. This is true even if the increases in primary energy productivity are adjusted for temperature, economic, and population growth (AGEB 2018, p. 7 f.). Moreover, assessments within various industry sectors point to a slowdown in the development trends with regard to energy efficiency improvements. For instance, the Energy Efficiency

Index collected by the Odyssee-Mure project shows that after an increase of 1.5%/year between 2000 and 2007, the optimization of energy consumption, including the progress in the implementation of energy efficiency measures, has slowed down to 1%/year since 2007 (ref. Figure 1-3 B) (ADEME 2017, p. 7). Further evidence of a negative development trend is provided by the Energy Efficiency Index of the German industry, a qualitative survey of industry experts conducted twice a year, which shows that energy productivity has leveled off in recent years (ref. Figure 1-3 C).

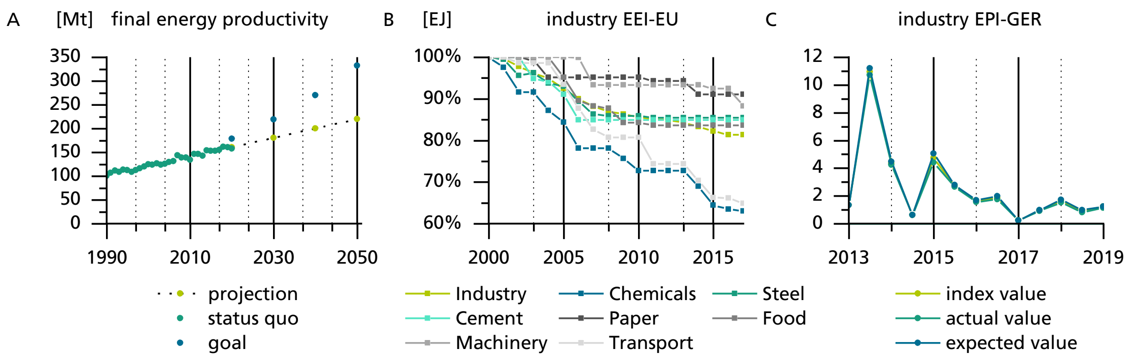

Figure 1-3 Development of final energy productivity (A); Odyssee-Mure Project – Energy Efficiency Index of EU industry sectors (B); Energy Efficiency Index of German industry (C) (own representation based on UBA 2020, ADEME 2017, EEP 2017)

Unlike in the energy-intensive process industry, direct energy costs in discrete parts manufacturing account for between 2.7% and 5.3% of total costs (Löschel et al. 2015, p. 843, Müller et al. 2009, p. 24).[1] In contrast, raw materials, auxiliary materials, and consumables account for up to 43% (Weissenberger-Eibl et al. 2014, p. 20). These figures suggest that the priority of reducing energy costs in a manufacturing company is low. However, in competitive market environments, the potential savings associated with energy as a resource have been identified as a lever to strengthen market position (Bunse et al. 2011, p. 667 f., Cagno and Trianni 2013, pp. 281, 283). Furthermore, the transposition of the European Energy Efficiency Directive (2012/27/EU – Article 8) into national law obliges EU companies to either conduct energy audits according to DIN EN 16247-1 or introduce Energy Management Systems (EnMS) according to DIN EN ISO 50001 or EMAS (EU 2012, p. 17 f., DIN EN 16247-1 , DIN EN ISO 50001). In several

[1] share of energy costs in energy-intensive industries: 2-11% (de Bruyn et al. 2020de Bruyn, Sander, Jongsma, Chris, Kampman, Bettina, Görlach, Benjamin & Thie, Jan-Erik. 2020. Energy-intensive industries - Challenges and opportunities in energy transition. Luxembourg: Committee on Industry, Research and Energy (ITRE), Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament. URL: https://cedelft.eu/publications/energy-intensive-industries-challenges-and-opportunities-in-the-energy-transition/ [Accessed 08.05.2022].)

countries, the introduction of EnMS is also motivated by tax relief, including the cap laid down in the German Electricity Tax Act and the German Energy Act (§ 10 StromStG, § 55 EnergieStG) and the limitation of the energy surcharge under the German Renewable Energy Sources Act (§ 64 EEG).

Accompanying existing regulatory frameworks, carbon pricing schemes have been introduced in many countries around the world as fiscal measures to mitigate climate change (ref. Figure 1-4) (The World Bank 2021). Emission Trading Systems (ETSs) and carbon taxes have been developed to provide incentives for different industries and individual companies to improve their sustainable operations by investing in low-emission technologies. An additional motivation for companies to pursue proactive emission reduction strategies is to secure access to prospective markets and customers (Boiral 2006, p. 328).

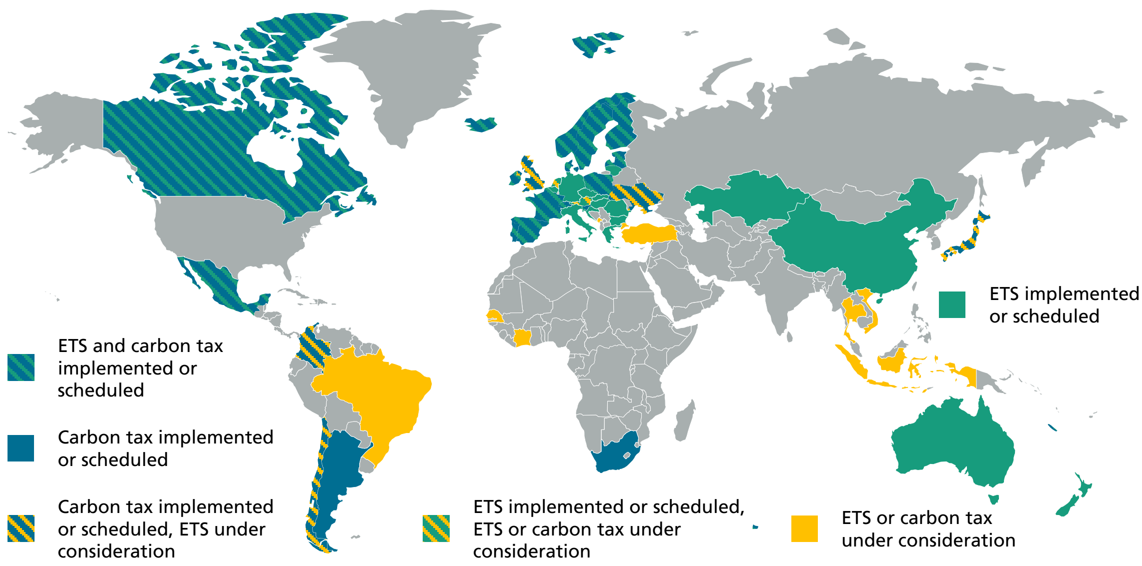

Figure 1-4: Overview of various carbon pricing initiatives worldwide (own representation based on Bloomberg 2017, The World Bank and Ecofys 2017, The World Bank 2021)

Europe was the first carbon market to be established globally. Today, the EU is still the most important market, covering about 40% of all carbon emissions (European Comission 2021). In 2005, the EU introduced an ETS that focused on the power generation sector, aviation, and energy-intensive industries. Under the ETS, energy and industrial companies purchase emission allowances and can trade them among themselves at market-based prices. In general, the number of new emissions allowances issued each year is steadily decreasing in order to increase pressure on carbon-intensive businesses (BMWi 2021b). In fear of "carbon leakage" and many energy-intensive industries moving their business activities to countries without a carbon pricing system, millions of ETS allowances were given out for free. As a result, the ETS price had fallen from an initial peak of almost 28 euros per ton of carbon dioxide (tCO_2) in 2008 to less than 5 €/tCO_2 in 2014. After a period of stagnation at levels between 4 to 7 €/tCO_2 during 2014 and 2018, the price for ETFs has recovered to exceed 38 €/tCO_2 in 2021 (Koch et al. 2014, p. 676, UBA 2015, p. 20 f.). By 2021, the transport and housing sectors will also be included in the so-called new emission trading system (nETS). The nETS starts with a fixed price of 10 euros per ton and rises continuously to 35 euros per ton until 2025 (BMWi 2021b).

In light of this changing environment, carbon neutrality has become a strategic priority for a growing number of countries and companies, leading to ambitious goals and commitments to become carbon neutral, climate neutral, or net-zero[1] in the years leading up to 2050 (Forbes 2019, Race to Zero 2021, Carbon Neutrality Coalition 2021).

Along the way of this transformation process, manufacturing companies have adjusted their management objectives and started to adopt energy efficiency measures and install carbon-free renewable energy supply systems. However, a low-emission economy relies on vast amounts of low-cost, zero-emission electricity and requires mechanisms to balance time-varying demand and supply (Davis et al. 2018, p. 7). Integrating energy producers, consumers, and those who do both ("prosumers") requires a smart grid infrastructure as a source of both competitive advantage and security of supply (Buchholz and Styczynski 2020, p. 4 f.). Consequently, industry in general and manufacturing, in particular, have begun to take steps to improve demand-side flexibility to match intermittent renewable energy supply and demand (Heffron et al. 2020, p. 2). Other considerations and technology options for reducing the manufacturing footprint include tapping energy-saving potentials in cross-sectional technologies (ref. BCG and Prognos 2018, pp. 139-141, Seidl 2017, pp. 279-292), the substitution of carbon-based fuels with biomass, synthetic fuels, or hydrogen (ref. Malico et al. 2019, pp. 971-973, Schemme et al. 2020, p. 13, El-Emam and Özcan 2019, p. 605 f., Rambhujun et al. 2020, p. 11) and the introduction of carbon capture and storage (CCS) technologies (ref. Boot-Handford et al. 2014, p. 130, Wilberforce et al. 2021, p. 2).

Given the multitude of available technology options and the urgent need to pursue climate-friendly business strategies, it is becoming increasingly difficult for corporate decision-makers to filter out those improvement measures that best fit their desired improvement goal.

Improving the economic and environmental performance of a production plant, therefore, requires a paradigm shift towards holistic and interdisciplinary planning approaches. Weissenberger-Eibl et al. (2014, p. V) sees holistic planning approaches as a prerequisite for achieving the vision of an efficient, emission-neutral, and ergonomic factory whose operation benefits people and protects the environment. In this context, May et al. (2016, pp. 629, 633-635) outline the eco-factory as a guiding principle and source of competitive advantage achieved through system efficiency and flexibility. In addition, practitioners

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[1] These terms are often used interchangably, although climate neutral and net-zero reflect a broader inclusion of different emissions

from the industry have called for more integrated approaches that combine the expertise of all parties involved in the planning process (e.g., architects, civil and process engineers) and use advanced planning tools that are able to consider resource and energy efficiency together with conventional economic planning objectives (INFO 2013b, p. 29, Gourlis and Kovacic 2017, p. 954, Sobottka et al. 2018, p. 414). In addition to the planning of new energy-efficient and climate-friendly factories, the modernizing of existing factories is a particular challenge. The complexity inherent to building stock arises from the large number of interwoven system components, which are designed by different employees and assembled from different product generations. These framework conditions further complicate the planning process and reduce the degrees of freedom available for implementing improvement measures.

Unfortunately, the general lack of holistic methods for assessment and prioritization is still a critical barrier to the widespread adoption of energy efficiency and other improvement measures in the industry sector (Sauer and Bauernhansl 2016, p. 6). Today, the evaluation of energy efficiency measures is usually carried out in isolation, taking into account narrow system boundaries. However, this does not reflect the reality of a networked factory environment. Also, research efforts in the past have focused predominantly on energy-saving measures at the level of individual manufacturing processes rather than on improving the overall factory system (e.g., Zein 2012, Böhner 2013). Several authors have noted the importance of considering the energy consumption of all factory subsystems, including peripheral systems such as lighting, heating, cooling, and ventilation (Hesselbach et al. 2008, p. 2, Thiede 2012, p. 38, Fischer et al. 2015, p. 138).

This is particularly important as studies at the European level report that cross-sectional technologies are responsible for about 45% of the total energy demand in the industrial sector (Bradke et al. 2002, p. 796 ff.). Findings from case studies in industry show that the share of energy demand from peripheral systems in factories can even be as high as 51% (Engelmann 2009, p. 76).

Hesselbach et al. (2009, p. 3) already emphasized the need to consider the interactions between different energy flows in manufacturing. Although it has been recognized that the interconnected structure of processes/machines, auxiliary equipment, technical building system (TBS), and the building envelope offer new opportunities for reducing the energy demand of manufacturing systems, current assessment methods lack the ability to represent the strong interdependencies and mutual relationships between these different subsystems of a factory (Thiede et al. 2016, p. 1118). The relationship between the energy demand of processes and peripheral systems requires new assessment methods that are able to quantify the negative or positive side effects of individual measures in the context of an entire factory (Apostolos et al. 2013, p. 632, Brunke 2017, pp. 3 f., 17, Flatau 2019, p. 135). This is intended to avoid possible problem shifts between the energy requirements of different factory subsystems and thus the over- or underestimation of the savings potential of individual measures (Herrmann and Thiede 2009, p. 221, Khattak et al. 2018, p. 2). In addition, performance metrics related to energy use in factories have become more diverse. Alongside conventional productivity targets, the improvement of energy efficiency and energy flexibility, and the use of renewable energy sources have become additional improvement targets (Beier et al. 2016, p. 659 f.). Fleiter et al. (2012, p. 503 f.) and Trianni et al. (2014, p. 208 f.) stressed the need to consider the multiple effects of individual improvement measures in order to increase their acceptance and thus the adoption rate. For example, in addition to energy and cost savings, energy efficiency measures can also be associated with non-energy benefits (e.g., productivity gains, reduced local emissions, or improved working conditions).

Hesselbach et al. (2009, p. 3) and Herrmann et al. (2011, p. 45) identified modeling and simulation as an adequate means of representing the complexity of a factory system and as a suitable method for representing the energy demand characteristics of a factory. Since then, progress has been made to integrate the different levels of a factory system into holistic energy simulations (e.g., Thiede 2012, Haag 2013, Hopf 2016, Beier 2017, Schönemann 2017). Nevertheless, the available solutions proved to be simplistic and "proof of concept"-like (Garwood et al. 2018, p. 909). Furthermore, the representation of the energetic characteristics of the entire factory leads to very complex models. The use of these models in search of appropriate improvement measures is likely to be guided by an unstructured trial-and-error approach. This results in new challenges, especially with regard to the applicability of the models and the validity of the derived simulation results. In order to promote the use of factory simulation models in industry practice, additional solutions are required to strengthen transparency and increase confidence in the simulation results obtained.

1.2 Research Focus and Central Aim

The research focus of this work is on improving energy use in factory systems. However, the shortcomings of available approaches underline the need to further develop existing methods. Model-based approaches can only be successful if they help practitioners make informed decisions about how to improve both the productivity and climate-friendliness of their factory operations. Therefore, energy simulations of factories must holistically address several energy-related objectives. Furthermore, their use must be embedded in a consistent assessment procedure that is able to evaluate various improvement measures to allow objective decision-making. The general research question can therefore be summarized as follows:

General research question

How is it possible to assess energy use holistically during
the planning of a factory modernization?

In this work, factory systems are considered as consisting of several interconnected subsystems, including processes/machines, auxiliary equipment, technical building system (TBS), the building envelope, and the energy supply system. From the life cycle perspective of factories, this work primarily aims to improve the planning practices during the modernization (e.g., redesign, revitalization, expansion, renovation, or restructuring) of existing (brownfield) factories with regard to their energy consumption. However, certain aspects of the methodology should also prove to be useful during the planning of new (greenfield) factories. The results are intended to support the decision-making process considering energy-related planning goals with the aim of optimizing the overall system rather than individual subsystems. To investigate the interdependencies of networked factory environments, simulation modeling is used to characterize the energy demand of a factory. The evaluation will examine the impact of energy efficiency and flexibility measures together with the use of renewable energies. The objective function in this work is holistic in that it considers non-energy benefits in addition to the conventional performance metrics energy demand, energy costs, and CO_2 emissions. The main application focus of the developed methodology is on discrete parts manufacturing. However, individual findings can also prove useful in the process industry.

The central aim of this thesis is to develop a methodology that supports the user during the modernization of factories, aiming at the improvement of several energy-related performance metrics. The central aim of this work can be summarized as follows:

Central aim

Develop a consistent simulation approach to help manufacturing companies in simultaneously evaluating multiple, energy-related performance metrics during the planning of a factory modernization.

1.3 Research Design and Structure of the Thesis

With reference to Popper's critical rationalism, science aims to explain reality through causal relations while searching for the most universally valid theories (Dyllick and Tomczak 2009, p. 67 f.). In contrast to fundamental science and research, which is "mainly concerned with generalizations and the formulation of a theory", this thesis classifies as applied research (Kothari 2004, p. 3). According to the definition by Ulrich (2001, p. 71) and OECD (2015, p. 29), applied research is "directed primarily towards a specific, practical aim or objective", while aiming for relevant and applicable solutions to pressing practical problems. Generally, the discovering of new scientific knowledge in the field of applied research "has specific commercial objectives with respect to products, processes, or services" (National Research Council 2005, p. 47).

From a philosophy of science perspective, the way to progress scientific knowledge in natural science and applied research is deeply routed in the research philosophy of positivism and the work of John Stuart Mill (Schülein and Reitze 2021, pp. 112-115, Mill 1843). From a positivism point of view, objective truth needs to be based on empirical evidence (Park et al. 2020, p. 690 f.). Generalizable theories and models can only be derived from observations, measurements, and experiments using quantitive methods (Fox 2008, p. 660). Critics of positivism argue that this perspective underestimates the influence of the researcher's theories, hypotheses, background knowledge, and values on what is observed (Robson and McCartan 2016, p. 22). Objectivity has always been the author's highest priority. However, with respect to these critics, the author cannot rule out the possibility that his own involvement biased the results of this research. With reference to Kubicek (1977, p. 5 f.), the heuristic frame of reference of this work is the author's background knowledge and experience as a scientist and consultant in the field of energy efficiency and factory planning. The research question of this work was motivated by practical problems encountered in manufacturing companies. The central aim was derived from the unavailability of ready-to-use methodologies to solve decision problems concerning the adoption of energy-related improvement measures and the development of related energy system designs.

In consequence, this work is more in line with the research philosophy referred to as critical rationalism and the work of Karl Popper (Popper 1935). In this research, the author questions diverse aspects of existing theories related to the assessment of energy use in factories. However, the proposed extension of existing methodologies does not claim to be universally valid. On the contrary, and following the falsification principle of Popper, the author hopes to motivate other researchers to examine and potentially falsify the presented results (Popper 1969, p. 216 f., Chalmers 2001, p. 52). With reference to the concept of Thomas Kuhn, it will remain for the scientific community to decide whether this work is able to contribute to a paradigm shift in the assessment of energy use in factories (Schülein and Reitze 2021, p. 168 f., Kuhn 1970). Finally, the author wants to make reference to Paul Feyerabend, who strongly opposed any dogmatism in the way science is conducted. From his perspective, "anything goes" (Feyerabend 1975, p. 19).

This thesis follows the research design outlined in Figure 1-5. The inner and outer loops illustrate the continuous refinement of the research objective and research demand based on the practical problems identified in manufacturing companies. The starting point is the definition of the subject domain, which in this thesis is energy use in manufacturing systems. The underlying research disciplines include systems theory, manufacturing, thermodynamics, modeling, and simulation.

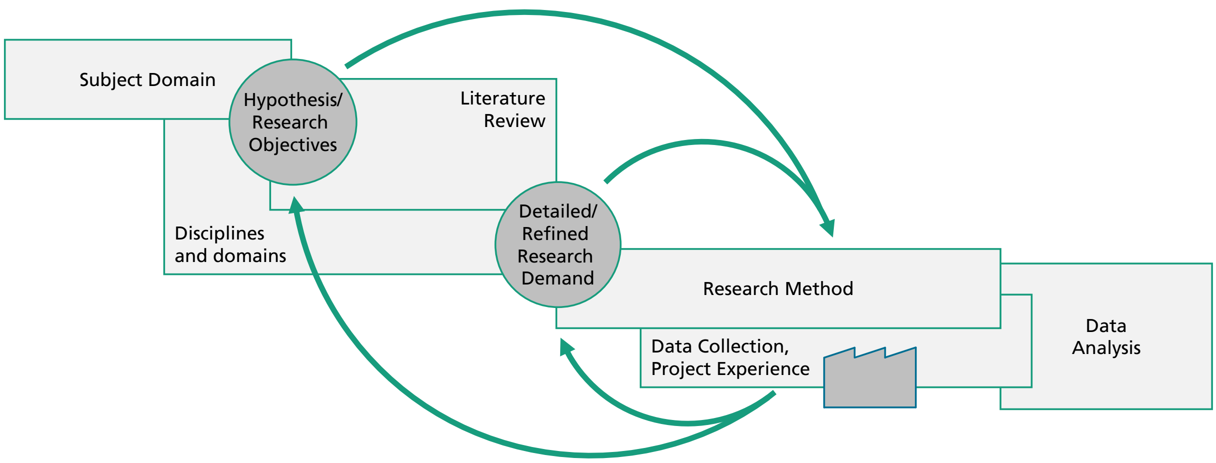


Figure 1-5 Research design (own representation adopted from Dekkers 2015, p. 4)

The research objective of this work follows the central aim introduced in Section 1.2. A literature review will be conducted to specify and detail the research needs. Although they are not considered rigid or distinct categories, one can generally distinguish between qualitative, quantitative, and mixed-methods research approaches (Creswell 2017, p. 3). This study takes a quantitative approach. The research method for data collection is based on measurements in the field. Data on factories in general and energy demand, in particular, are obtained through measurement campaigns in production plants. The collected data will be used for parameterization, verification, and validation of the developed factory model, including associated submodels. Statistical methods are used to analyze and interpret the measurement data and the simulation results. Following the outlined research design, this work is divided into a total of eight chapters. The following section provides a brief introduction to the content of each chapter. Chapter 1 introduces the subject domain and classifies its importance in a societal context. Chapter 2 provides the theoretical foundations relevant to the development of the methodology in the thesis. This includes general terms and definitions for factories, their energy use, modeling, simulation, and design of experiments. Chapter 3 gives an overview of the state of science and specifies the research demand. Chapter 4 derives the requirements for methodology development from the shortcomings of existing work. The chapter also specifies the scope of research and outlines its limitations. Chapter 5 presents the development of the methodology for a simulation-based assessment of energy use in factories. The development consists of three parts, namely the development of extended energy performance metrics, the development of an assessment procedure, and the development of the factory simulation model. Chapter 6 demonstrates the application of the developed methodology in a case study conducted in the aerospace composites industry. Chapter 7 evaluates the development methodology against the requirements established in Chapter 4 and with reference to the case study in Chapter 6. Chapter 8 summarizes the entire thesis. This chapter also provides an outlook on future research needs regarding the findings and shortcomings of this work. Figure 1-1 graphically summarizes the structure of this work.

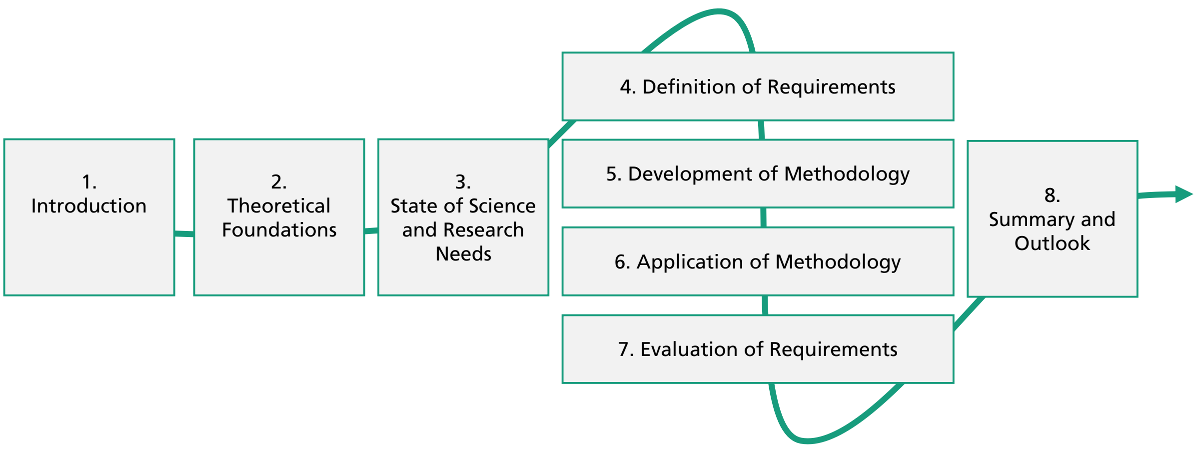


Figure 1-6 Structure and outline of this thesis

2 Theoretical Foundations

This chapter presents the basic principles and theoretical foundations on which this work is based. Section 2.1 defines the system considered in this thesis, factories, and also provides definitions for production and manufacturing systems. Section 2.2 provides an overview of available methods and tools that have proven useful in assessing energy use in factories. This is followed by a brief introduction to the available modeling and simulation techniques used in energy-related studies (Section 2.3). Then, a background on the design of simulation experiments is given in Section 2.4. Section 2.5 summarizes Chapter 2 and concludes with preliminary findings.

2.1 Introduction of Factories

2.1.1 Terms and definitions

Schenk and Wirth (2004, p. 7) define the factory as a "place of innovative, creative, and efficient value creation of industrial goods". VDI 5200 (p. 3) expands this definition and describes a factory as a "place where value is created by the manufacture of industrial goods based on a division of labor while utilizing production factors." Generally,

> "in a factory, manufacturing processes are assembled together to form a manufacturing system (MS) to produce a desired set of goods. The manufacturing system takes specific inputs, adds value, and transforms the inputs into products for the customer. It is important to distinguish between the production system which includes the manufacturing system and services it." (Black 2000)

Different definitions of production systems can be found in the literature. From a general point of view, Heinen et al. (2008, p. 20) define a production system as "a socio-technical system that transforms inputs (e.g., know-how, methods, materials, financial resources, energy) in value-adding (e.g., manufacturing or assembly) and associated processes (e.g., transportation) into outputs (e.g., products, costs, residual materials)." According to Schenk et al. (2014, p. 817), the production system comprises the "implementation of the production process, taking into account production preparation and manufacturing systems (parts manufacturing and assembly systems), including organization, personnel, and the respective corporate culture." From an organizational point of view, production systems include all business processes related to the manufacturing of products (e.g., Mercedes-Benz, Toyota production system) (Ohno 1988, Ohno 1993).

Factories only exist because there is a need to satisfy individual customer demands for manufactured products. With the definitions introduced in this subsection, a hierarchy can be set up according to Schenk et al. (2014, p. 48 f.). Customer demand is the trigger for product design, which affects the selection of the manufacturing processes, their composition as a manufacturing system, and their placement within a factory.

From a technical point of view, the factory houses the production system and consists of a building and its technical infrastructure. It is considered "a place and space for the provision of services" as well as an architectural expression that respects the surrounding environmental and infrastructural framework (Schenk et al. 2014, p. 49).

2.1.2 Factories from a systems perspective

General systems theory was developed in the 1930s by Ludwig von Bertalanffy. It is now understood as a framework for describing and solving complex problems (Westkämper and Hummel 2009, p. 57). Systems theory can help create a general understanding of factories as either closed or open systems (Wiendahl 1999, p. 7). Viewed from a systems perspective, factories consist of elements with individual characteristics and possibilities for action. The different elements are connected with each other and are functionally related. Some of these interconnected elements can be understood as separate subsystems with hierarchical structures and individual system boundaries embedded in another, larger system (ref. Figure 2-1). An open system is given if a system has relations to its environment. In the case of technical systems, it is generally assumed that the interactions between the various elements of a system outweigh those with the environment (Meyer 1978, p. 123). The elements of a production system are the factors of production, including equipment and other operating resources, materials, energy, and personnel (Müller et al. 2009, p. 37). Factories can also be understood as systems that transform inputs (resources – personnel, information, energy, material) into desired and undesired outputs (products, rejects, energy, and material emissions), influenced by controllable and uncontrollable factors. (Dyckhoff and Spengler 2010, pp. 4, 7, Schultz 2002, p. 43).

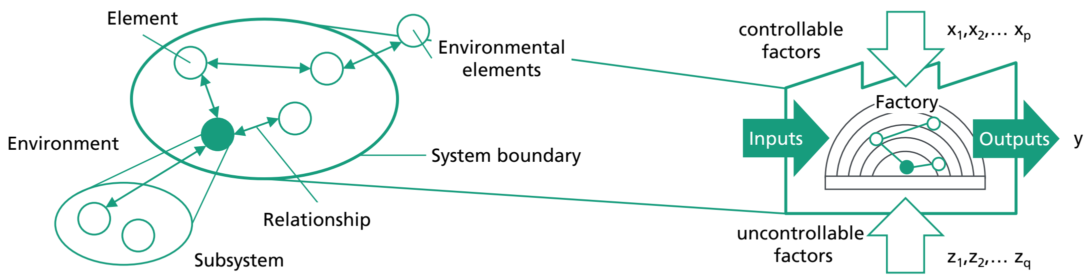


Figure 2-1 Left: Elements of a system (own representation based on Westkämper and Hummel 2009, p. 58); right: factory as a system that transforms inputs into outputs under the influence of controllable and uncontrollable factors (own presentation base on Montgomery 2001, p. 2)

Systems theory can also be used to structure problems related to the use of energy in factories. Energy analysis generally aims to gain relevant knowledge about the energy-related system elements of a factory, including their interaction within the system boundaries of a factory as well as their relationship to the environment. Hesselbach et al.

(2008, p. 625) and Hesselbach (2012, p. 15) introduced production machinery, technical building systems, and the building envelope as hierarchical categories to cluster and allocate the system elements of a factory that determine its energy demand. The authors have applied Wirth peripheral factory model shown in Figure 2-2 to the energy context. Further developments of the peripheral factory model can be found in Herrmann et al. (2014, p. 285), Posselt et al. (2014, p. 81), and Weeber et al. (2017, p. 436). These authors distributed the various energy consumers of a factory over an increased number of peripherals.

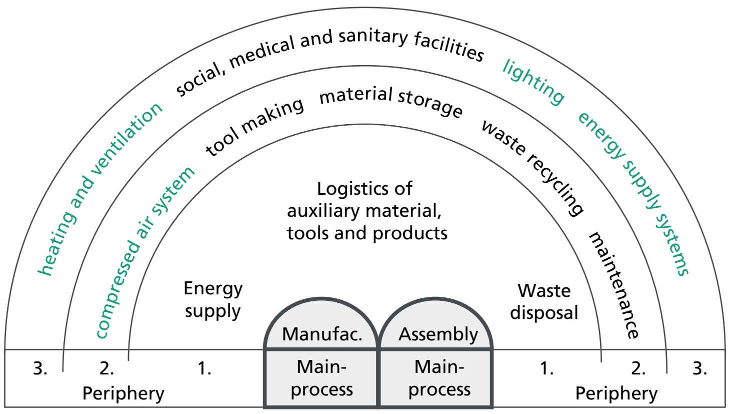


Figure 2-2 Peripheral factory model (own representation based on Wirth 1990, p. 25, Schenk and Wirth 2004, p. 94, Schenk et al. 2014, p. 137, and Haag 2013, p. 21)

2.1.3 Factories from a life cycle perspective

In addition to understanding the different elements of a factory system and their relationships, it is also important to consider temporal aspects when assessing and improving energy consumption in factories across the different life cycle phases. With reference to Figure 2-3, the life cycle of a factory as a plant is much longer compared to the life cycle of a product or manufacturing process. This means that while products and associated manufacturing processes are frequently changed over, factory buildings can house multiple generations of products and processes.

Changing long-term framework conditions (e.g., new technological developments, market trends, political and legal requirements, and sociocultural values) or short-term objectives (e.g., sales volumes, cost development, liquidity, or customer satisfaction) can require the modification and adaptation of existing production systems. Dyckhoff and Spengler (2010, p. 30) differentiate between strategic (approx. five years), tactical (approx. one to five years), and operational (up to one year) planning horizons. The tasks of production management at the strategic level include the selection of production sites or the development of existing factory sites with regard to new climate protection regulations. On a tactical level, tasks include layout planning or technology management. At the operational level, this involves short-term production planning and control or material requirements planning.

The time horizon of investments in the structure of a factory building and the associated technical infrastructure varies greatly. However, they are generally considered to be long-term. Consequently, the possibilities of making changes to existing factory setups depend heavily on the remaining useful life of the various elements. This is particularly true where the changes require substantial investments. In general, designing new factories in a greenfield approach offers more degrees of freedom compared to redesigning, revitalizing, expanding, renovating, or restructuring existing factories in a brownfield approach.

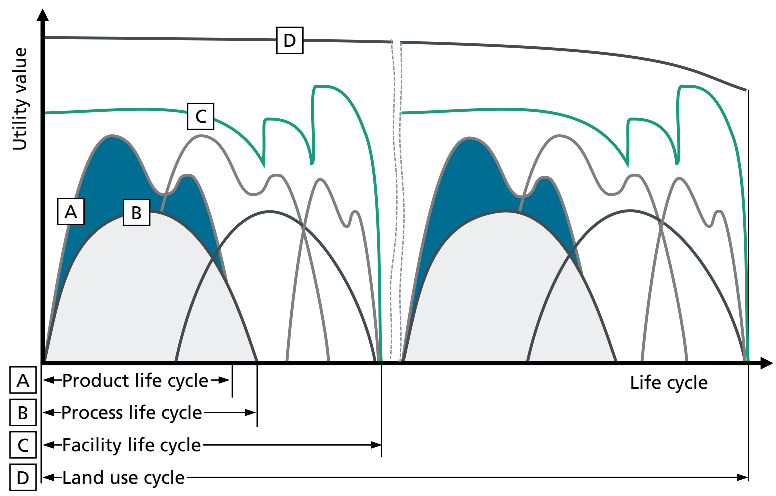


Figure 2-3 Comparison between product process, facility, and land use cycle (own representation based on Wirth et al. 2000)

The left-hand side of Figure 2-4 illustrates the difference between the useful life of primary, secondary, and tertiary structures of a building following the definition of Friedrichs (2000, p. 67). With a special focus on the elements of the secondary structure, the right-hand side of Figure 2-4 uses the depreciation periods described in VDI 2067 (pp. 29-36 Part 1 - Annex A) to illustrate the differences in useful lives for different categories of technical building systems. The box plot in Figure 2-4 shows that equipment used for building automation has the shortest average useful life. In contrast, heat transfer and distribution equipment have the longest average useful life.

Given the long-term perspective of investment in the (infra)structure of a factory, there are only a limited number of opportunities along the life cycle of a factory to implement major changes and realize substantial investments. This also applies to projects that focus on optimizing the energy use of a factory. In order to exploit these opportunities in a way that increases the likelihood of a project being implemented, a structured approach is needed to help demonstrate the economic benefits. This is where factory planning methods can be helpful.

The literature describes several ways to classify a planning process with respect to the factory life cycle phases. For example, Schenk and Wirth (2004, p. 104) distinguish between the factory life cycle phases of planning, installation, ramp-up, operation, and dismantling or re-utilization. Considering the sequence of factory planning activities, VDI 5200 (p. 8 f.) defined seven planning phases.

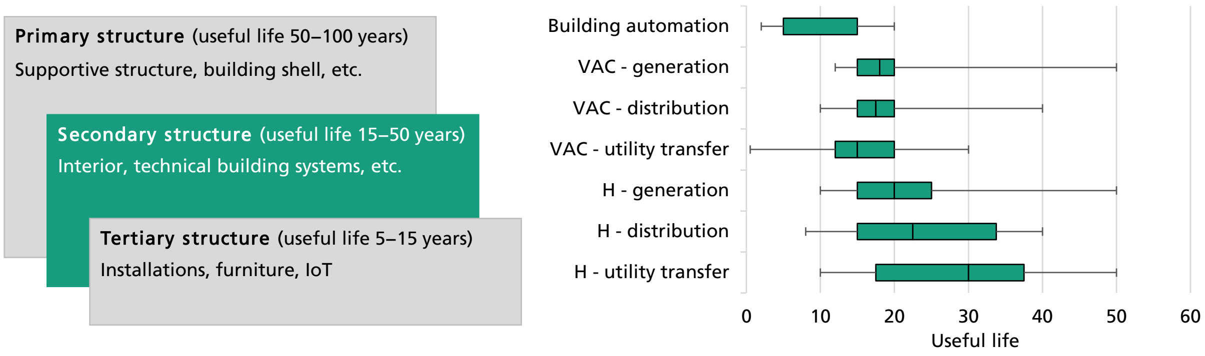


Figure 2-4 Left: Facility structure differentiated according to the useful life of its elements (own presentation based on Friedrichs 2000, p. 67); Right: Depreciation period for elements of the secondary structure of a facility, H – heating, VAC – ventilation, and air-conditioning, and building automation (own representation based on values from VDI 2067, pp. 29-36 Part 1 - Annex A)

The relationship between the phases of the factory life cycle, the factory planning processes and the performance phases of the HOAI ("Honorarordnung für Architekten und Ingenieure") is outlined in Figure 2-5.

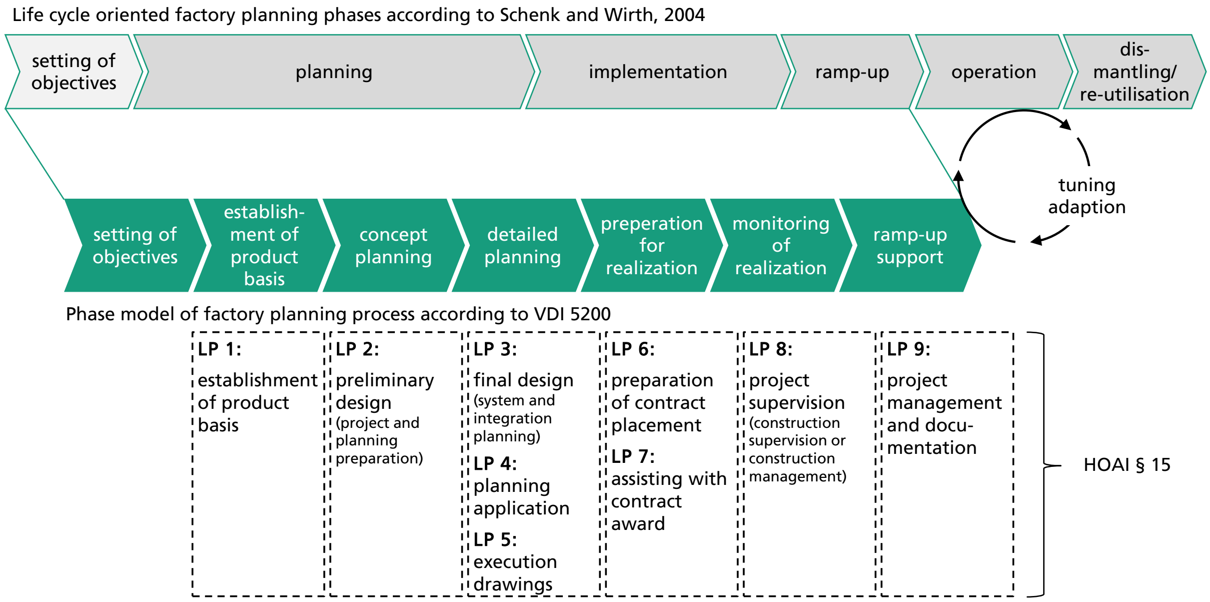


Figure 2-5 The phases of a factory planning process in connection with the life-cycle phases of factory (own representation based on Schenk and Wirth 2004, p. 104, VDI 5200, p. 8 f., Schenk et al. 2014, p. 115)

Given the specific challenges associated with improving environmental competitiveness when redesigning or revitalizing existing factories, Dombrowski and Ernst (2014, p. 338) extended existing factory planning processes and introduced tuning and adoption as an additional life cycle phase. Other motives for tuning and adapting existing factories can be found in the expansion, renovation, or restructuring of existing factory environments.

The long useful life of factory buildings and their technical equipment motivates a thorough planning process that estimates the current and future costs of investment decisions from a life cycle perspective. Figure 2-6 shows the possibility of influencing life cycle costs along the different life cycle phases of a factory. In a greenfield setting, the early life cycle phases related to planning determine a large part of the total life cycle costs. It is found that a life cycle-oriented planning approach is superior to conventional planning approaches and can quickly offset additional costs through savings in the operational and even the dismantling phase of a factory's life cycle.

Figure 2-6 also illustrates the possibility of improving the life cycle performance of factories in a brownfield setting if the available degrees of freedom (black dashed line) are used accordingly. The blue dashed line shows the reduction of future life cycle costs in existing factories as a consequence of improvements measures derived from suitable planning activities. Certainly, the redesign, revitalization, expansion, renovation, or restructuring of existing production sites may require additional investment (red shaded area), but with successful planning and implementation, future savings (green shaded area) can quickly offset this additional investment.

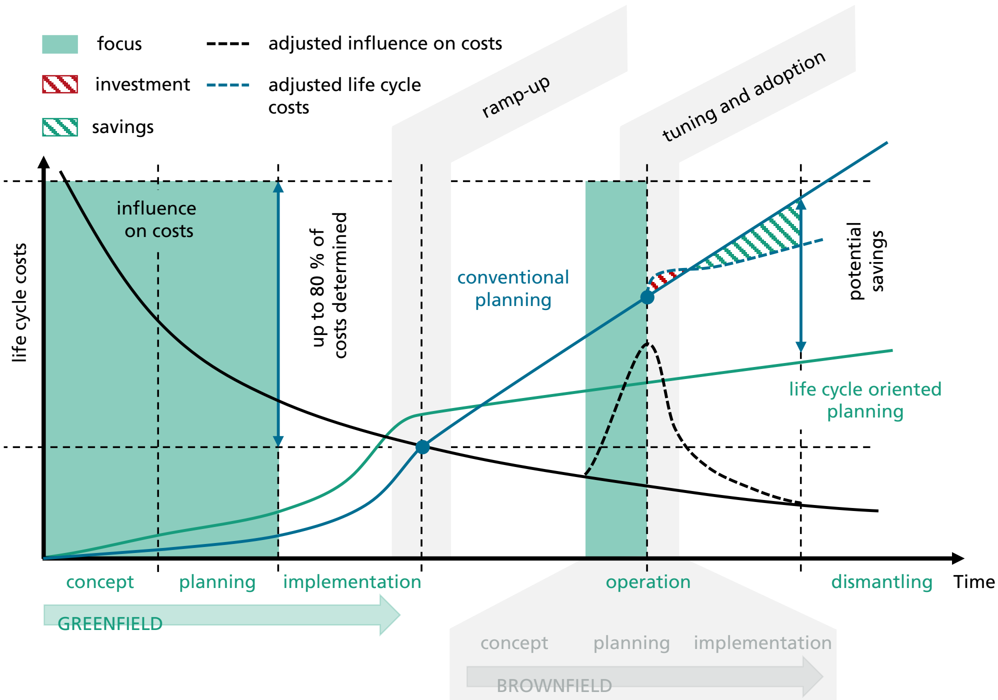


Figure 2-6 Possibility of influencing life cycle costs in different planning tasks (own representation based on BBSR 2011, p. 9)

2.2 Assessment of Energy Use in Factories

2.2.1 Terms and definitions

Thermodynamics and efficiency

Thermodynamics is at the core of understanding the opportunities and limitations of energy efficiency efforts. The first law of thermodynamics describes the conservation of energy in closed systems, which are ideally isolated from the environment. Although such systems do not exist in nature, one can use this concept to establish energy balances, which means that in a closed thermodynamic system, the change of internal energy ΔU is equal to the sum of energies $\sum_i E_i$, heat δQ, or work δW, extracted from or performed by the system (ref. Equation 2-1).

$$\Delta U = \sum_i E_i = \delta Q + \delta W \tag{2-1}$$

However, a production system is considered an open system in which inputs (e.g., materials and energy) enter the system boundaries, either to be transformed or not, before they leave the system as outputs (e.g., products) or remain in it. According to Gößling-Reisemann (2011, p. 266), the difference between the use and consumption of material or energy within a system is that in the latter, the quantity or quality must change as it flows through the system. In contrast, the term 'use' has a broader meaning. For the production of a product, e.g., material and energy are used. Losses (e.g., waste heat, production waste) are inherent to technical systems and require consideration on the basis of the second law of thermodynamics. The second law describes the irreversibility of thermodynamic processes. The difference between the consideration of the first and second law is illustrated in Figure 2-7.

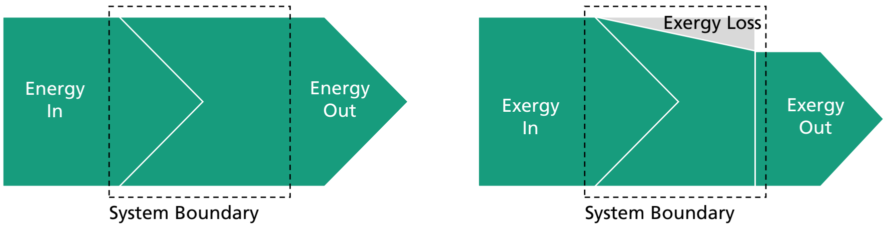


Figure 2-7 Comparison of Sankey (energy flow) and Grassmann (exergy flow) (adapted from Bakshi et al. 2011, p. 5)

The entropy of a system can only be constant or increase as long as there is no external work acting on the system. Entropy produced always corresponds to an exergy loss or a reduction of the energy available to do useful work. Entropy is also referred to as the degree of order or quality of energy. Two practical consequences of thermodynamics on the research field of efficiency are that 100% efficiency is impossible. Moreover, energy does not disappear but loses its quality (orderliness) over time (Song 2016, p. 17).

Energy efficiency, energy productivity, energy intensity

The efficiency paradigm intends to "do more with less" and is based on the first law of thermodynamics. "First law" efficiency (η) can be described, according to Equation (2-2), as the quotient of desired energy output to required energy input.

$$\eta = \frac{desired\ energy\ output}{required\ energy\ input} \tag{2-2}$$

Conservation of energy is considered in the first law of efficiency. Optimizations based solely on the efficiency paradigm, however, consider the energy quantities and not energy qualities. Changes in energy quality or irreversibilities can be quantified by the "second law" efficiency. According to Equation (2-3), (ε) can be expressed as the quotient of "first law" efficiency and maximum efficiency of an ideal reversible system, or the actual work required to complete a "task", divided by the minimum work required for a task (Gellings 2009, p. 16 ff.).

$$\varepsilon = \frac{\eta_{actual}}{\eta_{ideal}} = \frac{W_{actual}}{W_{min.\ required}} \tag{2-3}$$

For further definitions of energy efficiency, see Patterson (1996, p. 383 f.) and Phylipsen et al. (1997, p. 717), who describe energy efficiency (EE) in the form of activities or end-use services (e.g., number of products, m² heated area, km driven) divided by the corresponding energy consumption (ref. Equation 2-4). Consequently, the numerator is either an economic or physical indicator instead of heat content or working potential.

$$EE = \frac{activity\ or\ end\ use\ service}{energy\ consumption} \tag{2-4}$$

In addition to the definition of energy efficiency, the term energy productivity is often used synonymously. (EP) generally refers to the quotient of value-added and energy consumption (ref. Equation 2-5). Value-added and energy consumption are generally expressed in monetary units (Reinhart et al. 2010, p. 870). Depending on the approach taken, the value-added in a manufacturing company can be represented by the turnover achieved or the number of products manufactured per unit of time.

$$EP\ [\%] = \frac{value\ added}{energy\ consumption} \tag{2-5}$$

The inverse of energy efficiency is defined as energy intensity (EI) or specific energy consumption (SEC) (ref. Equation (2-6). Energy intensity is referred to as energy consumption per activity or end-use service. If one refers to the activity or end-use service in terms of economic or monetary values, e.g., the gross domestic product (GDP), energy intensity is the commonly used term. If one refers to physical units, e.g., the number of cars produced, the term specific energy consumption is used. (Phylipsen et al. 1997, p. 717)

$$EI/SEC = \frac{energy\ consumption}{activity\ or\ end\ use\ service} \tag{2-6}$$

From a macroeconomic perspective, factory-level energy efficiency ($EE_{Factory}$) is commonly referred to as the net production value in euros divided by primary energy consumption in megawatt-hours during a defined time period (ref. Equation 2-7) (Müller et al. 2009, p. 36).

$$EE_{Factory}\ [€/MWh] = \frac{net\ production\ value}{primary\ energy\ consumption} \tag{2-7}$$

Given the outlined definitions of energy efficiency, energy productivity, energy intensity, and specific energy consumption, it is important to mention that decisions based solely on the efficiency paradigm can be misleading. To this end, Duflou et al. (2012, p. 588) contrast the efficiency paradigm (doing things right) with effectiveness (doing the right things) using the example of a grinding operation. Improving the efficiency of a grinding operation can include the modification of the machine drive or the use of different cutting fluids. In contrast, an effective approach completely rethinks the process plan itself, potentially making the grinding operation obsolete.

Energy flexibility

In addition to the efficiency paradigm, the ability of a production system to use energy in a flexible manner has become an additional target dimension for improving energy use in factories. This is due to the crucial role of industrial energy demand within energy systems that include a growing share of fluctuating renewable energy sources. As part of a general strategy called demand-side management (DSM), energy flexibility in the context of production systems can be defined as their "ability (…) to adapt itself fast and without remarkable costs to changes in energy markets" (Graßl et al. 2014, p. 303). In general, there are three ways to provide energy flexibility, including augmenting, reducing, or shifting energy demand (Eisenhauer et al. 2018, p. 4). In today's energy market design, monetary benefits from energy flexibility can be achieved either through participation in the intraday, day-ahead, or futures market (Häfner 2018, S. 632). Access to these flexibility markets is usually restricted and requires a prequalification process (Leutgöb et al. 2019, p. 238). However, new time-of-use tariffs and associated payment models are continuously being tested and introduced around the world (IRENA 2019, p. 6 f.).

In the literature, there is still no uniform definition of energy flexibility as an energy-related key performance indicator in factories. However, at an aggregated level, the maximum flexible energy supply ($\Delta E_{flex,year}$) of a system during a one-year period, according to Equation (2-8) can be described as the sum of n individual energy flexibilities, each with a specific flexible load $\Delta P_{flex,n}(t)$ and duration $\Delta t_{total,n}$, where the flexible load is the difference between the current flexible load and a reference load without considering a flexibility corridor (ref. Equation 2-9) (Sauer et al. 2019, pp. 85, 103 f.). The duration of individual energy flexibility is composed of activation, duration, and deactivation times (ref. Equation 2-10).

Referring to the energy efficiency indicators introduced in this section, the author proposes a factory level energy flexibility indicator ($EF_{Factory}$) according to Equation (2-11) as the quotient of maximum flexible energy supplied by a factory during one year divided by the total energy demand of a factory during the same period.

$$\Delta E_{flex,year} = \sum_{i=1}^{n} \Delta P_{flex,n}(t) \cdot \Delta t_{total,n} \tag{2-8}$$

$$\Delta P_{flex}(t) = P_{flex}(t) - P_{ref}(t) \tag{2-9}$$

$$\Delta t_{total} = \Delta t_{activation} + \Delta t_{duration} + \Delta t_{deactivation} \tag{2-10}$$

$$EF_{factory}\ [\%] = \frac{\Delta E_{flex,year}}{E_{total}} \tag{2-11}$$

From primary energy to energy services

In order to provide a consistent description of energy use within a factory system, this section further specifies and presents the different forms of energy as well as conversion path (ref. Figure 2-8). The following definitions are based on Pehnt (2010, p. 7 f.) and VDI 4608 (p. 13 f.). **Primary energy** is defined as the energy content in primary energy carriers before conversion, for example, in combustion processes. Primary energy carriers can be either coal, crude oil, and gas or renewable energy sources such as solar radiation, geothermal energy, or wind (Pehnt 2010, p. 7). **Secondary energy** is generated when primary energy carriers are converted into refined products, e.g., gasoline or natural gas from crude oil or gas. Secondary energy also includes forms of energy that are provided by regional or national energy suppliers. Secondary energies therefore also include electricity, local and district heating or cooling networks. **Final energy** defines the stage after the secondary energy carriers have been delivered to a consumer or end-user and before they are converted into useful energy. Examples include electricity, natural gas, and oil. **Useful energy** includes all forms of energy ultimately required by the consumer. Examples are "heat, mechanical energy, light, electric and magnetic field energy (…) and electromagnetic radiation – in order to be able to perform energy services" (VDI 4608, p. 14). **Energy services** are

> "the requirements satisfied by or the goods produced from the use of useful energy and other production factors. Examples include lighting areas and spaces, movement and transportation, heating and cooling materials and goods, physical and chemical conversion of materials, forming of materials, and many more besides" (VDI 4608, p. 14).

The author further distinguishes between useful energy, which is used to provide intermediate energy carriers (e.g., cold, warm, or compressed media) and useful energy to provide energy services within directly value-adding tasks. On the way from primary energy to energy services, the various forms of energy are subject to losses on their way from storage, distribution, and conversion to delivery. The symbols used to describe this cascade are inspired by Schenk et al. (2014, p. 125), who describe processes within factory systems through the essential functions of conversion, transportation, and storage. Figure 2-8 summarizes the terms and specifies their application within factory systems.

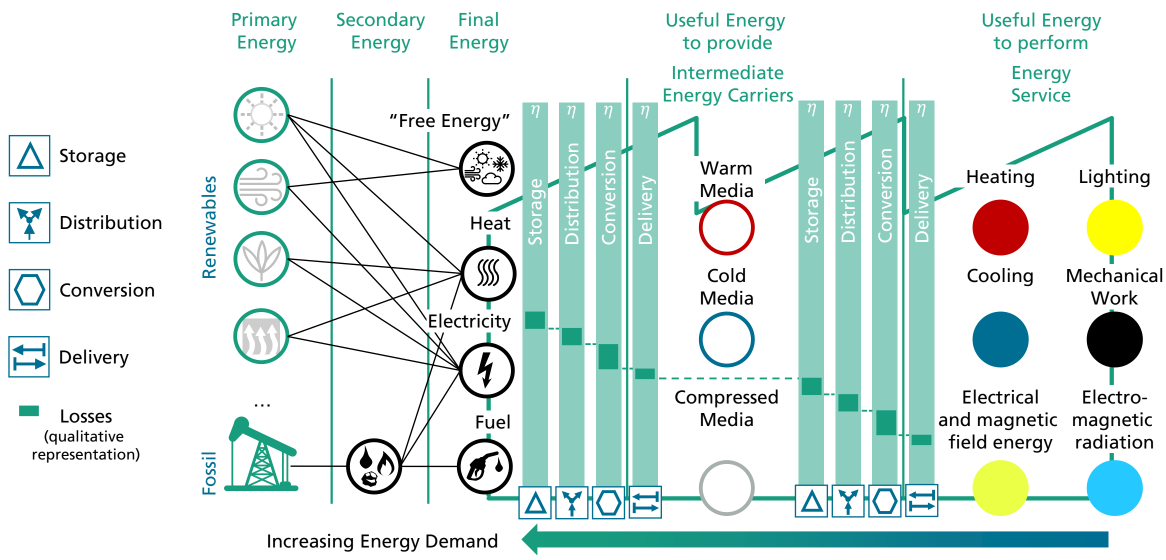


Figure 2-8 Conversion path from primary energy to energy services (based on Weeber and Sauer 2018, p. 822)

2.2.2 Quantification of energy demand

In the planning and assessment of factory environments, the value stream method with its extensions to energy and energy flexibility is a well-recognized approach to detect "energy waste" and to identify improvement measures. The general concept of the value stream method can be found in Erlach (2013, pp. 37-82). The adoption of the value stream method to include energy and other resources is discussed in more detail in Erlach (2009, pp. 23-26), Reinhart et al. (2010, pp. 871-873), Reinhart et al. (2011, pp. 253-255), Posselt et al. (2014, pp. 82-84), and Cosgrove et al. (2017, pp. 214-219). Further enhancements include, e.g., the consideration of CO_2 emissions and energy flexibility (Erlach and Sheehan 2014, pp. 655-657, Feder et al. 2015, pp. 313-315). Faulkner and Badurdeen (2014, pp. 10-14) took an even broader perspective. They developed Sustainable Value Stream Mapping (Sus-VSM) as an approach to evaluate and visualize the performance of manufacturing systems considering holistic performance metrics. The metrics are divided into environmental metrics, including process, raw material consumption, water, and energy consumption, and social metrics, including physical working and working environment conditions. Figure 2-9 summarizes the key elements of an energy value stream. The process blocks serve, among others, to collect information about operating time, process quantity, and cycle time.

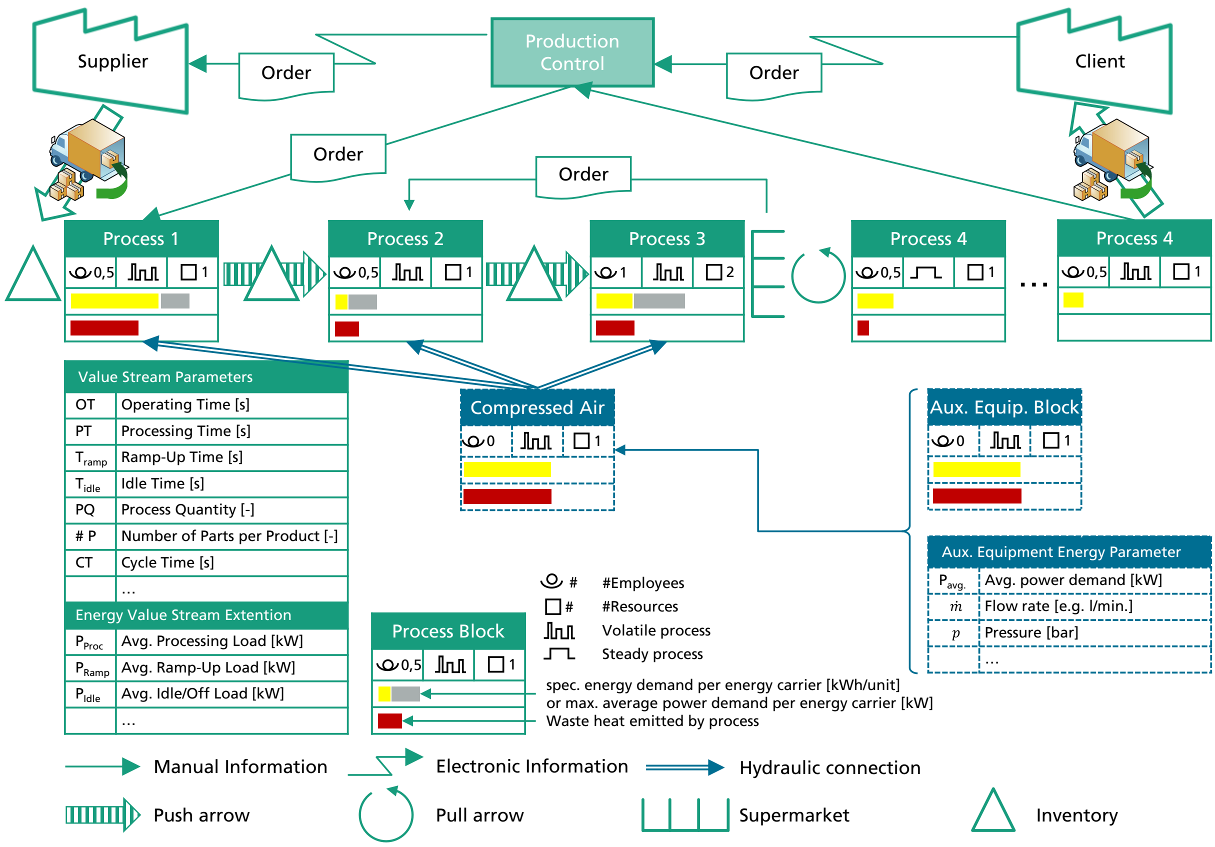


Figure 2-9 Value stream (own representation based on Erlach 2009, p. 80 f., Reinhart et al. 2011, p. 255)

The value stream in Figure 2-9 contains further information on the specific energy consumption per unit and energy carrier (e.g., electricity, compressed air), including the average power demand for different operating states (e.g., ramp-up, processing, idle, and stand-by). Extensions of the value stream also include blocks representing energy use in auxiliary equipment associated with the process, such as compressed air, cooling, or heating systems. The parameters monitored in these blocks typically include average power consumption, flow rates, and pressure levels but can be adjusted depending on the requirements of the evaluation.

Given the continuous improvement and adoption of the value stream method, it can be considered as a flexible tool with a wide range of useful applications that help in industrial practice. However, increasingly complex energy performance metrics require further improvements of the method, in particular, to enable continuous data collection and processing. However, the lack of value stream-oriented measurement concepts still limits the scope of analysis and optimization approaches that focus on energy use.

The usefulness of the energy value stream method depends heavily on the quality of the available and supplemented data. Therefore, the following section briefly introduces the underlying physical principles for measuring energy consumption in a manufacturing environment. The overview focuses on power and energy measurements in electric circuits and pipe-bound fluid flows due to their relevance in field applications.

Measurement of power and energy in single-phase electric circuits

Energy is the integral of power over time (ref. Equation 2-12). Given Ohm's law (Equation 2-13), the power in a single-phase circuit is the product of voltage and current (Steffen and Bausch 2007, p. 53).

$$W = \int_{t_1}^{t_2} P(t) \cdot dt \qquad (2\text{-}12)$$

$$P = \frac{1}{T} \cdot \int_{0}^{T} u(t) \cdot i(t)\, dt \qquad (2\text{-}13)$$

$W\ [Ws]$	Electrical work/energy
$p(t)$	Current power
T	Period

In direct current (DC) circuits, the power dissipated in a load can be determined by measuring the current flowing through and the voltage drop across the load. In an alternating current (AC) circuit with sinusoidal currents and voltages, a distinction must be made between apparent power S, real power P, and reactive power Q when measuring power. The relationship between apparent, real, and reactive power is described by the formula in Equation (2-14). The fraction of power that, averaged over a complete cycle of the AC waveform, results in a net transfer of energy in one direction is known as real power – Equations (2-15) with (2-17) and (2-18). Real power is the part of the power in an AC system that is converted into non-electrical (e.g., mechanical or thermal) forms of energy (Lerch 2007, p. 206). The portion of power that returns to the source in each cycle due to capacitive or inductive components in the circuit is known as reactive power (ref. Equation (2-16).

$$S^2 = P^2 \cdot Q^2 \tag{2-14}$$

$$P = U_{eff} \cdot I_{eff} \cdot cos\varphi \tag{2-15}$$

$$Q = U_{eff} \cdot I_{eff} \cdot sin\varphi \tag{2-16}$$

$$U_{eff} = \sqrt{\frac{1}{T} \cdot \int_0^T u^2(t)dt} \tag{2-17}$$

$$I_{eff} = \sqrt{\frac{1}{T} \cdot \int_0^T i^2(t)dt} \tag{2-18}$$

$S\ [VA]$	Apparent power
$P\ [W]$	Real power
$Q\ [var]$	Reactive power
$U_{eff}\ and I_{eff}$	Effective values of voltage and current
$cos\varphi$	Power factor with φ (angle between current and voltage)
T	Period

When evaluating energy use, the active power is measured. Although only the active power contributes useful work to a load, the components of an electrical power system must be sized with respect to the amount of apparent power. High reactive power components require power correction installations to avoid voltage dips and other failures in the circuit (Kasikci 2018, pp. 292-232).

In AC circuits, current and voltage are expressed by the root mean square (RMS) or effective values I_{eff} and U_{eff} (ref. Equations 2-17 and 2-18). When $U = U_{eff}$, the same power is dissipated in circuits with resistive loads for DC and AC configurations (Lerch 2007, p. 145). The power factor $cos\varphi$ describes the phase angle between effective current and voltage. Table 2-1 summarizes the relevant physical relationships for power measurement in single-phase circuits for both AC and DC systems.

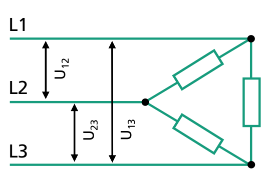
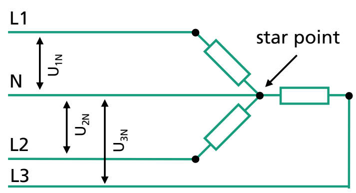
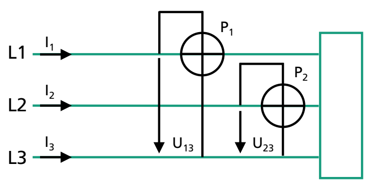
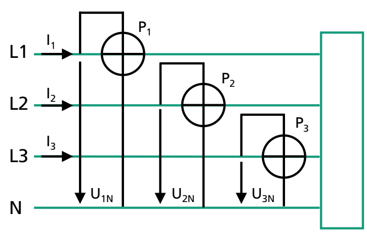
Table 2-1 Formula for power in DC and AC single-phase electric systems

		Direct Current (DC)	Alternating Current (AC)
Power	$P\ [W]$	$P = U \cdot I$	
Real Power	$P\ [W]$		$P = U_{eff} \cdot I_{eff} \cdot cos\varphi$
Reactive Power	$Q\ [var]$		$Q = U_{eff} \cdot I_{eff} \cdot sin\varphi$
Apparent Power	$S\ [VA]$		$S = U_{eff} \cdot I_{eff}$

Measurement of real power in multiphase electric circuits

A common application scenario is the measurement of electrical power demand in three or four-phase circuits with symmetrical or asymmetrical loads. The different measurement setups and calculation methods are shown in Table 2-2.

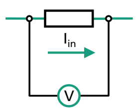
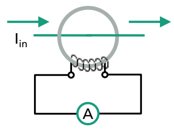
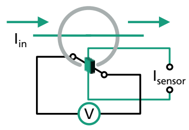
Table 2-2 Power measurement setups for multiphase electrical systems

Three-conductor system	Four-conductor system
	
Symmetrical loading	**Symmetrical loading**
$U_{12} + U_{23} + U_{31} = 0$ u. $U_{line} = \sqrt{3} \cdot U_{phase}$	$U_{1N} = U_{2N} = U_{3N} = U$
$I_1 = I_2 = I_3 = I$	$I_1 + I_2 + I_3 = I_N = 0$
$\cos\varphi_1 = \cos\varphi_2 = \cos\varphi_3 = \cos\varphi$	$\cos\varphi_1 = \cos\varphi_2 = \cos\varphi_3 = \cos\varphi$
$\boldsymbol{P = 3 \cdot P_{phase} = 3 \cdot \sqrt{3} \cdot U_{12} \cdot I_1 \cdot \cos\varphi}$	$\boldsymbol{P = 3 \cdot P_{phase} = 3 \cdot U_{1N} \cdot I_1 \cdot \cos\varphi}$
Asymmetrical loading	**Asymmetrical loading**
Aron circuit 	
$I_1 + I_2 + I_3 = 0$	$I_1 + I_2 + I_3 = I_N$
$P = P_1 + P_2$	$P = P_1 + P_2 + P_3$
$\boldsymbol{P = U_{13} \cdot I_1 \cdot \cos(\sphericalangle U_{13}, I_1)}$ $\boldsymbol{+ U_{23} \cdot I_2 \cdot \cos(\sphericalangle U_{23}, I_2)}$	$\boldsymbol{P = U_{1N} \cdot I_1 \cdot \cos(\sphericalangle U_{1N}, I_1)}$ $\boldsymbol{+ U_{2N} \cdot I_2 \cdot \cos(\sphericalangle U_{2N}, I_2)}$ $\boldsymbol{+ U_{3N} \cdot I_3 \cdot \cos(\sphericalangle U_{3N}, I_3)}$

For power measurements in a three-phase or four-phase circuit with symmetrical loads, only one wattmeter is usually required. In a uniformly balanced three- or four-phase circuit, it is sufficient to measure only one phase. In this case, the total electrical power demand is a multiple of the power demand measured on a single conductor.

In the case of unequally balanced phases or asymmetrical loadings, current and voltage must be measured separately for all conductors (Lerch 2007, p. 210). In the specific case of a three-conductor system with an asymmetrical load and no neutral conductor, the total electrical power demand can be quantified using a two-wattmeter method in an Aron-circuit measurement setup (Kories and Schmidt-Walter 2003, p. 186). In contrast to a four-conductor system with symmetrical loads, a current always flows through the neutral conductor – also called the star point – in the case of asymmetrical load conditions (Steffen and Bausch 2007, p. 266). In this case, three wattmeters are needed to measure the power across all three conductors separately (Kories and Schmidt-Walter 2003, p. 185). Wattmeters measure both voltage and current. Depending on the current, sensitivity requirements, and accessibility, the person conducting the measurement can choose between different sensors: shunt resistor, current transformers, and hall sensors. A comparative overview of these different sensors is shown in Table 2-3.

Table 2-3 Sensors for measuring electric current (based on O'Driscoll and O'Donnell 2013, p. 56 f.)

	Shunt resistor	**Current transformer**	**Hall sensor**
Principle of operation			
Installation	in-line	clamp on	clamp on
Method	resistance based	induction based	magnetic field based
Measurand	current	current	current
Advantage	low cost, small size	suitable for high currents	
Limitations	invasive		sensitivity to nearby magnetic fields

The evaluation of energy use in factory environments requires the use of different measurement setups. For example, power measurements at the mains supply of a factory building require a setup for a four-phase circuit with asymmetrical loads. In contrast, symmetric load conditions can be assumed when measuring the energy demand of a single electric motor. In general, for circuits with unspecified loads, a full measurement setup is preferred, which measures each phase individually (Plaßmann and Schulz 2009, p. 766 f.). For further guidance on the measurement of power and energy in electrical circuits, see also Plaßmann and Schulz (2009, p. 754 ff.), Kories and Schmidt-Walter (2003, p. 181 ff.), and Steffen and Bausch (2007, p. 266 ff.). A review on electrical energy metering systems and their use in manufacturing is presented by O'Driscoll and O'Donnell (2013, p. 55 ff.).

Measurement of power and energy of fluid-bound energy carriers

In addition to electrical energy, a large part of energy demand in manufacturing is distributed and supplied via fluid-bound energy carriers. These energy carriers are routed in pipeline systems and require different measurement concepts. In general, the energy transported in fluids can be described according to Equation (2-19), where $\dot{m}$ is the mass flow rate, c_p is the heat capacity of the fluid, and ΔT is the temperature difference between the measurement point (2) and the reference conditions (1). For compressed air systems, the reference conditions are generally ambient temperature and pressure (Fraunhofer ISI 2003, p. 2).

$$P_{fluid} = \dot{m} \cdot c_p \cdot \Delta T = \dot{m}_{fluid} \cdot c_p \cdot (T_{2.fluid} - T_{1.fluid}) \tag{2-19}$$

According to the continuity equation, the mass flow of a fluid through a cross-section $A_{1.i}$ with density $\rho_{1.fluid}$ must be equal to the mass flow through the cross-section $A_{2.i}$ with density $\rho_{2.fluid}$ (ref. Equation 2-20).

$$\dot{m}_{fluid} = const. = \rho_{2.fluid} \cdot \dot{V}_{2.fluid} = \rho_{2.fluid} \cdot A_{2.i} \cdot \bar{v}_{2.i} = \rho_{1.fluid} \cdot A_{1.i} \cdot \bar{v}_{1.i} \tag{2-20}$$

$\bar{v}_i$	Average flow velocity in cross-section area
A_i	Internal cross-section area
$\dot{V}$	Volumetric flow rate

Furthermore, the relationship between the density $\rho_{1.fluid}$ and $\rho_{2.fluid}$ can also be expressed according to the ideal gas law (ref. Equation 2-21).

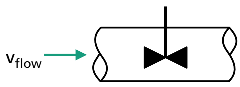
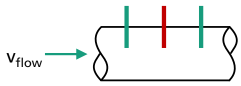
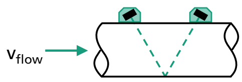
$$p \cdot V = m \cdot R \cdot T \; ; \; p = \rho \cdot R \cdot T \tag{2-21}$$

$$\rho_{1.fluid} = \frac{p_{1.fluid}}{R \cdot T_{1.fluid}} \; ; \; \rho_{2.fluid} = \frac{p_{2.fluid}}{R \cdot T_{2.fluid}} \tag{2-22}$$

R	Ideal gas constant
p	Pressure
T	Temperature difference between supply and return flow

According to Equations (2-19), (2-20), and (2-22), it is necessary to measure the volumetric flow rate, temperature, and pressure to quantify the power and energy transported in a fluid. Table 2-4 summarizes various sensors that can be used to measure the volumetric flow rate in fluids.

Table 2-4 Selection of sensors to measure the volumetric flow rate in fluids

	Impellor anemometer	**Thermal mass flow meter**	**Ultrasonic flowmeter**
Principle of operation			
Installation	in-line	in-line	clamp on
Method	volumetric	calorimetric	ultrasonic
Measurand	flow rate	flow rate	flow rate

An impeller anemometer measures the rotational speed of the impeller, which is proportional to the flow rate of the fluid. The thermal mass flow meter measures the flow rate through convection losses that occur at the surface of the sensor relative to the surrounding fluid. Ultrasonic flow meters transmit ultrasonic waves between a transmitter and a receiver unit through a liquid or gaseous fluid. The flow rate in the fluid deflects the emitted ultrasound waves and causes a transit time difference that is proportional to the flow velocity (Probst and Schnell 1993, p. 207 f.). Compared to the other sensor setups, ultrasonic flowmeters do not directly intervene with the measured fluid. They are installed on the pipe using a clamp-on technique. For further guidance on measurement concepts used to quantify volume and mass flow, see also Probst and Schnell (1993, p. 193 ff.) and Bonfig et al. (2014, p. 793 ff.).

Figure 2-10 shows the installation of various energy metering systems in a milling center with the purpose of quantifying the electricity and compressed air demand of a milling center together with the electricity demand for the operation of the connected cooling lubricant supply unit.

Figure 2-10 Example of an energy metering setup in a milling center. (A) – machine tool, (B) – compressed air flow measurement, (C) – current collectors installed on the main switch of the machine tool, (D) – voltage reference

Figure 2-11 shows the results of the energy metering setup quantifying the energy demand of the milling center (top) and the connected cooling lubricant supply unit (bottom). The setup measures the electrical power demand of the machine tool and the cooling lubricant supply. It also measures the flow rate and pressure requirements for compressed air used in the machine tool.

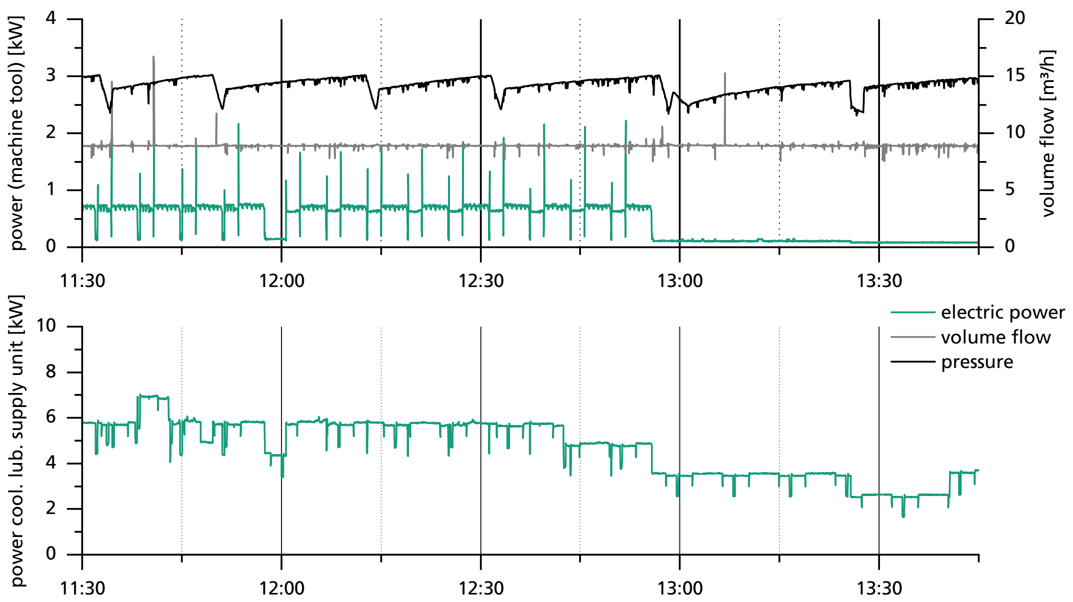


Figure 2-11 Exemplary results of a measurement setup used to quantify the energy demand of a milling center (top) together with the connected cooling lubricant supply unit (bottom)

Allocation of the energy demand to the operating states of a machine

The energy demand of production plants can be divided into constant and variable shares. Depending on the type of manufacturing system and the system boundary considered, the variable shares grow proportionally to increasing production rates.

Figure 2-12 shows how the production rate can affect the constant and variable shares of the energy demand of manufacturing systems in different ways. In the case of a machine tool (Example A), the variable shares can account for up to 65.8% of the total energy demand, while in Example B, the influence of the production rate is limited, and the energy consumption is dominated by baseload consumers with at least 85.2%.

Dietmair and Verl (2009, p. 130) first proposed the consideration of operating states in processes and machine models. The authors distinguished between "machine off", "run-up", "emergency stop", "machine ready", "drives active", "spindle running", "coolant running", "chipping/milling", and "chipping/milling end". Other authors adopted this approach and specified the operating states in more detail. Today, the operating states first classified by Weinert (2010, p. 62) and Weinert et al. (2011, p. 42) "turned-off'', ''start-up'', ''warm-up'', ''stand-by'', ''processing'' or ''stopping" are commonly used terms. The consideration of operating states, including the transition between the states, can already be implemented as a function in the Technomatrix Plant Simulation software environment, which is commonly used to model and simulate production systems.

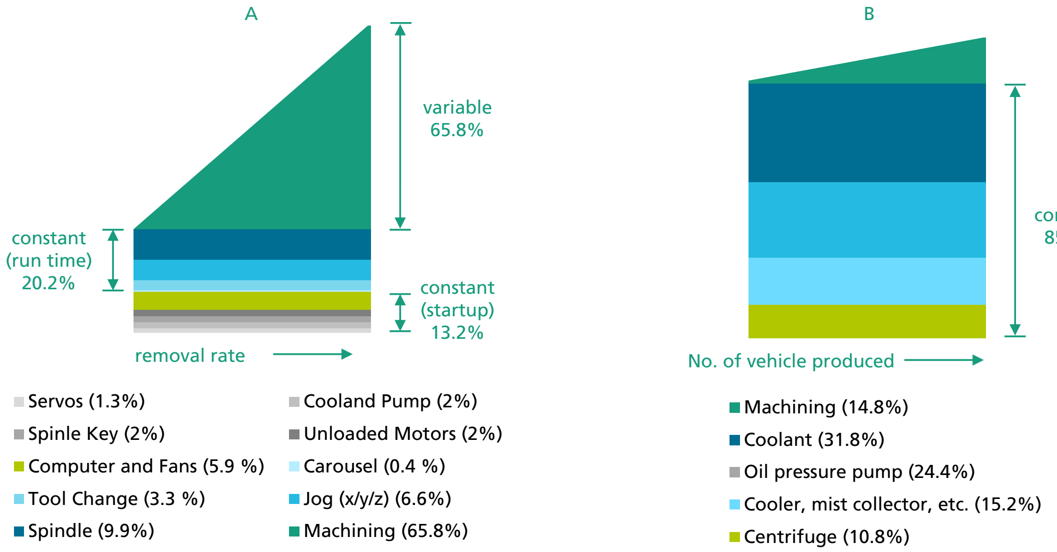


Figure 2-12 Shares of variable and constant energy demand as a function of different production rates for (A) a 3-axis CNC milling machine (Kordonowy 2002, p. 67), (B) machining operations at an automobile manufacturer (Gutowski et al. 2005, p. 4 and Gutowski et al. 2006, p. 2 f.)

Figure 2-13 shows an example analysis of machine operating states.

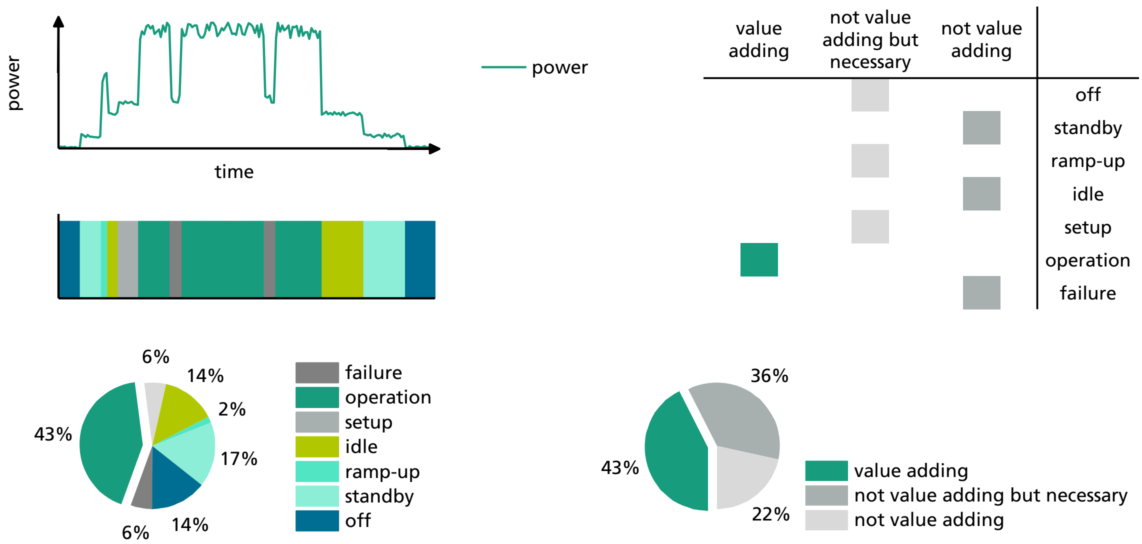


Figure 2-13 Exemplary analysis of the machine operating states

In our example, a total of seven operating states are used to characterize a representative load profile. In addition, the operating states are further differentiated into value-adding, non-value-added but necessary, and non-value-adding operations. This characterization can also be used when more than one input resource is under observation (e.g., electricity and compressed air). The information on characteristic operation states can be derived from measurements in the field and machine operation logs. The values are then used to implement characteristic load profiles in the respective simulation environment.

Slight variations of the operating states have been proposed in the literature depending on the characteristics of the different processes; for example "off", "start-up", "idle", "runtime/ready for machining", "operation" or "idle", "changeover", "ramp-up", "preproduction", "production", "stand-by", "failure" or "off", "on", "ramp up", "idle", "setup", "processing", "blocked" and "failure" (Thiede 2012, p. 21, Mousavi et al. 2016, p. 15 f., Schönemann 2017, p. 82).

Visualization of the energy demand

There are various ways in which energy consumption can be visualized. Conventional visualization techniques include load-curve diagrams that show the power demand of different energy carriers in a time-resolved manner. Sankey diagrams, named after Irish engineer Matthew Henry Phineas Riall Sankey, are suitable means of visualizing energy and material flows in multi-stage energy systems with many transfer and conversion stages.

In addition, heat-map visualization of power measurement data can support the search for anomalies in the energy demand characteristics of a factory system (e.g., peak loads, energy demand during non-working periods). Using the measured data visualized in Figure 2-14, it was possible to identify, for example, the exceptional peak energy demand in the first days of the year.

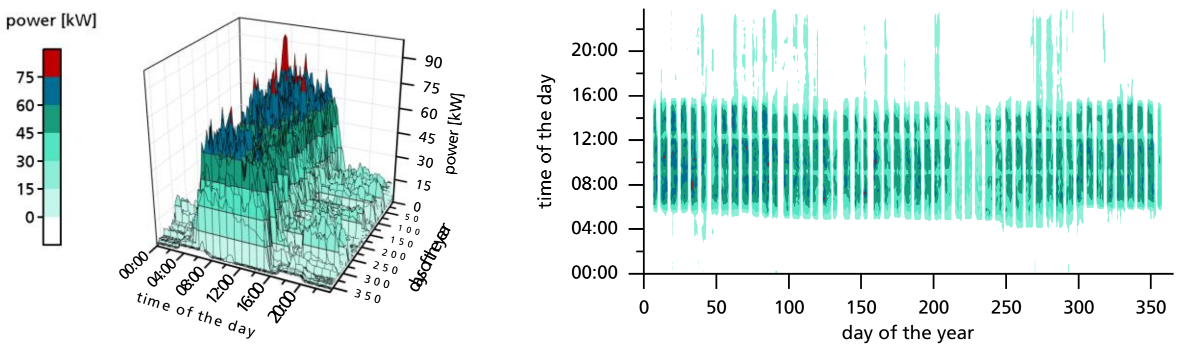


Figure 2-14 3D (left) and 2D (right) "heat map" visualization of power measurement data for a one-year period

2.2.3 Improvement of energy use

Improvement of energy efficiency

The product design triggers the selection of suitable manufacturing processes and their orchestration in a process chain. Auxiliary equipment supplies all the technical media required for the operation of individual machines and entire multi-machine ecosystems. The process chain is enclosed by a factory building envelope, while technical building systems ensure that the manufacturing environment is operated within specified temperature and humidity limits. Various improvement measures enable energy efficiency to be increased at different levels of a manufacturing system, either in an individual or collective manner.

Engelmann identified six generalizable categories for energy efficiency measures at the process/machine level (Engelmann 2009, pp. 93-97). This includes the use of highly efficient machine components (e.g., high-efficiency electric motors), the reduction of energy losses (e.g., compressed air leakage), energy recuperation (e.g., regeneration of braking energy), the substitution of energy carriers, processes, or materials (e.g., warm with cold metal forming), the improvement of equipment dimensioning to reduce the less efficient partial load operation (e.g., oversized process cooling system) and the improvement of machine utilization and its demand-oriented operation through optimized control (e.g., control of extraction systems according to machine operating states). In Kellens (2013, pp. 152-162) and Kellens et al. (2013, pp. 29-32), three main categories are proposed, namely optimized machine tool design, process and machine tool selection, and optimized process control. Furthermore, the authors specified 13 individual measures at the machine level. In addition, further energy efficiency categories have been added, such as the comparison of integrated and central peripherals (e.g., compressed air, cooling lubricant, or cabinet cooling systems).

Several use cases are presented in the scientific literature, which employ simulation in the assessment and improvement of energy efficiency. At the **unit process level**, Dietmair and Verl (2009, pp. 124-126), Abele et al. (2012, p. 234 f.), and He et al. (2012, pp. 168-171) present methods that focus on machine tools. Saidur et al. (2010, p. 1145) analyzed various energy-saving measures for compressed air systems at the **auxiliary equipment level**. The author's analysis also mentions the benefits of a model-based assessment using software tools such as AIRMaster+ and AirSim. Examples of improving the energy efficiency of cooling lubricant systems, including modeling methods, have been given by Brecher et al. (2012, p. 240 f.), Yingjie (2014, pp. 1125, 1128 f.), and Rahäuser (2015, p. 79 ff.). Pohl et al. (2013, p. 139 f.) present a model-based assessment of energy efficiency in compressed air systems and Puls et al. (2019, p. 1876 f.) for industrial cooling systems by the application of free cooling. Herrmann and Thiede (2009, p. 225) extend simulation-based energy efficiency assessments to the level of the **process chain** and **technical building systems.** Their approach aims to identify potential conflicts and trade-offs between different technical and organizational measures in terms of production time, electricity consumption, and electricity costs. Mose and Weinert (2015, p. 45 f.) also extended the system boundaries of an energy efficiency assessment and introduced a process chain assessment method. Instead of optimizing individual processes, their method focuses on improving overall energy efficiency by comparing alternative process chains. The authors presented an exemplary use case for a welding shop. Heinzl et al. (2013, p. 306) and Weeber et al. (2018, p. 338 f.) added further details to their model-based energy assessment, covering both the **building and energy system levels**.

A general procedure model for the assessment of energy efficiency in industry is described in VDI 3922 (p. 6). Thiede et al. (2012, pp. 30-32) and Böhner (2013, pp. 45-53) propose individual methods to assist in prioritizing the most promising areas for action, using either a Pareto analysis or a fuzzy logic approach. Building on the Plan-Do-Act-Check (PDCA) framework of the ISO 50001 energy management standard, Khattak et al. (2018, pp. 5-8) proposed an evaluation strategy that quantifies energy efficiency measures against baseline conditions using a holistic factory simulation. The authors reference their improvement measures to one of six general categories (stop, eliminate, repair, reduce, recover, change).

Improvement of non-energy benefits

Including non-energy benefits in the scope of an assessment may shed a different light on the overall benefits and associated productivity gains of energy efficiency measures (Worrell et al. 2003, p. 1082). There is evidence that non-energy benefits outweigh energy savings in many cases (Pye and McKane 2000, pp. 177-182, Hall and Roth 2003, p. 134). Worrell et al. (2003, p. 1082) identified five broad categories for non-energy benefits: reduced waste, lower emissions, improved maintenance, and operating costs, increased production and product quality, and an improved working environment. These categories were complemented by Nehler (2018, p. 4) and shown in Figure 2-15.

Looking for ways to quantify the real value of energy efficiency measures by integrating non-energy benefits in a management decision process, Rasmussen (2014, p. 738) categorizes non-energy benefits according to their level of quantifiability. However, Nehler and Rasmussen (2016, p. 479) added that the quantifiability of non-energy benefits is not an absolute prerequisite for the successful implementation of energy efficiency measures and that a qualitative approach can also favor the investment decision. An additional challenge in assessing non-energy benefits is that in many cases non-energy benefits cannot be attributed to individual measures, and there are potentially interdependencies between individual non-energy benefits (Nehler 2018, p. 17). When non-energy benefits are measured within the same category, there is a significant risk of double-counting them and thus underestimating the risk of the associated investment (Nehler and Rasmussen 2016, p. 480)

From an extensive literature review, Nehler (2018, p. 18 f.) synthesizes a scheme for the improved use of non-energy benefits in industry. It involves five steps: observation, measurement, quantification, monetization, and evaluation (including impact assessment), and can be used from either an ex-post (pre-implementation) or an ex-ante (post-implementation) perspective. According to the author, the assessment of non-energy benefits requires the combined use of user experience, observation, calculation, and/or estimation methods. In addition, model-based approaches are proposed to improve the transparency of the obtained results. Trianni et al. (2014, pp. 212-218) attributed different non-energy benefits to a wide range of cross-cutting technologies to support the selection process of promising energy efficiency measures.

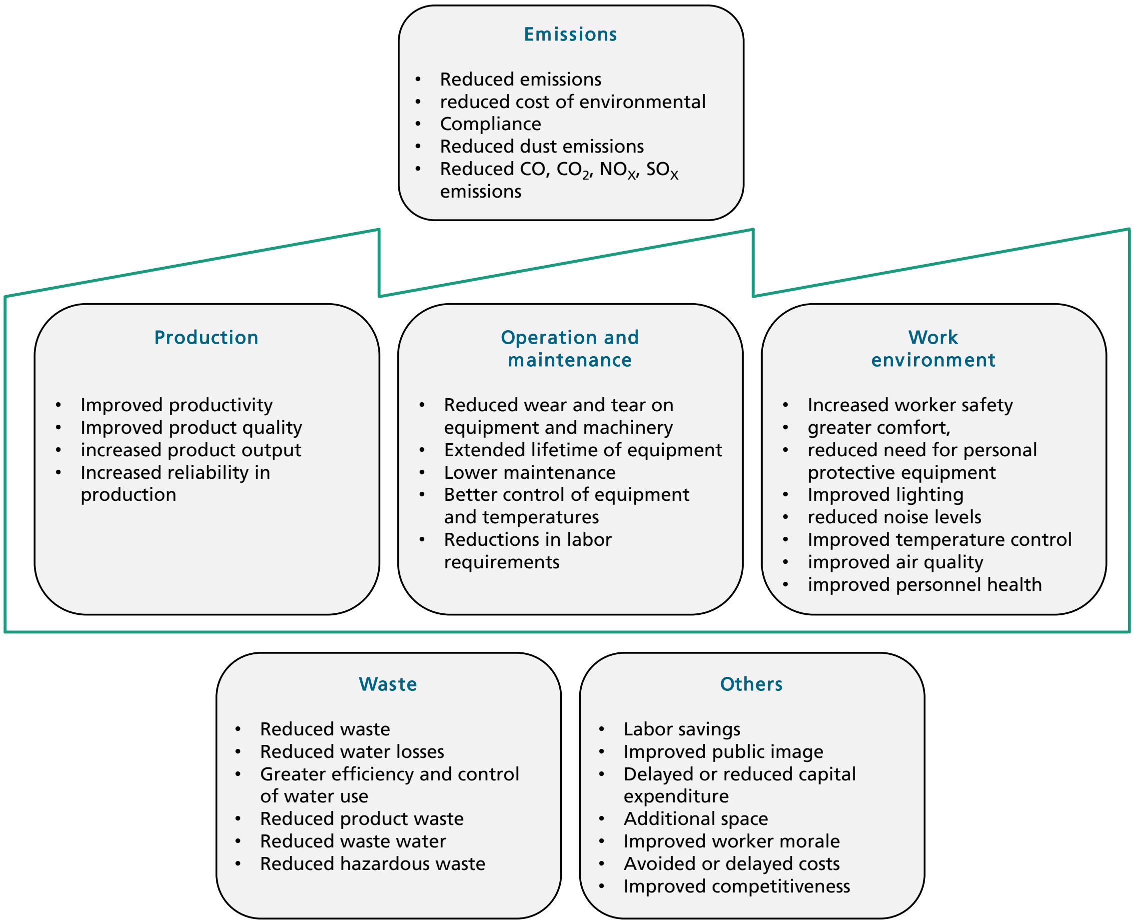


Figure 2-15 Categories of non-energy benefits (own representation based on Nehler 2018, p. 4)

Improving energy flexibility

Graßl and Reinhart (2014, p. 130) introduced a total of nine categories for measures to improve energy flexibility in manufacturing systems (ref. Figure 2-16), including the interruption of processes, the adaptation of staff free time, machine scheduling, order sequence, shift times, process start and process parameters, the changes in energy carrier and the storage of energy.

With minor modifications, Khripko et al. (2018, p. 703) summarized energy flexibility measures in just five categories, namely power-to-battery (flexibility through the use of battery storage), power-to-storage (flexibility through decoupling production and consumption over time by storing energy in converted form), power-to-product (flexibility through indirect energy storage from shifting mostly batch production processes), power-to-system (flexibility through switching between at least two energy sources), and flex-supply (flexibility through the grid-oriented operation of a decentralized energy supply system).

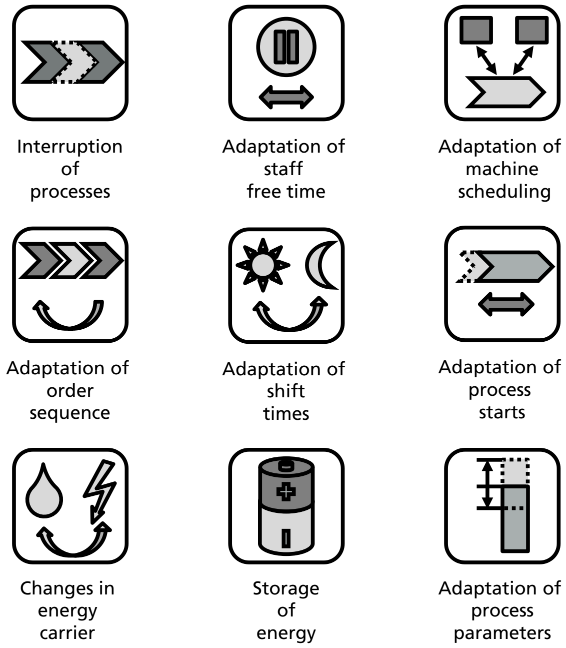


Figure 2-16 Categories for measures to improve energy flexibility (taken from Graßl 2015, p. 59)

Energy flexibility measures can be implemented at different levels of a manufacturing system. Stoldt et al. (2015, p. 448) generally distinguish between the energy supply level, the production level, and the infrastructure level. The following paragraph briefly summarizes the existing simulation modeling approaches that have been developed to improve energy flexibility at different levels of a manufacturing system. Further references on energy flexibility in manufacturing can be found in the literature review by Beier et al. (2017, pp. 649-652), which is organized according to three clusters: 1. planning or real-time approaches, 2. strategic, tactical, and operational time horizons, and 3. single-stage (one process) or multi-stage (process chains) approaches. The search for adequate energy flexibility measures can be supported by the six-step procedure model presented by Graßl (2015, pp. 107-120), which helps with identification and prioritization.

At the **unit process level**, Popp et al. (2017, pp. 79-81) showed that an energy flexible operation of machine tool components can effectively reduce residual loads at the factory level while maintaining machine productivity. Further approaches to increasing energy flexibility at the unit process level can also be found in Graßl et al. (2014, pp. 304-306) and Dietrich et al. (2020, pp. 4-6) using a Petri-net-based and a machine-learning approach, respectively.

In the scientific literature, various approaches are presented to increase energy flexibility at the **process chain level** by means of adaptive planning, scheduling, and control of manufacturing processes. For example, Fang et al. (2011, p. 235 f.) developed a multi-objective mixed-integer linear programming model (MILP) for a flow shop scheduling problem to jointly optimize cycle time and peak load along with total energy consumption and associated carbon dioxide emissions. While they also use a mixed-integer linear programming model, Emec et al. (2013b) developed a model-based method to reduce electrical energy cost by adjusting the production schedule of process chains operating at less than full capacity to spot market prices. This method has also been applied to a use case in the automotive industry (Emec et al. 2013a, p. 3 f.).

Further development includes a load management strategy for manufacturing systems with an on-site combined heat and power (CHP) plant. The authors followed a mixed-integer nonlinear programming approach to formulate the scheduling problem and used particle swarm optimization to reduce operating costs without compromising throughput (Sun et al. 2015, p. 115 f.). By augmenting conventional planning data with energy data, Keller et al. (2016, pp. 754-756) presented an approach to energy-oriented production planning and control that takes lot size, delivery, capacity planning, and machine scheduling into account. With the goal of reducing energy costs, a MILP approach is used to match energy demand and energy availability during lot sizing and capacity planning. In addition, a simulated annealing approach is implied to account for power demand constraints in machine scheduling (Keller 2018, p. 145 f.).

At the level of **auxiliary equipment and technical building systems,** Beier et al. (2015, pp. 21-23) demonstrated the feasibility of implementing demand-side management in the industry, without jeopardizing the availability of production equipment, by using compressed air systems as a means of storing electrical energy. Machalek and Powell (2019, pp. 101-105) explore the possibilities of using auxiliary equipment together with their integrated energy storage capacities (e.g., chiller with associated buffer storage) to balance demand peaks through short-time energy storage. With a particular focus on the flexible operation of heating, ventilation, and air-conditioning (HVAC) systems, Sun et al. (2016, p. 1651) developed a method for determining appropriate demand response strategies, taking into account production capacity, electricity pricing, electricity demand limitation, and ambient temperature.

At the **energy supply system level**, Khripko et al. (2018, pp. 704 f., 707 f.) demonstrated the usefulness of introducing a gas-fired combined cooling, heat, and power plant (CCHP) to meet the energy demand of a polymer processing factory while at the same time increasing its responsiveness to fluctuations in the local energy grid. With a special focus on battery storage systems (BSS) in industrial applications, Lehmann et al. (2016, p. 316) carried out an economic viability assessment based on the ability of a BSS to reduce peak loads and improve self-consumption. Looking for additional revenue streams to improve the net present value (NPV) of a BBS in non-intrusive energy flexibility application, Braeuer et al. (2019, p. 1426 f.) also considered the BSS to participate in the arbitrage trading and power control reserve (PCR) market.

Development of the energy supply system

The aim of planning and further development of energy supply systems is to ensure a low-emission supply of energy demand with maximum operating efficiency and minimum investment costs while ensuring the adaptability of the system design to uncertain changes in future framework conditions. Hinker et al. (2018, p. 1) summarized these uncertainties to be future energy prices, applicable subsidies, regulation, and the evolution of market design.

Adaptability has been identified as a prerequisite for the evolution of energy supply systems over time, as it reduces the costs for redevelopment and redesign, installation, and system integration. It thus improves the compatibility with future market requirements. Hinker et al. (2018, p. 9) differentiated adaptability into two main characteristics using the definitions from Wiendahl et al. (2007, p. 788). First, **scalability** – the ability of a system with spatial degrees of freedom to change and adapt incrementally, rather than in an all-or-nothing manner. Second, **modularity** – the use of interchangeable, autonomously operating elements with standardized interfaces (e.g., standardized thermal and electrical connections) enables coupling between different conversion and storage units.

The improvement of the adaptability of technical building systems and energy supply systems in factories through standardized units was also proposed by Weeber et al. (2017, p. 437 f.) and is shown in Figure 2-17.

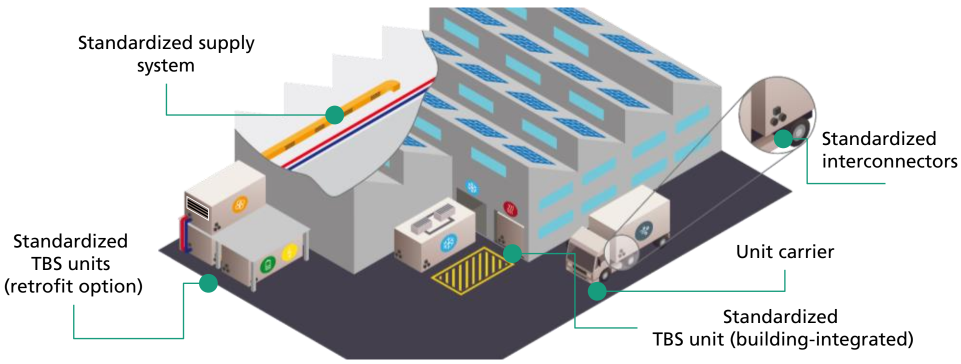


Figure 2-17 Adaptability of technical building systems and energy supply systems based on standardized supply units (Weeber et al. 2017, p. 438)

Heterogeneous energy system architectures with system components of different ages make future adaptations to the system architecture, as shown in Figure 2-18, particularly challenging. This also includes the coordinated operation of new and old equipment. In energy supply system design, Voll et al. (2015, p. 447) generally distinguish between three levels, the synthesis level, the design level, and the operational level. The synthesis focuses on the selection of the technical components of the system, its configuration, and layout. The design level determines the technical specification, including installed capacities, operating limits, etc. Finally, the operating level defines the operating strategies of the energy supply system as a whole and for its individual system components. The author emphasizes the need to engage simultaneously at all three levels of the design process in order to derive near-optimal solutions.

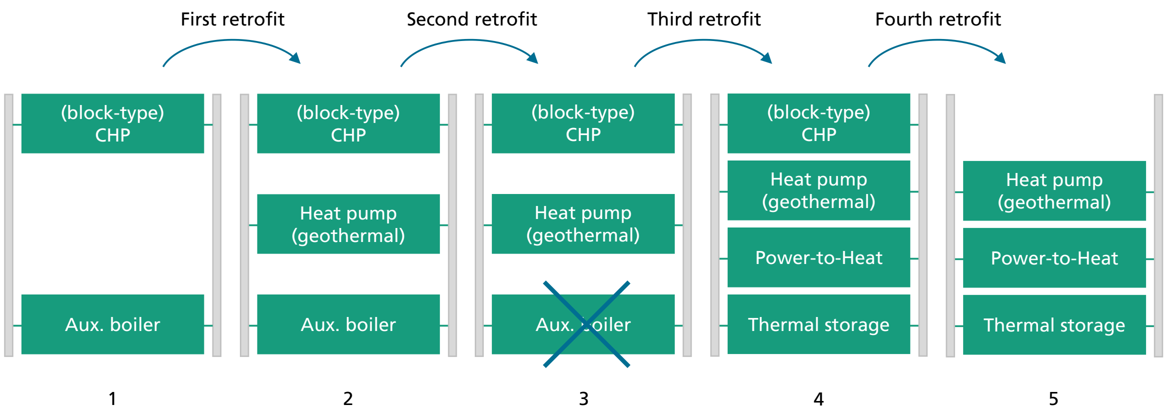


Figure 2-18 Evolution of energy system design (figure adapted from Hinker et al. 2018, p. 8)

At the synthesis level, co-simulation can be used to investigate different predefined energy supply scenarios (ref. Table 2-5). Use cases include companies that move their existing production to a new factory building (Bleicher et al. 2014, p. 444). Another possibility for the use of simulation at the synthesis and design level is to compare the suitability of different refurbishment concepts for the energy supply of a factory (Dunkelberg et al. 2018, pp. 792-799). The aim of this investigation is to identify energy supply system setups that help to increase supply flexibility and improve energy supply system efficiency considering specific manufacturing operations (e.g., injection modeling). At the operation level, multi-criteria simulation-optimization can help to improve the operating strategy of existing energy supply systems used in factories (e.g., an automotive assembly plant) (Feng et al. 2016, pp. 457-464). The investigation of different operating strategies can also assist during the identification of possible conflicts between energy demand, costs, and emission-optimized operating strategies.

Simulation modeling can be used at various levels of a planning process to improve the design and operation of a factory's energy supply system. However, Voll et al. (2015, p. 447) has carefully considered the practical advantages of deriving promising solution candidates over a single optimal solution. This is because simulation models never provide a perfect representation of the real system and modeling constraints (energy tariffs, energy demand, etc.) are objective to future changes. Therefore, an optimal solution shows only temporary validity, while near-optimal solutions provide insights into the recurring features of good solutions and enable robust decision-making.

Table 2-5 Predefined energy supply system setups (Bleicher et al. 2014, p. 444)

	Scenario 1	Scenario 2	Scenario 3
Heat supply (baseload)	CHP (natural gas)	district heat	groundwater well heat pump
Heat supply (peak load)	district heat	district heat	district heat
Heat recovery from exhaust air	heat pump	heat exchanger	heat pump
Warm water supply	solar thermal & electric	solar thermal & electric	solar thermal & electric
Cold supply	adsorption chiller	compression chiller	groundwater well
Electricity supply	PV CHP grid	PV Grid	PV grid

2.3 Modeling and Simulation of Energy Use in Factories

This chapter presents general definitions (2.3.1) and theoretical foundations on the subject of modeling and simulation (2.3.2), with a particular focus on the methods and tools used in the context of manufacturing and, more specifically, in the assessment of the associated energy consumption characteristics (2.3.3). For a more detailed discussion of modeling techniques and simulation methods, see Banks (1998a), Chung (2004), and Law (2015).

2.3.1 Terms and definitions

According to VDI 3633 (p. 3), a model is a "simplified reproduction of a planned or existing system with its processes in a different conceptual or concrete system". A reproduction implies that within a tolerance range, there is a difference between the real system and the features relevant to the study of the model. In general, the simulation comprises the "preparation, execution and evaluation of (…) experiments with a (…) model", the simulation itself is defined as the "representation of a system with its dynamic processes in an experimentable model to reach findings which are transferable to reality (…)" (VDI 3633, p. 3). In a broader sense, this is consistent with Biles (1984, p. 99), who defines simulation "(…) as the establishment of a mathematical-logical model of a system and the experimental manipulation of that model on a digital computer". This definition emphasizes two principal activities in a computer simulation: model development and experimentation. While various modeling and simulation techniques are presented in

Subsections 2.3.2 and 2.3.3, the theoretical principles applied in the design of simulation experiments are discussed in Section 2.4.

The use of computer models and simulation techniques is motivated by the constraints imposed by the properties of physical experiments. Performing physical experiments on complex systems or processes is often too time-consuming, expensive, or practically impossible (Sacks et al. 1989, p. 409). The benefits of simulation modeling include the ability to explore the behavior of a system without interrupting its ongoing operation, the opportunity to verify system behavior, and gaining insight into the interaction of system variables and their effects on system performance. Challenges include the need for specialized training, the difficulty of interpreting simulation results, and the effort associated with modeling, simulation, and analysis (Banks et al. 2010, p. 24).

2.3.2 Modeling paradigms and simulation techniques

Modeling paradigms

An overview of different modeling paradigms can be found in Banks (2012, p. 16), including physics-based, finite element, data-based, aggregate, and hybrid models. **Physics-based models** are represented by a mathematical equation based on fundamental physical principles. Although they are also based on physical principles and described by mathematical equations, **finite element models** are different. They decompose models of large complex systems into a set of interconnected smaller models called finite elements. This approach involves the construction of a mesh to discretize the spatial dimensions of the object under consideration. Applications include structural analysis and fluid dynamic problems. **Data-based/driven models** use various data sources from both qualitative and quantitative research methods to describe the various aspects of the model subject (e.g., experiments with the real system, interviews with subject matter experts, etc.). The relationship between model inputs and outputs is developed by recording and tabulating the response of the system under varying conditions. **Aggregate models** are not physics-based models and generally combine different objects and actions of models to evaluate their aggregate performance. **Hybrid models** are composed of different modeling paradigms to represent the properties of the object or system under consideration. Following Pritsker (1998, p. 36), we further refer to simulation modeling as the "principles for building and using models that are analyzed using simulation".

Simulation techniques

Law (2015, p. 5 f.) categorizes simulation models according to three dimensions. Depending on whether models evolve over time, they are referred to as either static or dynamic. Depending on the presence of a probabilistic component, simulation models can be further differentiated into deterministic or stochastic. Finally, one can distinguish between discrete simulation models "for which the state variables change instantaneously at separated points in time" and continuous simulation models "for which state variables change continuously with respect to time" (Law 2015, p. 3).

Figure 2-19 outlines the different simulation techniques presented in this subsection. The figure categorizes possible areas of application and the different levels of abstraction used in the underlying modeling approach.

Accordingly, a **discrete-event simulation (DES)** model can be defined as a model in which the state variables "change only at those discrete points in time at which events occur" (Banks 1998b, p. 8), whereas "an event is defined as an instantaneous occurrence that may change the state of the system" (Law 2015, p. 6). Software solutions are, e.g., ARENA (Rockwell Automation) and Tecnomatix Plant Simulation (Siemens).

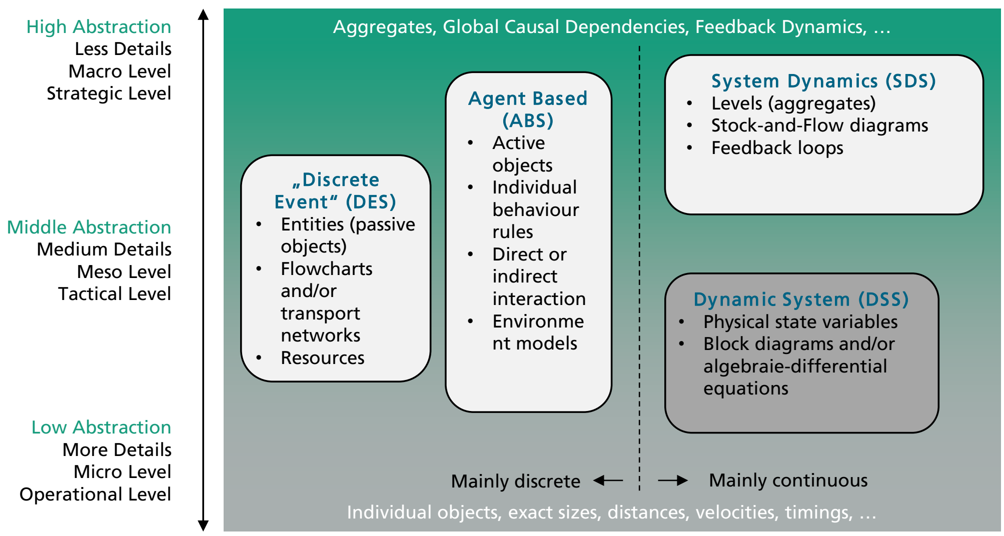


Figure 2-19 Simulation modeling according to different levels of abstraction (own representation based on Borshchev and Filippov 2004, p. 3)

Agent-based simulation (ABS) models are considered a variant of DES. This is due to the fact that in ABS equal to DES, changes of state occur at a countable number of points in time. ABS is defined as a DES "where the entities (agents) do (…) interact with other entities and their environment in a major way." In ABS, agents

> "are referred to as autonomous entities that can sense its environment, including other agents, and use this information to make decisions. Agents have attributes and a set of basic if/then rules that determine their behaviors. They may also learn (gain a better understanding of the status of other agents and their environment) and adapt their behaviors (change their decision rules) over time, which will require them to have some form of memory." (Law 2015, p. 694)

A widely used ABS software solution is AnyLogic (The AnyLogic Company). Open-source alternatives include MASON, NetLogo (Northwestern University), and Repast Simphony (Argonne National Lab) (Law 2015, p. 694).

Depending on the model abstraction level, continuous simulation can be further divided into dynamic systems and system dynamic simulations. In a **dynamic-systems simulation (DSS)** model, the state variables change continuously with respect to time. They are based on differential equations, which in most cases cannot be solved analytically and require the use of numerical solvers. Simulation software products include, for example, SIMULINK (MathWorks), Modelica, and Dymola (Dassault Systemes). (Law 2015, p. 707)

System-dynamics simulation (SDS) modeling is a high-level technique for simulating continuous models developed to evaluate policy or business strategies. While they can accommodate both deterministic and stochastic components, system dynamic models consist of three main components: stock of resources, flows of incoming and outgoing resources with corresponding valves to control the rate of flow, and information links that transfer information between the stock and the valve. Corresponding software products are, for example, AnyLogic (The AnyLogic Company) and Vensim (Ventana Systems) (Law 2015, p. 708)

Several systems require the implementation of both discrete and continuous characteristics in their simulation model representation. According to Pritsker (1998, p. 46), three types of general interactions can occur in a **combined discrete-continuous simulation** model. First, "a discrete event may cause a discrete change in the value of a continuous state variable"; second, "a discrete event may cause the relationship governing a continuous state variable to change at a particular time"; and third, "a continuous state variable achieving a threshold may cause a discrete event to occur" (Law 2015, p. 713).

Related to the static stochastic category, the last simulation modeling paradigm presented in this subsection is **Monte Carlo simulation (MCS)**. MCS employs random numbers to solve various stochastic or deterministic problems (Law 2015, p. 714). According to Diaz et al. (2012, p. 245), MCS is considered static compared to DES and SDS because "the simulation does not progress in time". Rather than being influenced by past behavior, the variables in MCS are stochastic, uncertain, and defined by a probabilistic distribution. An MCS "randomly samples values for each input variable distribution and uses that sample to calculate a model output" (Banks 2012, p. 15).

Carrying out simulation studies

In general, the use of simulation in finding a solution to a problem consists of three steps, namely the definition of the simulation goal, the solution search, and the selection process (Reinhart 2000, p. 27). For operational purposes, Maria (1997, p. 8) proposes a procedure model consisting of eleven steps. Step 1: identify the problem, Step 2: formulate the problem, Step 3: collect and process real system data, Step 4: formulate and develop a model, Step 5: validate the model, Step 6: document the model for future use, Step 7: select a suitable experimental setup, Step 8: set experimental conditions for runs, Step 9: perform simulation runs according to Steps 7-8 above, Step 10: interpret and present results, Step 11: recommend further courses of action.

Verification, validation, documentation, and communication are tasks that must continuously accompany the various steps of a modeling and simulation analysis (VDI 4465, p. 5). In general, verification and validation efforts are undertaken to "increase the credibility of models and simulation results by providing evidence and indication of correctness and suitability" (Brade 2004, p. 13). According to Balci (1998a, p. 41), "model validation is substantiating that within its domain of applicability, the model behaves with satisfactory accuracy consistent with the study objectives", whereas "model verification is substantiating that the model is transformed from one form into another, as intended, with sufficient accuracy." Banks (2012, p. 10) summarizes the issues related to verification and validation as follows: "Did we build the right thing (as to function and purpose)?" and "Did we build it right (as to the degree of correctness)?" In Balci (1998b, pp. 354-379), 75 different verification, validation, and testing techniques are presented that cover each life cycle phase of a simulation study. These techniques include, for example, model debugging, graphical (heuristic) comparison between graphs of values for model and real system variables, special input tests with boundary or extreme values to check if the model behaves appropriately, but also statistical techniques like analysis of variance, confidence intervals, or regression analysis. Chung (2004, pp. 162-167) highlights animation-based verification of model performance, testing of face and statistical validity using domain experts, and quantitative comparison between model and system output performance (Chung 2004, pp. 175-178).

2.3.3 Simulation modeling of energy use

Modeling and simulation of energy use in manufacturing systems

Strategies to reduce energy demand and resource consumption must cover the different levels of a manufacturing system, including unit processes at the machine level, process chains in a multi-machine ecosystem, and the facility including its technical infrastructure (Duflou et al. 2012, p. 588). The requirement to extend the scope of an energy assessment from individual processes to entire factories, and to include auxiliary equipment and technical building systems, was already recognized by Herrmann and Thiede (2009, p. 221). The authors further showed that simulation of a manufacturing system is a suitable tool to capture the inherent dynamics within a factory (Herrmann et al. 2011, p. 45).

Mourtzis et al. (2014, pp. 216-222) and Garwood et al. (2017, pp. 28-30) present a general overview of software tools used for the simulation modeling of manufacturing systems. With a particular focus on material flow and energy simulation modeling, Fuss and Beißert (2014, p. 42) identified several of-the-self software solutions, including Tecnomatix Plant Simulation (Siemens AG); Dosimis (SDZ GmbH); Any Logic (Any Logic Company); FlexSim (FlexSim Software Products Inc.); SIMUL8 (SIMUL8 Corporation); Witness (Lanner Group); Enterprise Dynamics (INCONTROL Simulation Solutions); ExtendSIM (Imagine That Inc.); and AutoMod (Applied Materials). There are also many domain-specific software tools for the modeling and simulating energy use in buildings and associated energy systems. According to a review by Jarić et al. (2013, p. 109), the most established software tools are Energy Plus, IDA ICE (EQUA Simulation AB), IES-VE (Integrated Environmental Solutions), and TRNSYS (University of Wisconsin-Madison).

Model coupling and cooperative (co)-simulation

Thiede et al. summarize the four main coupling concepts used in the simulation of manufacturing systems (ref. Figure 2-20). Offline coupled models are simulated separately, and the results are exchanged after each simulation run. Integrated models refer to different models that are created and executed within a software tool. To facilitate the exchange and integration of models, the Functional Mock-up Interface (FMI) specifies the standard interface of models that include differential, algebraic, and discrete models (Wetter 2011, p. 186). In this case, data exchange occurs either continuously at each time step or at discrete events. Co-simulation refers to the use of different domain-specific software tools and requires that the data exchange between the software tools is synchronized. Direct coupling refers to a scenario where only two software solutions are coupled, while model synchronization refers to a scenario where multiple simulation tools are coupled and a middleware software handles the synchronization and exchange of data. Heinzl et al. (2018, p. 690) further specify co-simulation as a multi-method cooperative simulation modeling approach that "uses multiple simulation environments –each implementing a distinct part of the overall model – as well as multiple computational algorithms (ordinary differential equation - ODE) solvers, discrete-event schedulers, etc.) where the submodels exchange data during runtime via specialized communication interfaces."

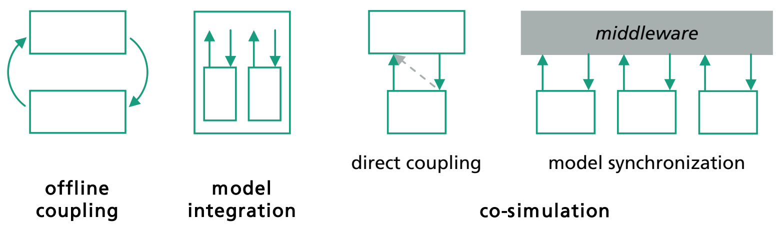


Figure 2-20 Concepts for model coupling (Thiede et al. 2016, p. 1122)

Motivated by the possibility of using domain-specific simulation tools, Leobner et al. (2011, pp. 64-66) introduced an abstract model for the analysis of energy flows within manufacturing systems, consisting of 16 subcomponents. The authors propose to synchronize the different components of the simulation model in fixed time steps by using a co-simulation environment such as the Building Controls Virtual Test Bed (BCVTB). BCVTP is a software framework that enables data exchange between EnergyPlus, Modelica (Dynmola), and MATLAB Simulink software. Other middleware includes the TISC software suite (Kossel et al. 2006, p. 486). Schönemann (2017, p. 142 f.) successfully applied TISC to a multiscale simulation of a manufacturing system.

Co-simulation allows the use of specialized simulation environments, model descriptions, and solver algorithms adapted to individual needs of the submodels of a manufacturing system representation with multiple levels (Bleicher et al. 2014, p. 442). Although co-simulation can help coordinate and automate the handling of simulation data and enable parallelization of simulation model execution, implementation still requires significant expert knowledge and effort. (Thiede et al. 2016, p. 1122).

A detailed discussion of the latest simulation modeling approaches used in the assessment of energy use in manufacturing systems is presented in Chapter 3.

2.4 Design of Simulation Experiments

This section provides a brief overview of the challenges around the design of simulation experiments (DoSE). Subsection 2.4.1 provides general terms and definitions and addresses the difference between the classical design of experiments (DoE) and the design of simulation experiments. Subsection 2.4.2 briefly introduces experimental designs in general, followed by a more detailed outline of the Taguchi orthogonal array designs.

The challenge with computer experiments is that one has to deal with many more parameters than usually present in real-world experiments (Kleijnen et al. 2005, p. 263). However, varying each parameters is an ineffective approach, especially for complex systems. Besides, a one-parameter-at-a-time approach cannot identify interaction effects between two or more parameters. This applies both to parameters that complement each other (positive interaction) and to parameters that partially replace each other (negative effects) (Kleijnen et al. 2005, p. 267). In addition, analysts tend to use a trial-and-error approach when testing different parameter configurations. As a result, they may never be able to uncover the true functional relationship between different parameters or parameter settings that lead to the best results (Simpson et al. 2001, p. 129).

Despite the general increase in computing power, the analysis of complex computer models can still be time-consuming, taking from minutes to hours or even longer. It is therefore critical that, within given time and budget restraints, there are sufficient resources left over after model creation and validation to train the model and schedule simulation runs that provide insights for decision-making. (Barton 2013, p. 342)

The design of a simulation experiment should help to improve both the efficiency and the quality of the simulation model analysis. This makes it possible to make better use of limited computational resources, overcome trial-and-error approaches, and improve the expressiveness of models with many parameters, taking into account their input and output relationships as well as possible interaction effects.

2.4.1 Terms and definitions

Design (and analysis) of simulation experiments, design of computer experiments, or design of computer experiments summarize a set of methods that originate in the statistical theory of the design of experiments and are adapted and used to design, conduct, and analyze experiments on computer models as a substitute for physical experiments.

The goal of using experimental designs is to extract as much information as possible from a limited number of experiments (Giunta et al. 2003, p. 1). It can therefore be defined as "a procedure for choosing a set of samples in the design space with the general goal of maximizing the amount of information gained from a limited number of experiments" (Giunta et al. 2003, p. 3). Kleijnen et al. (2005, p. 265 f.) summarize the three main objectives in the analysis of simulation models to be:

- development of a fundamental understanding of system behavior
- find robust decisions
- comparison of different decision options according to predefined goals

The use of a design of experiments is most appropriate in early design phases, where engineers want to gain insight into a system whose underlying mechanisms are not well understood or where access to real-world data is either limited or even nonexistent (Kleijnen et al. 2005, p. 266). In this phase, the focus is on generating, evaluating, and comparing potential conceptual configurations. In the search for good system configurations, tools are needed that offer a good compromise between accuracy and efficiency and which allow management of a large amount of uncertain information. (Simpson et al. 2001, p. 137 f.)

In computer models analysis, proper design of simulation experiments can help in finding robust “satisficing” solutions that work well across a wide range of scenarios, rather than finding optimal solutions that depend on a high number of future events and are inherently uncertain (Kleijnen et al. 2005, p. 267). Given a set of predefined objectives, the design of simulation experiments supports robust decision-making while achieving near-optimal design solutions in a manner that is superior to ad hoc "trial-and-error" or “one-parameter-at-a-time variation” approaches, which are often used in the analysis of simulation models (Giunta et al. 2003, p. 2).

In the literature on the design of simulation experiments, there is no consistent use of terms and notions in the description (Giunta et al. 2003, p. 2). Table 2-6 provides an overview of the predominant and discipline-specific terminologies in statistics and engineering. Following the prevailing usage in the literature, this work uses the terms from statistics, with the exception of the overall combination of factor levels, which is referred to as the design point or sample, and the term response surface, which is more commonly referred to as the meta-model.

Table 2-6 Comparison between discipline-specific terms and notions used in the literature to describe simulation experiments – the terms in bold are used further in this work (based on Giunta et al. 2003, p. 2 f., Kleijnen et al. 2005, p. 264 f., Fang et al. 2006, p. 4 f., Barton 2013, p. 345)

Statistics (DoE)	Engineering (DoSE)
Factor	input, parameter, design variable, independent variable, controllable variable
Factor level	
Level combination	sample, **design point**, experimental point, scenario
Experiment	run, trial
Response	output, performance parameter, dependent variable
Response surface	model, **meta-model**, surrogate function, auxiliary model, emulator

The classical design of experiment and the design of simulation experiments have specific differences that originate in the deterministic nature of simulation models, as illustrated in Subsection 2.3.2. For this reason, the main principles used in the design of laboratory experiments, namely replication, blocking, and randomization, are not suitable for simulation experiments (Santner et al. 2018, p. 2). In contrast to error-prone physical, field, or laboratory experiments, deterministic computer simulations have no sources of random error arising from measurement error or other sources (Giunta et al. 2003, pp. 1, 4-5). Since the replications of a sample within a simulation model simply reproduce its output (apart from numerical errors), the problem of non-repeatability can be dropped (Giunta et al. 2003, p. 5). Due to the lack of random error, the use of various statistical methods commonly used to analyze models and test the significance of parameters cannot be appropriately used in computer experiments. These include mean-square error and least-square regression, which are used to fit polynomial models as well as f-statistics, which are commonly used to test the significance of parameters and to decide whether to include or exclude certain parameters in or from a model (Simpson et al. 2001, p. 142). The randomization principle used in laboratory experiments to protect against time-related changes in the experimental environment also has a different meaning in the context of the design of simulation experiments. Random errors are either absent (deterministic models) or are implemented intentionally, resulting in a stochastic model. However, statistical methods can be applied to approximate the simulation model code. These approximations are called "models of the model" or meta-models (ref. Figure 2-21) (Simpson et al. 2001, p. 129).

Simulation models describe the unknown relationship between inputs (cause) x and outputs (effects) y in a "real world" physical system under observation by a function $f(x)$, objectified to an approximation error $\varepsilon_{bias,1}$ (ref. Equation 2-23). A meta-model is a simplified functional representation $g(x)$ of the relationship between inputs x and outputs

$\bar{y}$ compared to the full simulation (Giunta et al. 2003, p. 2, Kleijnen et al. 2005, p. 265). The bias between the simulation model and the meta-model representation is described by $\varepsilon_{bias,2}$ (ref. Equation 2-24).

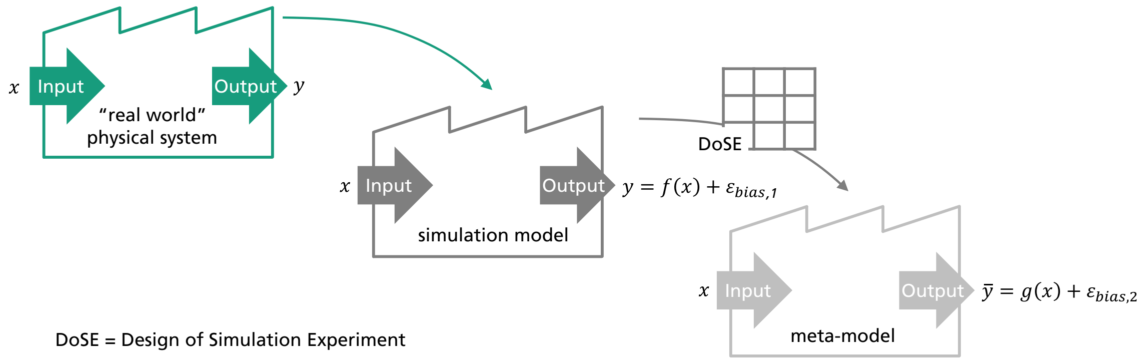


Figure 2-21 Development of meta-models from the real system using simulation models and design of simulation experiments (own representation inspired by Gregor et al. 2008, pp. 66-68)

Modeling practice aims at meta-models that capture the properties of a system's behavior in its simplest form (Kleijnen et al. 2005, p. 270).

$$y = f(x) + \varepsilon_{bias,1} \tag{2-23}$$

$$\bar{y} = g(x) + \varepsilon_{bias,2} \;\; and \;\; f(x) + \varepsilon_{bias,1} + \varepsilon_{bias,2} \tag{2-24}$$

In general, the use of a design of experiments in the analysis of simulation models, according to Kleijnen et al. (2005, p. 263), needs to meet the following qualitative attributes:

- Simplicity of design construction
- Flexibility of analysis
- Efficiency of application (time and resources required for the study)

After introducing the specific terms and definitions used in the design of simulation experiments, the next subsection provides general information on selecting the appropriate experimental design to efficiently analyze engineering systems in their simulation model representation.

2.4.2 Experimental design techniques

The review of the design of experiment techniques presented in this section is far from exhaustive, although the specific selection aims to provide the reader with the necessary background used to develop the methodology presented in Chapter 5.

Figure 2-22 categorizes the use of different experimental designs in terms of the number of factors considered and the complexity of the meta-model.

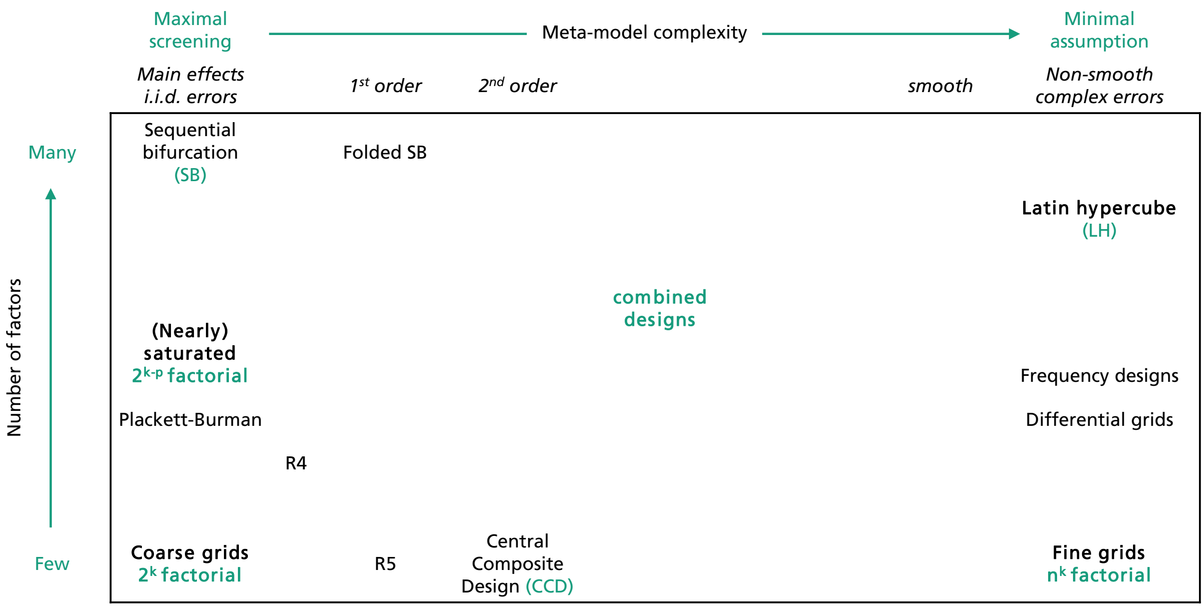


Figure 2-22 Recommended designs classified according to the model complexity assumptions and the number of factors (own representation based on Kleijnen et al. 2005, p. 275)

The next sections present more information on the designs highlighted with bold letters in Figure 2-22. For further information on the design of experiments, the author refers to the textbooks by Siebertz et al. (2017), Klein (2014), and Saltelli et al. (2008).

Full factorial designs

A full factorial experiment design allows the study of the joint effect of the factors on a response (Montgomery 2001, p. 218). Meta-models derived from full factorial designs include all factor interactions, and when more levels per factor ($n > 2$) are included, the derived meta-model is also able to represent nonlinear effects. According to Equation (2-25), the number of level combinations for all factors or experiments is given by the number of factor levels n to the power of k, the number of factors considered.

$$m = n^k \tag{2-25}$$

m	Number of factor level combinations
n	Number of factor levels
k	Number of factors

Common designs for evaluating main effects and interactions of factors with two levels are 2^k designs. The low and high factor levels are usually indicated by -1 and +1 or + and – (Sanchez 2005, p. 73). Interpolation of models derived from experiments with factors at two levels is only useful if the factors can be continuously adjusted. Moreover, extrapolation is not allowed because new physical effects can occur outside the tested design space (Siebertz et al. 2017, p. 24). 3^k designs are used in case of main effects, and factor interactions are subject to nonlinear behavior (Simpson et al. 1997, p. 2 Giunta et al. 2003, p. 8.). However, authors report that nonlinear effects are usually overestimated, especially for factors with small distances between the different factor levels (Siebertz et al. 2017, p. 23). The number of experiments m grows exponentially as the number of factors k increases. For example, a full factorial design for an experiment with $k = 10$ factors at $n = 2$ levels already requires 1024 trials (Simpson et al. 1997, p. 2, Kleijnen et al. 2005, p. 276). When an analyst intends to consider a high number of factors in full factorial designs, one primarily analyzes the interactions of two or more factors. If at least higher factor interactions can be omitted, the locations in the design reserved for factor interactions can be replaced by additional factors. (Kleppmann 2016, p. 122 f.)

Fractional factorial designs

Fractional factorial designs are used to efficiently analyze a high number of factors while accepting a minimum amount of information loss. In the literature, these designs are also referred to as screening designs (Siebertz et al. 2017, p. 28.). Fractional factorial designs are used in situations where the problem statement is still quite vague, but one needs to know which are the most relevant factors as well as how and in which direction the change of a factor level affects the objective function (Kleppmann 2016, p. 122). Fractional factorial designs can be implied to reduce the number of simulation runs. They usually come at the cost of aliasing or biasing effects and loss of design resolution (Simpson et al. 2001, p. 130 f.). The number of experiments m or factor level combinations in fractional factorial designs can be described according to Equation (2-26). m is given by the number of levels per factor n to the power of the number of factors k minus the fraction of the full factorial design p used.

$$m = n^{k-p} = \frac{1}{n^p} \cdot n^k \tag{2-26}$$

m	Number of factor level combinations
n	Number of levels per factor
k	Number of factors
p	Portion of the full factorial design

Figure 2-23 shows various experimental designs for three factors, including the full factorial design, the fractional factorial design, the central composite design, the face-centered central composite design, the Box-Behnken design, and the space-filling design.

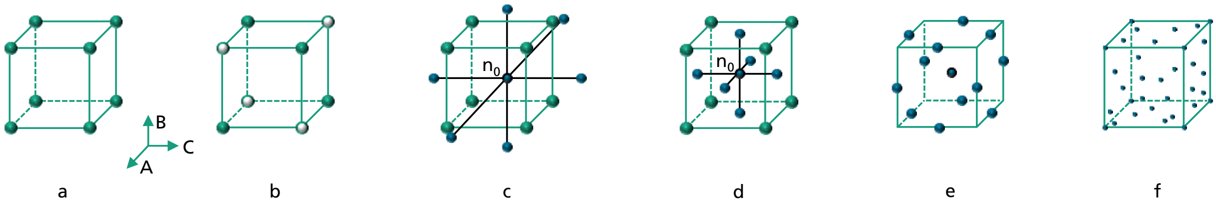


Figure 2-23 Examples of different experimental designs for three factors. A: full factorial design (2^3), B: fractional factorial design (2^{3-1}), C: central composite design, D: face-centered central composite design, E: Box-Behnken design, F: space-filling design

In a 2^3 full factorial design, one can evaluate the combination of eight-factor levels for three factors and analyze the main effects (A, B, C), all two-factor interaction (AB, AC, BC), and one three-factor interaction (ABC) separately (ref. Figure 2-23a). In general, the aliasing of effects in a fractional factorial design is given by the design resolution. If one reduces, for example, the number of experiments to half a fraction of the 2^3 full factorial design, we obtain 2^{3-1} fractional factorial designs of Resolution III, aliasing main effects with two-factor interactions and two-factor interaction with each other (ref. Figure 2-23b). Assuming that the effect of the three-factor interaction (ABC) can be omitted, an additional fourth factor (D) can be included in the experiment while maintaining the number of required simulation runs. This results in a 2^{4-1} fractional factorial design of Resolution IV. In Resolution IV designs, the main effects are not aliased with other main effects nor with any two-factor interactions. 2^{k-p} fractional factorial designs commonly used in screening are two-level Plackett-Burman designs with $k = n - 1$ factors and $n = 4 \cdot m\,; m = \mathbb{Z}^+$, where n is a power of two. If factor interactions are negligible, an unbiased estimate of all main effects can be obtained from Plackett-Burman designs. While maintaining the smallest possible variance, they require only one more design point than the number of factors (Simpson et al. 2001, p. 131). Central composite designs are used when a first-order model has a lack of fit. By adding a center point n_0 and two 'star' points for each factor positioned at $\pm\alpha$ from the midpoint, the derived models include quadratic effects in addition to main effects and two-factor interactions (ref. Figure 2-23c). For $\pm\alpha =$

1, the design is called a face-centered central composite design (ref. Figure 2-23d) (Simpson et al. 2001, p. 131, Kleijnen et al. 2005, p. 277). When design points at the extremes of a design space are difficult or impossible to test, Box-Behnken designs can be used. In these designs, the design points are analyzed at the center of each edge of the hypercube rather than at the vertices (ref. Figure 2-23e) (Montgomery 2001, p. 458 f.). In general, 3^{k-p} fractional factorial designs are possible; however, their practical application is very limited, and the effects are very difficult to interpret. For example, in a 3^{3-1} design, each main effect is aliased with an interaction component. Montgomery (2001, p. 380) advises to use them only if all interactions are negligible. Kleppmann (2016, p. 213 f.) also does not advocated their use for quantitative factors, but concedes their usefulness in screening qualitative factors (Kleppmann 2016, p. 213 f.).

If a preselection of dominant factors is required for a large number of samples, fractional factorial designs can be used as a way to "screen" for important factors (Simpson et al. 2001, p. 131). The prerequisite is that one assumes that the principle of the sparsity of effects is valid and that the system under consideration is dominated by main effects and low-order interactions (Montgomery 2001, p. 303, Fang et al. 2006, p. 8).

Space-filling designs

The number of experiments is generally less limited in computer experiments than in laboratory or field experiments. While classic experiments draw their conclusions from observing the extremes of the design space, the interior of a design space remains largely unexplored. Many researchers advocate the use of space-filling designs (ref. Figure 2-23f) in the analysis of deterministic simulation models to treat all regions of the design space equally (Simpson et al. 2001, p. 131). Computer experiments can imply space-filling designs to gain a more accurate understanding of the functional relationship within the design space. Therefore, it is possible to increase the prediction accuracy over the entire experimental range while reducing the bias error between the real response of a model and the assumed or estimated responses (Santner et al. 2018, p. 151, Giunta et al. 2003, p. 4 f.). Space-filling designs that imply random number-based sampling methods, including Monte-Carlo and Latin-Hypercube, are effective methods to distribute samples uniformly across the design space and thus reduce the bias error in the estimated response (Giunta et al. 2003, p. 5). However, these designs come at the cost of a large number of simulation runs and thus computer execution time, as well as a large data management overhead. In contrast, by carefully selecting and using experimental designs, a user can answer more specific questions while using fewer computational resources. (Saltelli et al. 2008, p. 54, Siebertz et al. 2017, p. 44)

Since the main goal of this work is to screen complex design spaces in early design phases and identify the most influential factors, as well as to understand how these factors affect different design goals, understanding the exact functional behavior is not the main focus, so further discussion of space-filling designs is not included in this subsection. For more background information on space-filling designs, see Siebertz et al. (2017, p. 189 ff.) and Santner et al. (2018, p. 145 ff.).

2.4.3 Orthogonal array-based matrix designs

Orthogonal array-based matrix designs are special fractional factorial designs with factors on two, three, or even more levels. These designs are often identical to Plackett-Burmann's experimental designs (Simpson et al. 2001, p. 131). Mixed-level orthogonal arrays are generally denoted by $L_N(s^m \times t^n)$, where N is the number of experiments required, m the number of s-level factors, and n the number of t-level factors. Orthogonality is a desirable property for matrix experiments because it simplifies the computation (Kleijnen et al. 2005, p. 273).

In orthogonal designs, the columns within the design matrix are orthogonal to each other, which means that the factors are uncorrelated (Chen et al. 2006, p. 280). The pairwise correlation between any two columns and their factor levels is zero (Siebertz et al. 2017, p. 7, Sanchez 2005, p. 74). Furthermore, the different level settings appear equally often in each vertical column (Kujawski 2014, p. 429). Moreover, all possible level combinations for each pair of factors appear only once in the design matrix (Chen et al. 2006, p. 278). Furthermore, orthogonal array-based designs maintain orthogonality even when the position of the rows and columns in the matrix is changed (Siebertz et al. 2017, p. 34). Since all factors and their levels are equally represented within the experiment, orthogonal array-based designs are considered balanced (Cavazzuti 2013, p. 21). Table 2-7 shows a selection of standardized orthogonal arrays.

The use of orthogonal arrays gained popularity in quality engineering and engineering design through the work of Dr. Genichi Taguchi on robust parameter design outlined in Taguchi (1987). In industrial practice, there are a large number of use cases that underline the appropriateness and usefulness of the Taguchi method in solving engineering design problems (Simpson et al. 2001, p. 139). Criticisms of the method include the use of highly fractional factorial designs, the combined evaluation of controllable factors, noise factors in a cross (inner/outer) array design, and the combination of response mean and variance (referred to as signal-to-noise ratio) in a single loss function (Montgomery 2001, p. 491, Simpson et al. 2001, p. 139).

With reference to the experimental designs presented in Subsection 2.4.2, an $L_8(2^7)$ orthogonal array can analyze seven two-level factors in eight simulation runs, while the same design is able to accommodate a 2^3 full factorial design to study all possible combinations of the three two-level factors, or a 2^{4-1} fractional factorial design of Resolution IV to study four two-level factors, aliasing only the two-factor interactions with each other. If one omits the active interactions, the potential for reducing the number of experiments becomes even more apparent, for example, if one compares the 18 experiments of an $L_{18}(2^1 \times 3^7)$ orthogonal array with the 4374 experiments required if all possible factor combinations were to be analyzed.

The limitations associated with orthogonality in experimental designs are that one is not able to specify an arbitrary number of factor combinations (Giunta et al. 2003, p. 10). Moreover, different combinations of factor levels may not be feasible in practice, making exploration in an experiment unnecessary (Kleijnen et al. 2005, p. 273). Because of their highly fractional factorial design characteristics, critics also claim that Taguchi orthogonal arrays can only characterize the average effect of each factor level. However, quadratic effects and the effects of higher-order factor interactions are not presented (Siebertz et al. 2017, p. 58). Moreover, the orthogonal designs proposed by Taguchi target experiments conducted in factory environments and the derived models are limited to main effects. These restrictions may be too limiting for certain simulation environments. (Kleijnen et al. 2005, p. 278)

Table 2-7 Standard orthogonal arrays (Klein 2014, p. 97, Su 2016, p. 61)

Orthogonal array	**Number of rows**	**Maximum number of factors**	**Maximum number of columns**			
			Level 2	Level 3	Level 4	Level 5
L_4	4	**3**	3	-	-	-
L_8	8	**7**	7	-	-	-
L_9	9	**4**	-	4	-	-
L_{12}	12	**11**	11	-	-	-
L_{16}	16	**15**	15	-	-	-
L_{16}	16	**5**	-	-	5	-
L_{18}	18	**8**	1	7	-	-
L_{25}	25	**6**	-	-	-	6
L_{27}	27	**13**	-	13	-	-
L_{32}	32	**31**	31	-	-	-
L_{32}	32	**10**	1	-	9	-
L_{36}	36	**23**	11	12	-	-
L_{36}	36	**16**	3	13	-	-
L_{50}	50	**12**	1	-	-	11
L_{54}	54	**26**	1	25	-	-
L_{64}	64	**63**	63	-	-	-
L'_{64}	64	**21**	-	-	21	-
L_{81}	81	**40**	-	40	-	-

Although the focus of orthogonal array-based designs is on evaluating main effects, it is possible to adapt the design to analyze a limited number of factor interactions (Klein 2014, pp. 100-113). Factor plots, according to Figure 2-24, can be used to identify possible interactions between factors. In Figure 2-24 a, the parallel lines imply that as the three-level factor A changes from A1 to A2 to A3, the corresponding change in the response trend y is the same, regardless of the magnitude of Factor B. The same applies to the change of factor B and the corresponding effect on Factor A. The factors are referred to as additive. Figure 2-24 b indicates a weak interaction, meaning that a change in the level of Factor A leads to a change in y, which is affected by the level of Factor B. Even if interactions are present, the trend of the effect (either positive or negative) remains the same. Klein (2014, p. 52) refers to this type of interaction as synergetic. In the latter case, Figure 2-24 c shows a strong interaction. The crossing lines indicate that there is an inconsistent change in response for Factor A and Factor B. This suggests opposing effects in the change in the levels of Factors A and B. Therefore, the model responding to factor changes cannot be considered additive. (Klein 2014, p. 52, Su 2016, p. 65)

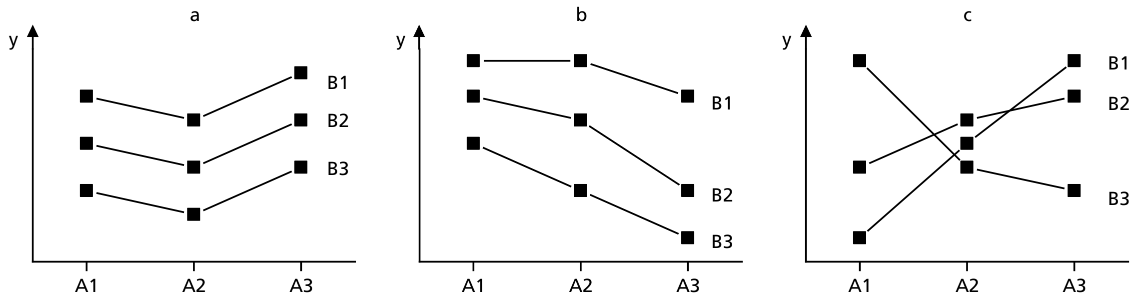


Figure 2-24 Factor plots with different types of factor interactions (Klein 2014, p. 52, Su 2016, p. 65)

Orthogonal array-based designs can be used to screen systems for factors that have a large effect on a response by performing only a small number of experiments. The reduced number of experiments comes with the disadvantage that no higher-order interaction between the individual factors can be analyzed. Orthogonal array-based matrix designs are shown to be advantageous in a situation where a large number of factors need to be analyzed for their importance before fine-tuning in subsequent steps (Ho et al. 1993).

For example, the use of orthogonal array-based designs to improve the design of technical systems has been studied by Shang et al. (2004, p. 3835 f.) for supply chains, by Huynh (2011, pp. 213-220) for maritime threat security and a bandwidth allocation algorithm, by Obara and Morel (2017, p. 26 f.) for energy systems, and by E et al. (2018, p. 511 f.) for the battery cooling system.

2.5 Summary and Preliminary Findings

Chapter 2 presents the theoretical foundations relevant to the research question introduced in Chapter 1. Section 2.1 introduces the object of consideration of this work, the factory, from both a system and a life cycle perspective. After general definitions, systems theory, life cycle thinking, and factory planning are presented as ways to structure tasks around the questions of where, when, and how best to identify opportunities to improve a factory's energy use. Section 2.2 provides background on energy-related terms, definitions, and performance metrics along with their application to factory environments. In addition, the physical principles required to quantify the energy demand in electric circuits and thermodynamic systems are presented as well as techniques for visualizing the measurement results. Finally, Section 2.2 presents different categories of measures to improve energy use in a factory. The categories include measures related to energy efficiency, non-energy benefits, energy flexibility, and energy supply system design.

Given the complexity inherent in the characteristics of energy consumption in factories, modeling and simulation is introduced as an adequate method to evaluate different improvement measures in terms of extended performance metrics. In Section 2.3, after the introduction of different modeling paradigms and simulation techniques, an overview of the available procedure for structuring simulation studies follows. The section concludes with an introduction to state-of-the-art modeling and simulation approaches used in the assessment of energy use in manufacturing systems. The introduction includes coupling concepts for the connection, integration, and (co-)simulation of individual submodels and domain-specific simulation tools for representing the various peripheries of a factory system.

Section 2.4 concludes Chapter 2 with an introduction to the key terms and definitions used in the research field, referred to as the Design of Simulation Experiments (DoSE). After contrasting the discipline-specific terms of statistics with those commonly used in engineering disciplines, various experimental design techniques are presented. Following the introduction, their advantages and disadvantages are discussed with respect to their use in deterministic computer simulations and the challenges and requirements specific to the research question. Finally, orthogonal array-based matrix designs are presented as a feasible way to evaluate different improvement measures simultaneously within complex factory simulation models considering different energy-related performance metrics.

3 State of Science and Need for Research

Chapter 3 provides an overview of the state of science relevant to the research field and the research questions raised in Section 1.2. Section 3.1 defines the scope of the literature review and presents the criteria used in its evaluation in Section 3.2. Based on the evaluation in Section 3.3, the research needs are refined.

3.1 Scope and Evaluation Criteria

The scope of the literature review is restricted to simulation approaches that couple at least two peripheries of a production system using one or more simulation environments and focus on the assessment of energy consumption within manufacturing systems given predefined performance metrics. Research with a predominant focus on identifying and prioritizing energy-related improvement measures was not considered within the scope of this review. The approaches described in the literature are evaluated using four categories and corresponding sub-criteria. Table 3-1 summarizes the findings.

Suitability

The "suitability" category evaluates in which phase of a factory life cycle the presented methodology can offer valid decision support to the user, taking into account the specific restrictions (e.g., availability of planning specification and energy demand characteristics) of the respective phase. The sub-categories are chosen according to the life cycle phases of the factory: planning, operation, tuning and adoption (ref. Subsection 2.1.3). In the life cycle phase of tuning and adoption, existing building infrastructure, and equipment installations are common barriers to improvements during redesign, revitalization, expansion, renovation or restructuring. The demolition phase is not taken into account.

Completeness

"Completeness" assesses which energy-related objectives and performance criteria are addressed by the existing methodologies and to what extent they are taken into account. The category evaluates the holistic nature of the objective function within given system boundaries. In addition to energy demand and costs, energy efficiency, flexibility on the demand side, and the use of renewable energies are also taken into account. Fulfillment is given if, first, the criteria are taken into account, and second, a certain level of detail is presented. For example, the energy efficiency can be evaluated at the factory level as the quotient of production output and energy input (low level of detail) or for individual machines and equipment, taking into account various operating states and utilization rates (high level of detail). Non-energy benefits themselves are considered a multi-dimensional criterion. Again, the criterion is met if, first, the non-energy benefits are generally considered within a given framework of performance criteria and, second, if they are elaborated to a certain level of detail.

Inclusiveness

"Inclusiveness" evaluates the system boundaries and granularity presented in the simulation model (e.g., how many different peripheries of a factory system are included or represented as submodels). The sub-criterion refers to the peripheral factory model presented in Subsection 2.1.2. In contrast to the conventional peripheral factory, model-specific levels are either combined (e.g., process and machine) or subdivided (e.g., auxiliary equipment and technical building systems and energy supply systems). This is done to highlight the diversity presented in the literature and differentiate the existing approaches. The levels considered are product, process/machine, process chain, auxiliary equipment, technical building systems, building envelope, and energy supply systems. In general, the criteria are met when a model for a particular level is described and implemented. If a particular level of the factory is neither described nor implemented in the model, the criterion is not met. Harvey Balls are used to summarize and visualize the results. Empty Harvey Balls represent the levels of the factory system that are not considered in the literature reference. Depending on the level of detail and the quality of implementation, Harvey Balls filled to one quarter, one half, or three-quarters are used. For example, Harvey Balls filled to one quarter are assigned when the level is described in theory, but the informative value of the description is low or unspecific. Harvey Balls filled to one-half or three-quarters are assigned, depending on the level of detail of the modeling approach. Filled Harvey Balls represent levels described in theory and implemented as models with an increased level of detail.

Comprehensiveness

The category "comprehensiveness" evaluates the transparency and reproducibility of the presented modeling and simulation approach. The individual criteria are designated as "transferability", "generalizability", "precision", "usefulness", and "integrability".

The criterion **"transferability - ease of model adoption and specification"** is fulfilled if the modeling and simulation approach can be adopted, specified, or extended according to new requirements and different use cases. The criterion thus assesses the extent to which the framework presented is consistent and generalizable. The criterion is not met if the approach is specific to a particular field of application and the effort to adopt the model is high.

The criterion **"precision - accuracy and verification of simulation models"** evaluates the accuracy of the approaches presented and whether or not the models presented have been verified. Trade-offs between precision and transferability are possible, as precision requires specific models, which may subsequently limit transferability. However, the quality of the acquired results can compensate for these trade-offs. The criterion is fulfilled if the approach has been verified and shows a realistic system behavior that is a good approximation to reality. The criterion is not met if no verification of the model has been carried out or if the deviation between model and reality is significant.

The criterion **"usefulness/effectiveness – application in practice"** of an approach is assessed according to the possibility of being applied in practice. The application in practice requires that the knowledge gained is relevant, can be achieved with a favorable cost-benefit ratio, and is "ready for decision". Therefore, the criterion also evaluates the time effectiveness of the simulation approach, considering both modeling and computation time. The criterion is fulfilled if the use of the presented approach can be directly transferred to applications in practice, and the gained knowledge (benefits) justifies the efforts (cost) associated with its use. The criterion is partly fulfilled if the findings advance the development of the methodology in general; however, the high complexity requires extensive user expertise, and the time-consuming application may prevent further use in practice. If none of the above characteristics are taken into account, the criterion is not met.

In accordance with the criterion usefulness, simulation models should provide decision support. While the process of modeling itself is capable of improving the understanding of a system's behavior, more importantly, the purpose of the model is to test and evaluate measures before they are implemented in reality. The criterion **"generalizability – systematics of assessment method"** therefore evaluates whether the model is presented together with a methodological approach for the simulation-based evaluation of different improvement measures. If such a methodological approach is presented, the criterion is fulfilled. The criterion is not met if only a random selection of measures is made, and their evaluation is carried out on a trial-and-error basis.

The criterion **"integrability – consideration of digital factory concepts"** is completely fulfilled if software and/or a hardware-based link is established between the simulation results and the factory environment (e.g., active control of room temperature or planning and scheduling of production orders based on simulation results). The criterion is not met if no indication is given of how the simulation approach, including data acquisition and/or active control loops, could be established in a factory environment. This is the case if no subsequent events are automatically triggered by the simulation results, but the results are used to support experts in decision-making processes.

3.2 Simulation Approaches for Evaluating Energy Use in Factories

Junge (2007) developed a simulation-based framework for improving energy demand in the plastics processing industry through non-technical measures such as improved production planning and scheduling. The objective function evaluated in his study calculated the trade-offs between logistical, economic, and energy planning targets. For the simulation experiments, a prototypical coupling between the logistics model (SIMFLEX/3D), the machine model, and the building simulation (TRNSYS) was implemented via TCP/IP. Three energy-efficient production planning and scheduling strategies were evaluated against standard priority rules: "outdoor temperature trend", "difference between day and night", and "ventilation-related heat losses" – a control-based approach to the operation of a ventilation system based on the maximum allowable concentration (MAC) of substances in the workplace. The results presented showed that 26.5% of the heating demand could be reduced. However, evaluation of the trade-offs between logistical, economic, and energy targets showed that none of the energy-efficient strategies outperformed conventional planning and scheduling strategies.

The aim of the "ENOPA" project (energy efficiency through optimized coordination of production equipment and technical building services) was to determine the energy demand of manufacturing facilities for various final energy needs (e.g., electrical energy, compressed air, heating, and cooling) (ENOPA 2011). To overcome the uncertainties of conventional planning approaches that approximate energy demand based on simultaneity factors and estimate load curves based on empirical values, the ENOPA consortium extended a material flow simulation to include information on energy demand and heat emissions. Subsequently, the results from the extended material flow simulation were assigned to other simulation environments to derive time-discrete demand profiles for different final energy needs (Martin et al. 2008, pp. 178, 181). The approach coupled the SIMFLEX/3D simulation software used for the material flow simulation with TRNSYS for the calculation of building energy demand, HKSim for the design of the technical building services, and AnyLogic for the evaluation of different production management measures (Hesselbach et al. 2008, p. 627 f.). With regard to the "ENOPA" project, Herrmann and Thiede (2009) presented process modules characterized by standardized parameters to facilitate the implementation of process chain models.

In the context of the "SIMTER" project, Heilala et al. (2008) introduced a hybrid simulation approach that combines discrete event simulation with analytical calculation. The method is intended to support the joint analysis of environmental impact, level of automation, and ergonomics as part of an evaluation and optimization process for manufacturing systems in the design phase. To reduce the modeling effort, the authors relied on commercial software, namely 3DCreate and 3DRealize from Visual Components, a factory and robotics simulation environment with reusable submodels. The environmental inventory data were taken from public databases. In the case study presented, the per product energy consumption was assessed based on machine operating states (idle - standby, down - off, busy – operation). Direct and indirect environmental impacts were also calculated. The authors mentioned the possibility of shifting production in order to reduce peaks in energy consumption. However, no further details on how to implement these measures were presented. Building on the results of the "SIMTER" project, the "EPES" project further developed the process-oriented sustainability simulation toolkit, which combines life cycle assessment (LCA), values stream mapping (VSM), and discrete event simulation (DES). The project focused on material flows, process cycle times, resource utilization, equipment, and even human operator activities. The advantage of the proposed methodology is its usefulness for non-simulation experts, as well as their integrated product-process-production system modeling, which enables the design of manufacturing systems through a simultaneous assessment of production requirements and environmental aspects. (Heilala et al. 2013)

Michaloski et al. (2011) suggested integrating Energy Management Systems (EnMS) and Manufacturing Executing Systems (MES) using Discrete Event Simulation (DES). The authors claim that opportunities to improve sustainability, including a reduction in energy demand, can be addressed by connecting and integrating EMS and MES data. The possibility of using such integrated systems in demand-side management applications is mentioned. The objective of the presented research is to modify the production schedule according to a predefined set of performance metrics (KPIs). The authors present KPIs for MES (e.g., throughput, yield, machine and process efficiencies, waste or scrap cost, and maintenance scheduling), EMS (e.g., energy consumption, energy losses, and indoor climate conditions) but also HVAC control, Overall Equipment Effectiveness (OEE), and product quality. However, no information is given on how the different KPIs are combined in a decision process to reorganize production jobs. Other limitations of the research conducted were the low level of detail presented on the DES simulation model as well as its practical implementation. Furthermore, only a qualitative description of the simulation results was presented.

Hao et al. (2011) developed an integrated simulation approach that is able to take into account both building design and daily production schedules while aiming for minimum energy consumption in a welding shop. For this reason, the authors derived the process energy demand analytically based on the process parameters and production schedules. Subsequently, the derived results were integrated into the EnergyPlus simulation environment to consider the effects of welding operation on building energy consumption. Due to the complexity of the energy flows within the buildings, no singular analytical expression for the objective function could be determined. Therefore, the authors present a two-level simulation-based optimization approach for both the building design and the production schedule. At the first level, an ordinary optimization (OO) assuming common working shifts is performed to derive the optimal window position and glass transmittance. Assuming additional constraints, including an equal amount of finished products per day, maximum working hours, as well as varying energy prices and outdoor temperatures, a genetic algorithm (GA) was used at the second level of the optimization in order to find the best time to execute welding jobs. A general framework for solving multi-objective optimization problems using simulation modeling has been presented in the research. However, the practical application is limited as no details on data processing between EnergyPlus (for deriving energy consumption) and MatLab (for optimization) have been presented. Moreover, the optimization requires a high number of iterative simulation runs ($N \geq 1000$). In the context of the above work, Liu et al. (2013) provided further information on the two-level simulation-based optimization approach. Information was also given on the statistical programming problem concerning uncertainty arising from varying weather conditions and energy prices and on ordinary optimization.

As a result of the "THERM" project (THrough Life and Energy Resource Management), Oates et al. (2011) and Oates (2013) presented a model that combines energy flows in manufacturing with those in factory buildings using only one simulation environment. The authors addressed the limitation of discrete event simulation, which is used to model stochastic behaviors but does not characterize the continuous thermal behavior of machine operations in a factory environment. First, a graphical representation of the energy and material flows was presented. Second, individual models for industrial processes, auxiliary equipment, and the factory building were introduced into Matlab/Simulink using the International Building Physics Toolbox (IBPT). In addition, the material flow model represented the heat transfer between the material and its environment. The model was validated against the commercial building physics software IES. A variation of max. 15% was found. Simulation results for the operation of a drying process were presented, which show that energy-saving measures on the process level increase the energy demand on the facility level (e.g., for heating purposes). Further results from the THERM Project can be found in Despeisse et al. (2013) and Wright et al. (2013).

Thiede (2012) expressed the importance of going beyond improving individual machines and looking at energy efficiency in factories in an integral manner considering machines, auxiliary processes, and technical building systems. In a related publication, Thiede co-authored a paper on the importance of estimating time-based consumption patterns for the various resources used in factories (e.g., electricity, compressed air, etc.). The authors propose to use the estimated consumption pattern for demand-oriented dimensioning and control of auxiliary processes (e.g., compressed air) and technical building systems (e.g., heating and cooling), the assessment of energy costs and environmental impacts as well as the derivation and selection of energy efficiency measures (Herrmann et al. 2011). Given the above requirements, the author proposed an energy-aware planning and evaluation tool based on a multilevel simulation framework. He developed various parametric modules to represent auxiliary processes (e.g., compressed air system and steam generation). Co-simulation of discrete events was performed using the AnyLogic software environment. The scope of performance metrics considered by Thiede was limited to energy costs and GHG emissions. Although the developed simulation approach is generic, modular, and scalable, the authors suggest further research on automated methods for optimization and multi-criteria decision-making.

Moynihan and Triantafillu (2012) coupled DesignBuilder and EnergyPlus to evaluate energy efficiency measures in production plants. DesignBuilder was used to model the construction, HVAC system, lighting, and zone activities. EnergyPlus contained information on energy costs and the operation of the boiler system. However, in their approach, the authors only consider average values for internal gains without specifying the operating schedule of processes and equipment. The accuracy of the simulation approach was assessed by calculating the percentage error between the energy consumption determined by the simulation and the actual energy consumption determined by the energy supplier. The authors considered activities in the building zones such as occupancies and internal heat gains from machine operation based on average values.

In the "INFO" project, researchers at the Vienna University of Technology, together with industry partners, developed a co-simulation approach for production systems by linking various simulation environments (INFO 2013a, INFO 2013b). As part of the project, Leobner et al. (2011) presented a generalizable model for the integrated simulation-based assessment and optimization of energy use within production plants. Synchronization and data exchange between various simulation programs was accomplished using a Building Controls Virtual Test Bed (BCVTB), middleware software developed by the Lawrence Berkeley National Laboratory at the University of California (Wetter 2011). Within the specific application in the "INFO" projects, MATLAB (used for modeling the machine tool) is connected with Dymola/Modelica (used for modeling the energy system) and EnergyPlus (used for modeling the building). Focusing on greenfield planning tasks, the researchers evaluated different scenarios for the energy-efficient design of technical building systems and the building envelope. However, the relationship between energy efficiency measures at different levels of a production system was not the specific focus of the project. In addition, demand-side flexibility and non-energy benefits were not considered as evaluation criteria. Further results from the "INFO" project can be found in Bleicher et al. (2014).

Haag (2013) proposed a method that aims to assist factory planners and operators in energy-related planning, evaluation, and optimization tasks. A simulation approach is chosen to evaluate the impact of organizational improvement measures on the energy consumption of machine tools and their peripheral equipment. The submodels take into account the energy consumption depending on different operating states. Using Plant Simulation, the author has evaluated various scheduling and sequencing strategies, together with varying process and logistic parameters (e.g., buffer size), in terms of their energy and productivity performance. However, a verification of the individual submodels is not carried out. In addition, equipment in the periphery of the factory is considered using simplified models. The combined effects of energy efficiency measures were not evaluated in the research conducted.

In the context of the "EMC2-Factory" research project, Stahl et al. (2013) presented "Total Factory Simulation" as a coupled simulation framework to support different stakeholders involved in the factory planning process, e.g., architects, civil engineers, and production planners. The core of the presented model was built in a discrete event simulation (DES) environment, namely Plant Simulation. This is done to account for the influence of production schedules, batch sizes, and other value stream-related parameters. The production plants are modeled considering different operating states (off, starvation, set-up, failure, blocked, and working), implying the EnergyBlock methodology developed by Weinert et al. (2011). In addition to production equipment, the EMC2 Factory project also included modules developed for peripheral systems, e.g., compressed air systems. The coupling with the energy building simulation software EnergyPlus was suggested by the authors but not specified. The main contribution of the presented research was the development of a module for the simulation of the energy demand of peripheral systems, e.g., of a compressed air system and its implementation in Plant Simulation.

Brundage et al. (2014) developed an energy-conservation strategy for production lines and technical building facilities that does not affect throughput. The goal of the research presented was to optimize the energy consumption of production lines and HVAC systems by shutting down machines and adjusting the setpoints of the HVAC system during periods of peak energy demand. Therefore, the concept of energy opportunity windows and recovery times was developed and applied to each machine of a production line. The concept took into account machine speed, buffer sizes, and random downtime events. To quantify the energy-saving potential, the authors coupled a production line model (represented by a continuous flow model in MATLAB/Simulink) and a thermal model of the factory building (using the conduction transfer functions for the heat balance algorithm in EnergPlus). The machines were considered at two operating states, operation (100%) and shut down (0%).

Davé et al. (2016) presented an eco-efficiency modeling framework based on resource and production data. First, performance indicators (e.g., power factor, water footprint, energy mix, material yield, energy per unit, and thermodynamic minimums) have been developed for use in various subdivisions (e.g., facilities, facility zones, single-zone utilities, and manufacturing cells) and for different assets of a factory (e.g., heating, lighting, compressor, machine tool, etc.). Second, the authors performed a regression analysis to compare models derived from cursory (per quarter time-step) and detailed (per hour time-step) measurement data. The strongest correlation between cursory and detailed models was found at the facility level. In addition, the need for detailed models for utility and manufacturing cell subdivisions was derived. In summary, a different time-step granularity is required for different assets to enable informed decisions on technical interventions. Although the presented research can be characterized as conceptual, the findings from the case study at a furniture manufacturer contribute to improving the efficiency of future modeling approaches through an appropriate choice of model granularity. Further details on the modeling approach can be found in Davé et al. (2015).

Mousavi et al. (2016) investigated the energy efficiency assessment of unit processes and their dynamic interaction within process chains. First, the different dynamics of unit processes in terms of operational states and production load were discussed (e.g., milling and turning processes compared to furnace processes). Depending on the sensitivity of a process to changes in system parameters, the authors proposed either a screening or an empirical modeling approach. Thus, the authors suggested that certain processes (e.g., furnaces) allow for simplified process models due to their stable power consumption. Second, an energy-oriented framework for the simulation of manufacturing systems was presented. Finally, a hybrid model structure combining both state-based and empirical modeling methods for processes and process chains was proposed. The authors presented the results of an energy efficiency assessment for different combinations of lathes and milling machines, assuming a heterogeneous machine park with the possibility of processing products on different machine tools. Also, the effects of changing the process parameters and batch sizes were evaluated for the three most efficient combinations, showing, for example, that increasing the material removal rate can more than double the energy efficiency. Limitations of the presented research include the limited consideration of TBS within the modeling framework. In addition, strategies to improve the systems performance focus on short-term planning problems, including scheduling, product routing, and lot sizing rather than strategic mid- to long-term decisions towards energy efficiency.

Schönemann (2017) developed a multiscale simulation approach for a battery production system. As a novelty, the author presented a co-simulation approach that incorporates the product perspective into a holistic simulation framework. The author claims to have improved existing co-simulation frameworks that provide an integrated assessment of technological, economic, and environmental objectives. Further contributions included improvements with respect to the structuring of individual simulation models, the definition of relevant system elements, their input and output parameters, and connecting interfaces as well as a detailed procedure model to improve the applicability of co-simulation approaches in general. Schönemann developed the process chain model to be the central submodel that links the multiscale simulation approach. The core model was developed in the AnyLogic software environment. Matlab/Simulink was used for the compressed air generation system and the building model. The coupling was realized using the middleware software TISC. To enable the use of different simulation environments, data exchange between models and simulation environments is required. Schönemann co-authored a related publication that discusses the advantages and disadvantages of different coupling concepts and their application in holistic factory models (Thiede et al. 2016).

Khattak (2016) developed a hybrid simulation approach to evaluate energy and exergy efficiency within energy management. In subsequent publications, Khattak and his co-authors have further extended the approach and presented additional case studies (Khattak et al. 2016, Khattak et al. 2018). The approach combines a physics-based energy modeling with a data-driven approach that is able to compare improvement measures with predefined baseline scenarios. The authors use 'rough-cut' profiles when the availability of energy consumption data at the process or factory level is limited. No modeling approach for the machine or process chain level was presented. Khattak et al. implied a holistic understanding of factories that took into account the interaction between production equipment and factory buildings. This also includes the consideration of heat emissions dissipated into the factory environment during machine operation. The models of the building and the technical building system are calibrated and verified by comparing the simulated heating demand with the demand measured by the building management system. The approach was applied to a production line for an engine cylinder head and a food factory. The improvement measures assessed included the use of a heat recovery unit, the connecting of an external heat exchanger (free cooling) to the cooling system, and the integration of a photovoltaic system (Khattak 2016, p. 56 f., Khattak et al. 2018, p. 9 f.).

Greinacher (2017) introduced a model-based approach to optimize manufacturing systems with respect to multi-objective lean and resource-efficiency goals. Its simulation model includes individual modules for manufacturing processes, the process chains as well as simplified modules for parts of the technical building and the energy supply systems. The various modules were implemented in Siemens Plant Simulation. The methodology presented by the author implies the design of the experiment to analyze the effects and interdependences of improvement measures within manufacturing systems. Based on the Fast Flexible Filling Design response data, the author uses Kriging to compute Gaussian-process meta-models for cost per finished part, throughput time, specific energy consumption, and delivery reliability. Although considerable effort is required to create meta-models in the first place, they outperform simulation models when it comes to performing multi-objective optimizations. This is true as long as the considered design space of the underlying system parameters does not change significantly. (Greinacher 2017, Greinacher et al. 2020)

As part of the "Balanced Manufacturing" project, Gourlis and Kovacic (2016) used thermal modeling to assess the impact of refurbishment measures on the energy performance of industrial buildings. Their simulation in EnergyPlus is based on an exact representation of waste heat emissions of machines and auxiliary equipment. Retrofit measures focus on the building envelope and include passive measures to reduce thermal discomfort due to summer overheating (Gourlis and Kovacic 2017, p. 1181). Also, in the context of the "Balanced Manufacturing" project and building on the results of the "INFO" project, Sobottka et al. (2018) and Sihn et al. (2018) developed an integrated hybrid simulation approach capable of optimizing the scheduling and sequencing of orders within complex production systems. The approach integrates discrete and continuous simulation models at the component level, referred to as "cubes". Cubes can be used at different levels of a production system, including machines and auxiliary equipment, buildings, and energy converters (Smolek et al. 2018, pp. 383-387).

To cope with the restrictions of co-simulation models, such as the limited reusability and the high computational costs, the hybrid simulation approach aims at improving the possibility to perform simulation-based optimizations based on iterative simulation runs. The authors described the example of a furnace process that combines the continuous behavior of energy-related variables, represented by balance equations, with the discrete behavior of the material flow. The authors also develop an objective function that takes into account not only energy and associated CO_2 costs but also storage costs for goods completed before the delivery date and penalty costs for late deliveries. A genetic algorithm (GA) with pattern search is implied to solve the optimization problem. The runtime is improved by splitting the optimization procedure into two parts. In the first part, scheduling and sequencing are optimized. In the second part, the production schedule is determined, and the operation time of the equipment in the periphery is optimized in order to reduce energy costs. The developed approach has been tested in an industrial bakery, and scenario-dependent energy-cost savings between 5-25% are reported. Although the authors assume a holistic understanding of networked factory environments, the focus is on scheduling and sequencing. Further measures to improve energy efficiency are not taken into account. In addition, the strategy for flexible operation of the peripheral equipment is not specified. Furthermore, the authors admit that the hybrid simulation approach is difficult to use for non-simulation experts.

Kuhlmann (2020) investigated the possibility of designing agile energy supply systems for factories. In order to conduct the agility analysis, the author developed a procedure model consisting of five steps. These steps included the analysis of agility drivers, the derivation of technological and organizational agility options, and the modeling, simulation, and evaluation of these agility options within the energy system (steps three, four, and five). The author developed an agent-based factory simulation model and applied Monte Carlo simulation to evaluate scenarios with different agility enabling options, also considering uncertainties with respect to the agility-increasing characteristics (modularity, mobility, compatibility, universality, and scalability). The factory model proposed by the author combines individual models for the production system, including machines and peripheral equipment, the energy supply system including the usage of on-site renewable energy sources, and the energy pool including energy storage capabilities used to balance energy supply and demand. Based on his results, the author suggested augmenting the factory model and including the factory building and its technical building systems. He also suggested complementing additional performance metrics in order to enable a holistic evaluation of agility options. (Kuhlmann 2020)

With reference to the evaluation criteria used in this work, the improvement of agility in energy supply systems is considered a specific non-energy benefit.

Table 3-1 Evaluation of the state of science (degree of fulfillment: not ○, partial ◔◑◕, complete ●)

Authors	Kuhlmann 2020	BALANCED MAN. 2018	Schönemann 2017	Greinacher 2017	Khattak 2016	Mousavi et al. 2016	Davé et al. 2016	Brundage et al. 2014	Stahl et al. 2013	Haag 2013	INFO 2013	Moynihan et al. 2012	Thiede 2012	THERM 2012	Hao et al. 2011	Michaloski et al. 2011	SIMTER & EPES 2011	ENOPA 2011	Junge 2007
Suitability – Factory life cycle																			
Planning	●	○	●	○	○	○	◑	○	◔	◑	●	○	◑	○	◑	○	●	●	○
Operation	○	●	◑	●	◑	●	○	◑	◕	◕	○	◑	●	●	◕	●	○	●	●
Tuning and adoption	○	◑	○	○	●	○	◔	○	○	○	◑	◑	○	○	○	○	○	◑	○
Completeness – Objectives																			
Energy demand/costs	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●
Energy efficiency	○	●	◑	◑	●	●	◔	◔	◑	◑	◑	◔	●	◔	◔	◑	◑	◑	◑
Energy flexibility	◔	◑	◑	○	○	○	○	●	○	○	○	○	○	○	○	◔	◔	○	○
Manufacturing KPIs	○	◑	●	◕	○	◕	○	◔	◔	●	○	○	◕	○	◔	◔	◕	◔	◕
Non-energy benefits	◑	○	○	○	○	○	○	○	○	○	○	○	◔	○	○	◑	◑	◔	○
Inclusiveness – System boundaries																			
Product	●	○	◑	○	○	◔	○	○	○	◑	○	○	○	○	○	○	◑	○	○
Process/machine	●	●	●	●	○	●	◑	◑	◑	◕	◕	○	●	◕	◕	◑	●	◕	◕
Process chain	○	●	●	●	◑	●	◑	●	●	○	○	○	●	◑	○	◑	●	●	●
Auxiliary equipment	◑	●	●	◑	○	◑	◑	○	●	◑	◕	○	●	●	○	○	○	◕	○
Technical building system	○	●	◕	◑	●	◑	◑	◕	○	○	●	●	◕	◕	◕	◑	○	●	◕
Building (envelope)	○	●	◕	○	●	○	○	◕	◑	○	●	●	○	◑	◑	○	○	◕	◕
Energy supply system	●	◑	○	○	◑	○	○	○	○	○	◑	◔	○	○	○	○	○	○	○
Comprehensiveness – Modeling and simulation approach																			
Transferability	●	◑	◑	◑	●	◑	◔	◔	◑	◑	◕	◕	◕	◑	◑	◔	◕	◕	◕
Precision	◑	◕	◕	◑	◑	◑	◔	◑	◑	◑	●	◕	◑	◕	◑	◔	◑	◕	◕
Usefulness/effectiveness	◕	◕	◑	◑	◕	◕	◑	◔	◕	◑	◕	◕	◕	◑	◔	◔	◕	◑	◑
Generalizability	●	◔	○	●	○	◑	○	○	◔	○	◔	○	◑	○	○	○	○	○	○
Integrability	○	◔	○	◑	◔	○	○	◔	○	○	○	○	○	○	○	◑	○	○	○

3.3 Summary and Refined Research Needs

This section summarizes the findings of the literature review conducted with reference to the evaluation criteria introduced in Section 3.1. This includes the analysis of shortcomings present in existing methodologies in general and the limitations of available factory simulation approaches in particular. The section concludes by refining the research needs.

Suitability

Reviewing the state of research showed the limitations of existing methodologies with regard to a holistic assessment of energy use within existing manufacturing facilities. While several methods have been developed to reduce the energy use of factory operations through improved production planning and scheduling (e.g., Junge 2007, Michaloski et al. 2011, Haag 2013, Sobottka et al. 2018), few authors have addressed the specifics related to the redesign, revitalization, expansion, renovation or restructuring of existing factories (e.g., Moynihan and Triantafillu 2012, Khattak et al. 2018).

Completeness

Energy demand and associated costs, as well as energy efficiency, are performance metrics considered by all methodologies studied. In addition, several authors also include conventional manufacturing KPIs in their energy assessment, such as process time, throughput (ref. Mousavi et al. 2016, p. 22), inventory levels (ref. Junge 2007, p. 98), machine utilization (ref. Schönemann et al. 2019, p. 166), overall equipment efficiency (OEE) (ref. Haag 2013, p. 108 f.), reliability of delivery (ref. Greinacher et al. 2020, p. 168), production output (ref. Thiede 2012, pp. 117-121), or production deficits (ref. Sobottka et al. 2018, p. 418). However, only a few authors take into account additional performance metrics, such as energy flexibility or the share of energy demand met by renewable energies.

In their assessment, Heilala et al. (2008, p. 1925), Michaloski et al. (2011, p. 95) extend the existing performance metrics and take into account ergonomics, as well as worker comfort, safety, and health aspects, in their assessment of energy use in factories. Kuhlmann (2020, pp. 90-103) introduced agility as an additional performance metric. However, none of the authors has yet introduced non-energy benefits as an independent category of performance metrics that can be evaluated in a factory simulation model.

Inclusiveness

First factory models that couple different subsystems and focus on energy use in factories have already been presented by Junge (2007, p. 81) and the consortium of the ENOPA project (ENOPA 2011). Thiede (2012, p. 108 ff.) added further submodels for auxiliary equipment and technical building systems. Additional efforts were made by the INFO project consortium that resulted in an improved level of detail for models representing technical building systems, the building envelope, and the energy supply system (INFO 2013a, p. 24). Haag (2013, p. 92) and Schönemann (2017, pp. 88-93) added the product perspective at the lower end of a multiscale factory model, while Khattak (2016, p. 54) and the Balanced Manufacturing project consortium have further detailed the energy supply system on the upper end of the scale.

Although the overview shows a general trend toward extending the system boundaries of factory simulation models, the level of detail still varies considerably. In addition, many models either focus on the modeling of machines and process chains (e.g., Heilala et al. 2008 – SIMTER, EPES project, Michaloski et al. 2011, Stahl et al. 2013, Greinacher 2017) while others focus their attention more on the technical building systems and the building (e.g., Moynihan and Triantafillu 2012, INFO 2013a, Khattak 2016). In general, the energy supply system is still one of the least considered parts in existing factory simulation models.

Comprehensiveness

The **transferability** of existing multiscale factory models and co-simulation approaches is limited, as most models and/or co-simulation approaches are tailored to specific applications (Raich et al. 2016, p. 1). Although individual authors developed scalable factory models based on building blocks and with a modular structure (e.g., Thiede 2012, p. 97), the initial construction of representative factory models still requires considerable time and effort. In addition, so far there is no simple approach to adapt and verify complex multiscale factory models to individual use cases. Furthermore, there is no consensus on whether to pursue an integrated modeling approach (using only one modeling and simulation software) or to couple domain-specific software tools with a middleware. While Thiede (2012) advocates an integrated approach, the INFO project and Schönemann use a middleware software, either BCVTB or TISC Suite, to couple different software environments or submodels (INFO 2013a, pp. 23-25, Schönemann 2017, p. 142).

In particular, with reference to the criteria **precision** and **usefulness**, the trade-offs between the use of approved domain-specific modeling and simulation tools must be weighed against the challenges associated with coupling them. Today, the level of detail and consistency of existing factory simulation models varies considerably with respect to the different levels of a manufacturing system. Various multiscale factory models represent either one or the other submodel in a simplified form. For example, Moynihan and Triantafillu (2012, p. 76), Khattak et al. (2016, p. 102), and Gourlis and Kovacic (2020, p. 7) simplify the representation of the underlying manufacturing process and process chain model but specify the technical building systems, building, and energy supply system model. The opposite is the case with Stahl et al. (2013, p. 494), Mousavi et al. (2016, p. 14), Greinacher et al. (2020, p. 169), and Greinacher et al. (2020, p. 169), who specify the process chain model but simplify the technical building systems and building model. Different levels of detail within complex multiscale factory model representations, inconsistent levels of model verification and validation, high computational overhead (ref. Smolek et al. 2018, p. 391, Greinacher et al. 2020, p. 157), and insufficient standardization are major shortcomings of existing factory simulation models and limit their practical application and user acceptance. Mawson and Hughes (2019, p. 104) also identified the neglected dynamics and interdependencies between different levels of manufacturing systems and the lack of model verification and validation to be limitations in existing multilevel factory simulation. While there are many references in the literature to the development of submodels and model structures, there is only a limited number of references on the usefulness of these complex models in industry case studies as well as on the efforts to implement and adapt them. Focusing on the improved operation of machines, process chains, and auxiliary equipment, Thiede reports relatively little effort in applying his modeling approach to use cases in the die casting, weaving mill, electronics industry (Thiede 2012, p. 175). During the relocation of production equipment to a new building, Bleicher et al. used a multiscale factory simulation based on domain-specific modeling environments to compare different energy supply system designs. The authors affirm the validity of the coupled factory simulation based on verified submodels. However, no indication is given of the implementation effort nor the runtime of each simulation (Bleicher et al. 2014, p. 444). In summary, the data collection effort for model parameterization, as well as the data exchange between different models and simulation environments, requires significant time and effort (ENOPA 2011, p. 71 f.). The development of initial factory models also involves considerable expertise (Sihn et al. 2018, p. 450).

The literature reports a steadily increasing level of detail of multilevel factory simulation models, but still lacks a **generalizable** approach for the combined and simultaneous assessment of different energy-related improvement measures. So while models are accessing an ever-expanding design space, there has been limited progress in managing the increasing complexity involved. Thiede (2012, p. 141) uses scenarios to evaluate individual or a combined set of measures, Mousavi et al. (2016, p. 22 f.) run simulations for all parameter combinations to evaluate the combined effect of machine selection, process parameter selection, and job sequencing on completion time, electricity consumption, and energy efficiency. Greinacher et al. (2020, p. 170) first applied the design of experiments (Fast Flexible Filling Designs) to deal with a large number of factor combinations. The authors derive meta-models that are further used to optimize a production-planning problem. Compared to the use of simulation models, meta-models allow performing multi-objective optimization almost in real-time, although they must be regenerated each time the system setup is changed (Greinacher et al. 2020, p. 171).

With regard to the criterion of **integrability**, this extends the possibilities to use the knowledge gained from simulation models in different operational planning tasks. Michaloski et al. (2011, p. 98 f.) discussed the use of data from energy management and manufacturing executing systems (EMS and MES) in a simulation model to improve process scheduling and technical building systems operation. However, none of the references in the literature report the implementation of continuous feedback loops based on the information obtained from multiscale factory simulation models.

Taking into account the aforementioned, the refined research needs and the aspired novelty can be summarized as follows. This work addresses the lack of comprehensive and generalizable assessment procedures that imply simulation modeling and can be used for the development of new and the modernization of existing factory sites considering multiple energy-related performance metrics. The aspired novelty in this work is to develop a methodologically sound way to exploit the complex design space captured by multiscale factory simulation models in the search for appropriate combinations of improvement measures and to quantify the combined effect of a large number of improvement measures while targeting near-optimal design solutions.

The refined research question can be summarized as follows:

Refined research question

How is it possible to evaluate different improvement measures simultaneously in terms of multiple energy-related performance metrics using a factory simulation model?

4 Requirements on the Methodology

Based on the review of the state of science in Section 3.2 and the research needs that were specified in Section 3.3, Chapter 4 outlines the objectives and associated requirements for the development of a new model-based methodology and its use in the assessment of energy use in factories. Again, the objectives and requirements are linked to the same categories and subcategories introduced in the assessment of the state of science in Section 3.1.

4.1 Specification of Requirements

This section sets out the objectives for the development of the methodology and identifies the related requirements. Finally, the requirements are clustered in requirements for the assessment procedure in general and the factory simulation model in particular.

Taking into account the category **“suitability”**, the methodology intends to provide decision support for various energy-related planning tasks and the associated factory life cycle phases. A particular goal of the methodology is to consider the challenges associated with energy planning in a brownfield environment during the modernization (e.g., redesign, revitalization, expansion, renovation or restructuring) of existing factories. Yet, certain aspects of the methodology should also prove to be beneficial for the energy planing in greenfield environments. In order to provide a solid basis for investment decisions, the methodology must allow a quantified assessment of improvement measures in relation to the resource energy. Four different requirements are derived from this objective. First, a comprehensive representation of the energy consumption characteristic within the model is required, covering all peripheries of the factory system. Second, the model architecture must be modular and extensible to accommodate the individual characteristics of existing factories. Third and fourth, the effort for model implementation and adjustment must be low while maintaining high accuracy and good verifiability.

Referring to the category **“completeness”**, the methodology must take into account the diversity of multi-criteria planning objectives. This results not only in the requirement to complement conventional energy-related performance metrics with non-energy benefits, but also to implement models that enable their evaluation. The detailed assessment of additional performance metrics requires the methodology to embed advanced models and verified software tools from different engineering domains (manufacturing engineering, architecture, energy systems engineering, etc.). This results in the requirement to use a co-simulation approach that allows the flexible coupling of domain-specific software tools.

The aim of the methodology is to improve the assessment of energy use within factories and to match energy demand and supply, taking into account energy-efficient supply systems and strategies to reduce CO_2 emissions. For this reason, the methodology must also be able to evaluate improvement measures, their mutual effects, and their relationship to the energy supply system design. However, according to the evaluation in Section 3.3, the existing approaches do not comprehensively cover the energy supply system as part of a multi-peripheral factory simulation model. The **"inclusiveness"** category thus requires that the energy supply system model be extended to include additional energy carriers and energy conversion technologies.

Another goal of the development is that the methodology can be applied to use cases in different companies and across different manufacturing sectors. Looking at the **"comprehensiveness"** category and its subcategories **"transferability"**, this underlines the requirement for rapid model implementation and adaptation. The individuality of companies and their manufacturing systems, as well as the dynamics of future technology developments, also require a methodology that employs a modular and expandable model architecture.

In the pursuit of good model accuracy and verifiability, the methodology aims to use a model architecture based on information sources readily available in the industrial environment (e.g., from the electronic nameplate, technical documentation, or temporal measurements). This includes the objective of assembling a multi-peripheral factory model from individual submodels and identical parameter settings in order to improve the verifiability of individual components within complex models. With regard to the subcategory **"precision"**, the listed objectives reinforce and strengthen the requirements in terms of implementation time, adaptation effort, modularity, accuracy, and verifiability.

Designated **"usefulness or effectiveness"**, the subcategory summarizes all objectives and requirements that are intended to strengthen the practical relevance and applicability of the developed methodology in industry practice.

The first objective is to assist the practitioner in the selection of improvement measures. This objective is addressed by the requirement to develop a set of standardized improvement measures for different categories and project focus areas (e.g., energy efficiency, energy flexibility, use of renewable energy sources, etc.). Decision-makers need a methodology that provides robust and statistically relevant solutions with a good trade-off between model accuracy, modeling effort, and simulation time. This is an additional requirement to allow efficient experimentation with the simulation model. Another objective is to provide simulation results in a way that can be easily accessed by all parties involved in a planning process (general managers, production engineers, architects, specialist planners, etc.). This requires that both the decision-making process (e.g., selection of the design parameters) and the presentation of results are supported with graphical methods.

The methodology aims to overcome trial-and-error approaches while experimenting with a multi-peripheral factory model. The subcategory **"generalizability"** summarizes the objectives and requirements introduced to improve the systematics of model evaluation. The first objective is to support the screening (selection and combination) of improvement measures, also taking into account their individual design parameters. The second objective is to enable the simultaneous evaluation of combined improvement measures in order to identify interdependencies and tradeoffs (mitigating and reinforcing effects) between individual measures. The third objective is to assist in the development of conceptual designs for energy supply systems that represent a near-optimal configuration of individual system components and corresponding parameter settings with respect to extended performance metrics. These goals highlight the importance of developing efficient and statistically sound ways to systematically experiment with complex simulation models while guiding users to near-optimal solutions. It also adds the requirement to prioritize parameters that are of practical relevance to decision-makers and can be actively influenced (e.g., the installed capacity of the chiller unit or the tank size of a cooling reservoir.)

The subcategory **“integrability”** is composed of goals and requirements that relate to the concept of digital factories. Related to this subcategory, the presented work intends to advance the use of measurement data within multi-peripheral factory models. This is mainly to improve the verifiability of the simulation model and to strengthen the credibility of the simulation results obtained.

All requirements are summarized in Table 4-1.

Table 4-1 Summary of requirements for the factory simulation model and assessment procedure

	Factory simulation model		Assessment procedure
1.	Comprehensive representation of energy consumption characteristics	1.	Extended performance metrics
2.	Modular and extensible model architecture	2.	Efficient way of experimenting with simulation models
3.	Fast model implementation and adaptation	3.	Statistically sound way of experimenting with simulation models
4.	Fast model execution	4.	Improved use of measurement data
5.	Flexible model coupling	5.	Practical relevance of the selected parameters
6.	Good verifiability of the model	6.	Graphical support of the decision-making process and presentation of results
7.	High model accuracy		
8.	Extended energy supply system model		

4.2 Research Scope and Limitations

The proposed methodology aims to provide decision support during the modernization planning of manufacturing systems, with the objective of improving its energy-related performance metrics. However, there are some aspects that limit the scope of the present work. These are presented below.

Based on the factory life cycle phase proposed by Dombrowski and Ernst (2014, p. 338), the methodology focuses on conceptual designs during general planning rather than technical design specifications during detailed planning (ref. Figure 4-1).

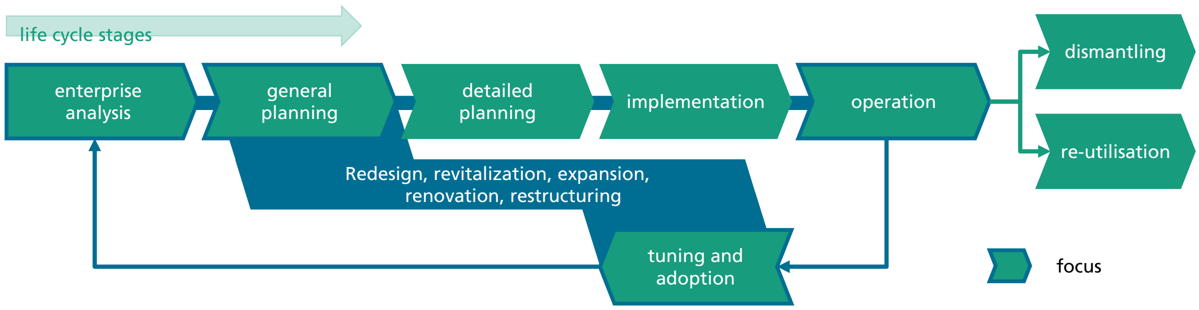


Figure 4-1 Phases of factory life cycle addressed by the methodology (own representation based on Dombrowski and Ernst 2014, p. 338)

This research extends existing performance metrics; however, it is not intended to weigh and balance different energy-related performance metrics. This work does not present a hierarchy of the extended performance metrics, nor does it intend to classify their importance in the context of performance metrics for holistic manufacturing systems.

The model in this thesis intends to cover different peripheries of a manufacturing system, from processes, machines, and auxiliary equipment to technical building and energy supply systems. The modeling approach does not include the product level and does not consider levels outside the perimeters of the factory site.

Another limitation of this research is the focus on discrete parts manufacturing. The methodology presented does not intend to take into account the energy demand characteristics and specificities of process engineering plants.

The lack of measurement data from consistent energy metering setups is still a major challenge in the verification of complex multi-peripheral factory models. This is especially true for heterogeneous manufacturing environments in existing factories. Within the scope of this work and considering the practical constraints, the aim is to verify only single submodels of the multi-peripheral factory model.

There are no specific requirements for the previous knowledge of the users of this method. However, background knowledge in the field of modeling and simulation, as well as statistics, enables an adequate interpretation of the informative value derived from simulation results.

Considering various performance criteria, this research aims to advance solutions on how to efficiently explore the design space of complex factory simulation models in the search for an optimized system design. However, it is not the intention of this research to employ optimization algorithms (e.g., genetic algorithms, evolutionary strategies, simulated annealing, etc.).

With the concept of a digital factory in mind, this work aims to significantly improve the connection between the real world and its virtual representation through the increased use of measurement data. However, no attention is paid to evolving the factory simulation model to automatically adapt to the latest changes and events within the real factory environment. Since the focus is on planning and not on operation optimization, it is also not intended to actively trigger events or control equipment installations in the factory environments based on the findings from the factory simulation model.

4.3 Summary

Chapter 4 specifies the requirement for the development of the methodology. All requirements are derived from the different requirement categories, namely suitability, completeness, inclusiveness, and comprehensiveness. Two main fields of action were identified in the requirements. First, the development of the factory simulation model, and second, the improvement of existing assessment procedures with a focus on enhanced performance metrics and efficient ways to experiment with complex simulation models. A total of eight requirements were specified for the factory simulation model and six for the assessment procedure. Finally, Section 4.2 narrows the scope of the development goals.

5 Simulation-Based Assessment of Energy Use in Factories

In this chapter, a methodology for a step-by-step assessment of energy use in factories using simulation modeling is proposed. Section 5.1 outlines the methodology, while Sections 5.2 to 5.4 detail the development and application of the assessment procedure and the factory simulation model.

5.1 Outline of Methodology

The methodology starts by introducing extended energy-related performance metrics for factory systems (ref. Section 5.2). Section 5.3 presents the assessment procedure and deals with the selection and allocation of improvement measures to individual peripheries of a factory. The assessment procedure also includes a new approach for the joint evaluation of improvement measures using design of simulation experiments. To improve transparency and facilitate decision-making, this is further complemented by a new approach for visualizing and evaluating intermediate and final simulation results. The simulation experiments are applied to the factory simulation model developed in Section 5.4. The model covers several peripheries of a factory, including machines, process chain, auxiliary equipment, building , technical building systems, and energy supply system.

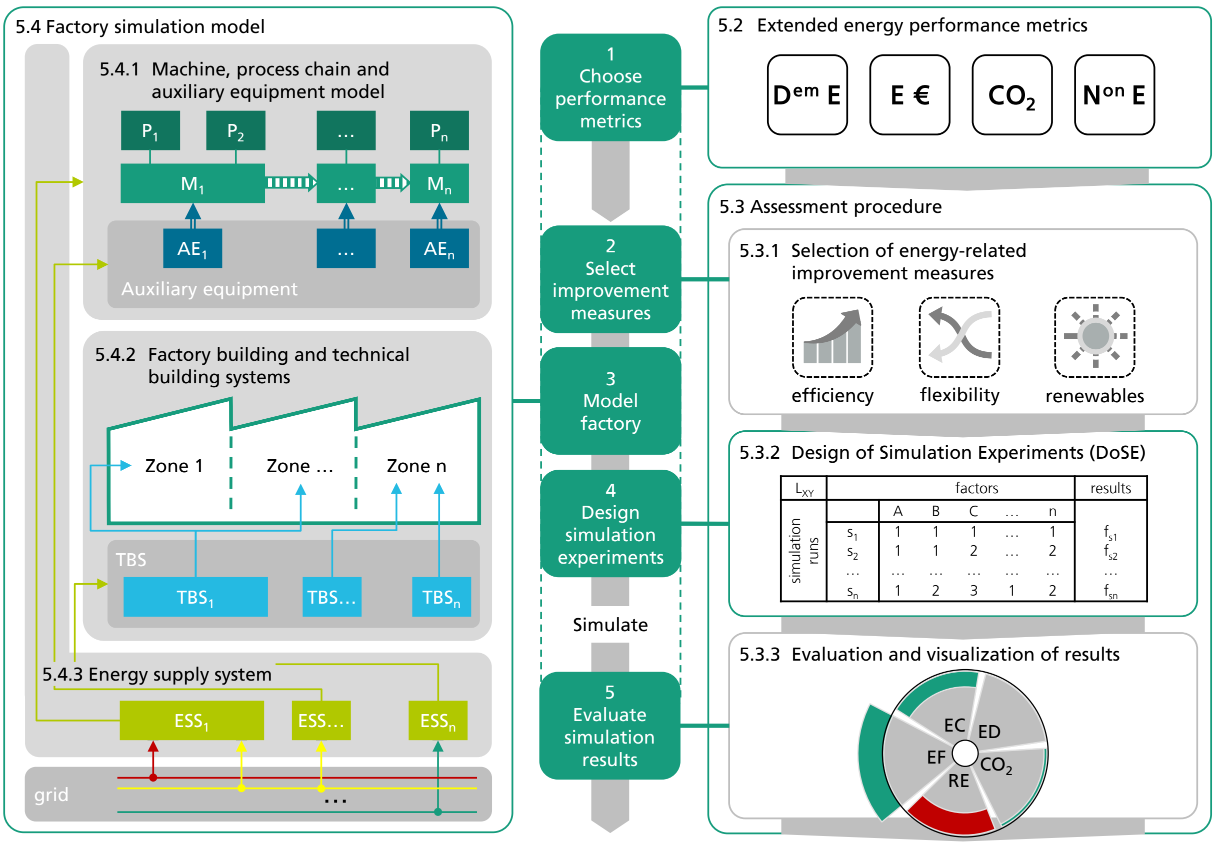


Figure 5-1 Outline of the methodology

5.2 Development of Extended Energy Performance Metrics

This section presents the performance metrics which focus on energy as a resource (ref. Figure 5-2). Unlike existing metrics, which assess the combination of energy demand, energy costs, and CO_2 emissions, the non-energy benefits are added. To improve factories in terms of the above metrics, three categories of measures are identified. These are energy efficiency and energy flexibility measures, and measures to improve the use of renewable energy sources. The portfolio of measures within these categories is set out in Subsection 5.3.1.

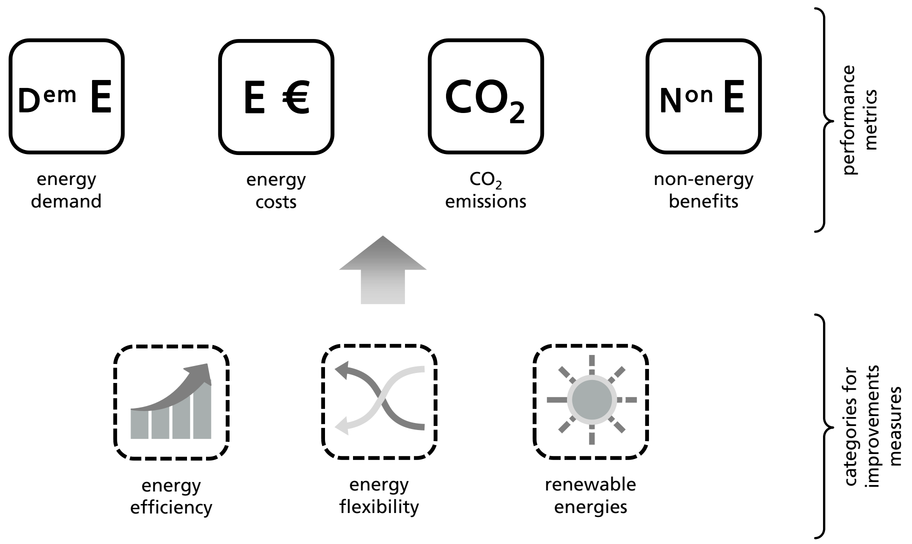


Figure 5-2 Summary of performance metrics including categories for improvement measures

The individual performance metrics are determined according to Equations (5-1), (5-2), (5-3), and (5-4). Considering an observation period of one year, the final energy demand $E_{final,i}$ of a factory within the boundaries of its factory premises is the difference between energy demand $E_{dem,i}$ from the grid and energy supply $E_{sup,i}$ to grid plus the energy sourced from renewables on-site $E_{on-site,i}$. All final energy carriers i have to be considered.

$$Energy\ demand = \sum_i \int \left(P_{dem,i}(t) - P_{sup,i}(t) + P_{on-site,i}(t)\right) dt \quad (5\text{-}1)$$

$$Energy\ demand = \sum_i E_{final,i} = \sum_i E_{dem,i} - \sum_i E_{sup,i} + \sum_i E_{on-site,i} \quad (5\text{-}2)$$

$P_{dem,i}/P_{sup,i}$	Power demand/supply of final energy carrier i from/to grid
$E_{dem,i}/E_{sup,i}$	Annual energy demand/supply of final energy carrier I from/to grid
$E_{on-site,i}$	Annual final energy i sourced from renewables on-site
$E_{final,i}$	Annual demand of final energy for all energy carriers i

The energy costs are quantified according to Equation (5-3). The factor $c_{pur/sal,i}(t)$ takes into account the time-dependent energy prices for individual energy carriers.

$$Energy\ costs = \sum_i \int P_{dem,i}(t) \cdot c_{pur,i}(t) \cdot dt - \sum_i \int P_{sup,i}(t) \cdot c_{sal,i}(t) \cdot dt \qquad (5\text{-}3)$$

$c_{pur/sal,i}$	Purchase costs and sales revenue for final energy carrier i

The energy-related CO_2 emissions of the factory within the boundaries of the factory site are quantified according to Equation (5-4). f_i represents the emission factors for each individual energy carrier i.

$$CO_2\ emissions = \sum_i f_i \cdot \int \left(P_{dem,i}(t) - P_{sup,i}(t)\right) \cdot dt \qquad (5\text{-}4)$$

f_i	Emission factor for final energy carrier i

Non-energy benefits include additional criteria that can be used to assess the impact of individual improvement measures in more detail. The selection shown in Figure 5-3 summarizes six additional criteria derived from the review presented in Subsection 2.2.3.

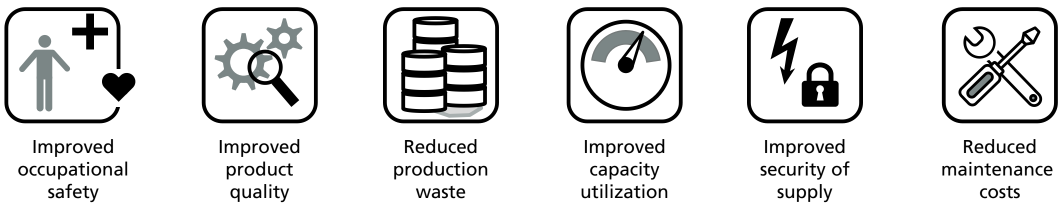


Figure 5-3 Summary of non-energy benefits

In the following, the six categories for non-energy benefits are presented and illustrated by examples. The examples intend to demonstrate that, aside from reducing energy demand, costs, and emissions, individual improvement measures usually have an impact on more than one non-energy benefit at the same time. The selection of non-energy benefits is considered during an energy assessment, and the associated method of quantification differs for different companies and use cases. With reference to the application of the method in Chapter 6, the author refrains from proposing individual quantification methods in this section.

Improved occupational safety

Example: Retrofitting an air-conditioning system reduces energy requirements and stabilizes ambient temperature and humidity in the working environment. It also improves air quality and reduces discomfort caused by cold drafts. Ultimately, retrofitting the air-conditioning system reduces sick days.

Benefits: Improved occupational safety, improved product quality

Improved product quality

Example: Changing the light fixtures reduces energy consumption and improves the lighting quality in terms of brightness and contrast. It also reduces reflections and shadowing, ultimately allowing workers to complete their tasks with a higher standard of quality. The new lighting system also alleviates the need for cleaning and maintenance.

Benefit: Improved product quality, reduced maintenance costs, improved occupational safety

Reduced production waste

Example: The change from convection-based to infrared-based drying reduces energy requirement and leads to more homogenous temperature distribution so that more products are dried according to the quality requirements, and fewer products are declared production waste

Benefit: Reduced production waste, reduced costs for disposal

Improved capacity utilization

Example: The installation of an additional air compressor unit shifts the operating point toward a more energy-efficient level. In addition, the new system setup reduces the risk of production downtime caused by a system malfunction without redundancy

Benefit: Improved capacity utilization, improved security of supply

Improved security of supply

Example: The installation of an emergency power generator and/or an electrical energy storage system increases the capability of the on-site power infrastructure to absorb peak loads and consequently reduce energy costs. The new system components can also improve the safety and quality of the power supply by increasing the system's ability to withstand power outages and blackouts. In addition, an improvement in the power supply quality can also have positive side effects on the equipment operation and thus on product quality.

Benefit: Improved capacity utilization, improved product quality, reduced production waste

Reduced maintenance costs

Example: Replacing a hydraulic press with its electrically driven counterpart reduces the energy required to operate the machine tool. In addition, maintenance costs are reduced as no regular maintenance intervals are required for the hydraulic system.

Benefit: Reduced maintenance costs

It is important to note that the positive side-effects of implementing energy-related improvement measures can also be countered by negative ones. Thus, the implementation of measures may ultimately increase system complexity and make the system more susceptible to errors and failures. However, the assessment of complexity in energy-related factory infrastructure and the development of risk mitigation strategies related to diverse improvement measures are not addressed in this work. Furthermore, it is important to note that improvement measures are usually triggered by the goal of improving non-energy benefits (such as occupational safety, product quality, etc.) rather than by energy-related performance metrics. In fact, improving non-energy benefits may ultimately have a positive impact on energy-related performance metrics, rather than the other way around.

In the context of this work, energy efficiency, energy flexibility, and the use of renewable energy sources are individual categories of measures to improve energy use in a factory. However, the extent of their implementation can also be evaluated on the basis of the following additional key figures. At the factory level, energy efficiency is defined as the ratio between the annual demand of useful energy required for the operation of machines, auxiliary equipment and buildings, and the final energy demand supplied from the grid (ref. Equation 5-5). This energy efficiency metric takes into account all energy carriers. While generally being in line with the energy efficiency definitions presented in 2.2.1, this definition varies in such that it relates energy values only and does not combine monetary and energy values such as, for example, Equation (2-7). Equation (5-5) can be interpreted as the efficiency of energy conversion within a factory system.

$$Energy\ efficiency = \frac{\sum_i E_{useful,i}}{\sum_i E_{final,i}} \tag{5-5}$$

$E_{useful,i}$ Annual demand of useful energy for all energy carriers i

$E_{final,i}$ Annual demand of final energy for all energy carriers i

In this work, energy flexibility is defined as the sum of energy stored ($E_{stored,j}$) and withdrawn ($E_{stored,j}$) from the different energy storage systems (ESS) j used on the factory site, divided by the annual final energy demand of the factory (Equation 5-6). With reference Equation (2-8), the energy stored and withdrawn from the storage systems are composed of n individual flexibilities, each with a specific flexible load and duration.

$$Energy\ flexibility = \frac{\sum_j E_{stored,j} + \sum_j E_{withdrawn,j}}{\sum_i E_{final,i}} \tag{5-6}$$

$E_{stored,j}$	Annual amount of energy stored in all ESS j
$E_{withdrawn,j}$	Annual amount of energy withdrawn from all ESS j
$E_{final,i}$	Annual demand of final energy for all energy carriers i

The key figure used to assess the renewable energy share on-site is shown in Equation (5-7). It is also quantified for a period of one year as the ratio between the amount of energy sourced from different on-site renewable energy sources k and the final energy demand of the factory system for the same period.

$$Renewable\ energy\ share = \frac{\sum_k E_{renewable,k}}{\sum_i E_{final,i}} \tag{5-7}$$

$E_{renewable,k}$	Annual amount of energy generated from different on-site renewable energy sources k
$E_{final,i}$	Annual final energy demand for all energy carriers i

5.3 Development of Assessment Procedure

5.3.1 Selection of improvement measures

Identifying measures to improve energy use in a factory requires a common understanding of where improvement measures should be implemented. For this reason, the peripheral factory model introduced in Subsection 2.1.2 was extended and adapted to the energy context. Table 5-1 summarizes the architectural perspective on factories based on the categories of site, building, and zones, with the manufacturing perspective considering all the technical equipment necessary to service each manufacturing process and to operate the surrounding factory buildings.

At the core of a factory operation are the individual manufacturing processes that are carried out within machines or other manufacturing equipment. Some processes (P) require the feeding of media (e.g., cooling lubricant) or the extraction of process residuals (e.g., dust or swarf). These functions are usually implemented by auxiliary equipment that is either located in a decentralized manner (1), close to the process, or in a centralized manner (4), supplying multiple processes. The same differentiation applies to the architecture of technical building systems within buildings, which can also be positioned either centrally (5), supplying multiple zones with heating, cooling, and ventilation, or decentrally (2) with individual equipment supplying the individual zones with their specific heating, cooling, and ventilation requirements.

Table 5-1 Extended peripheral factory model

Manufacturing perspective	Architectural perspective
P – Process	
1 – Decentralized auxiliary equipment	Zone
2 – Decentralized technical building systems	
3 – Decentral distribution systems	
4 – Centralized auxiliary equipment	Building
5 – Centralized technical building systems	
6 – Building envelope	
7 – Central distribution systems	
8 – Central power house for auxiliary equipment	Site
9 – Central power house for technical building systems	
10 – On-site renewables	
G – Grid (link to local/trans-regional energy system)	

Periphery (6) refers to the building envelope of a factory. In addition to the passive components that are relevant to energy use, such as the insulation, the building envelope can include several active functions, such as the control and shading of openings, including natural lighting and ventilation. In addition, the surface of the building envelope offers the possibility of integrating equipment for the use of renewable energies such as building-integrated photovoltaic systems. Central (7) and decentralized (3) distribution systems refer to technical equipment for the distribution of media between generation and consumption. Representatives of this category are, for example, pumps and vans and are found in cooling, heating, or steam networks. Peripheries (8) and (9) denote powerhouses that host auxiliary equipment and technical building systems. This centralized system design is generally used for large industrial sites that consist of several individual buildings and multiple processes. For example, compressed air can be supplied from a central powerhouse for auxiliary equipment and provided to all individual buildings on the industrial site. Another example is the steam generation in boilers to supply process heat or the space heating demands in the individual buildings of the industrial site. Periphery (10) denotes equipment used on-site for the generation of energy from renewable sources such as sun, wind, water, or geothermal energy. This includes, for example, photovoltaic systems, wind turbines, hydroelectric power stations, or boreholes for geothermal probes. Figure 5-4 illustrates the extended peripheral factory model.

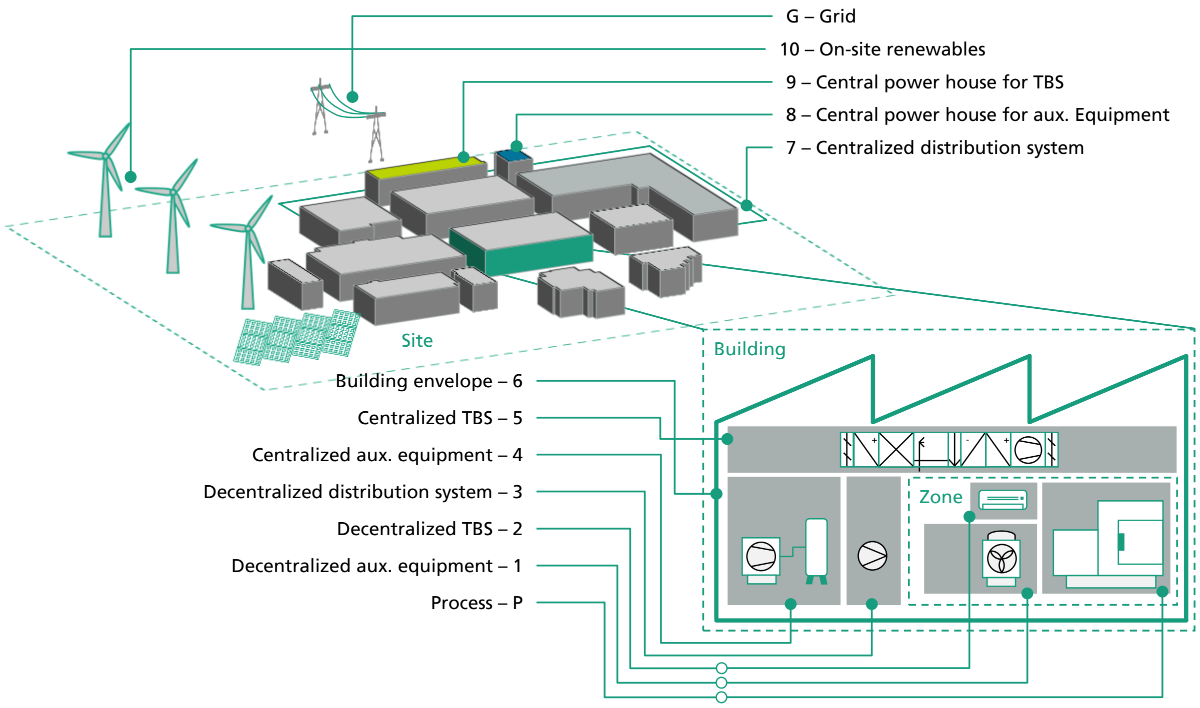


Figure 5-4 Extended peripheral factory model representing peripheries P through G

Categories of energy efficiency measures

Measures to increase energy efficiency are intended to reduce the energy demand within a factory. There exist three general fields of action to improve energy efficiency, which can be divided into planning, controlling, retrofitting or installing. The first relates to general strategic or organizational decisions, e.g., introducing an appropriate management framework for energy-related issues, negotiating terms and conditions for energy supply, or introducing a strategy to reduce the carbon footprint of the energy supply system at a factory site. Controlling, retrofitting or installing are operational domains and require a bottom-up understanding of the technical aspects of the underlying manufacturing processes and the surrounding environmental conditions of a factory. The improved control of energy flows and energy use focuses on the adjustment of equipment setups and on the (re-)configuration of the individual or higher-level control of all technical equipment installed in the various peripheries of a factory system. Although analysis and adaptation can be very time-consuming, the control customization is generally considered very cost-effective because it involves software updates rather than the purchase of new equipment. One example is the use of machine control that switches off components in standby mode, thus reducing energy consumption during idle periods. Retrofitting existing technologies or installing new ones is the third option for streamlining the use of energy in a factory. Retrofitting an existing refrigeration system with new, more energy-efficient system components is one example. The installation of a heat recovery system in the compressed air supply is another. To assist users in evaluating energy efficiency measures in a factory environment, Figure 5-5 presents nine categories for energy efficiency measures.

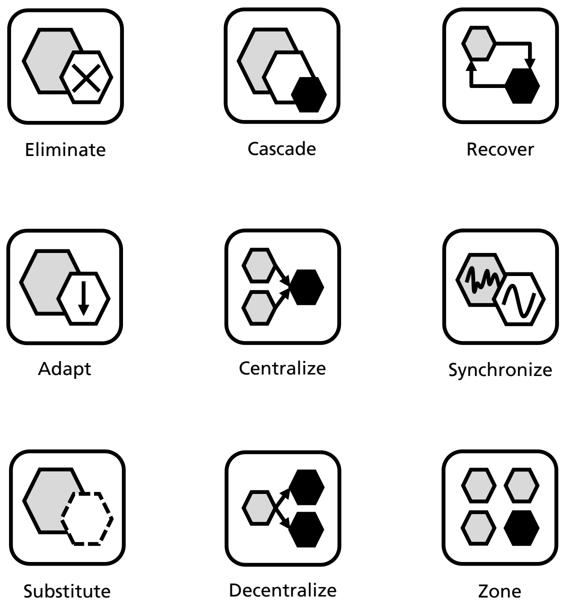


Figure 5-5 Categories of measures to improve energy efficiency (adapted from Steinhilper et al. 2017)

The subcategories respect the networked nature of a factory environment and allow for different combinations. In the following, each category is described by an example.

Eliminate

Description: Eliminate energy waste, including inefficient modes of operation or oversized system components

Example: Eliminate energy waste in a machine tool through improved utilization rates (e.g., reduced idle-times) and/or improved machine control (e.g., energy-saving mode, switching to standby mode)

Effect: Reduced energy demand for the operation of machines and equipment

Adapt

Description: Adapt energy supply to demand

Example: Adapt the setpoints for temperature, humidity, and ventilation rate to the required indoor climate conditions

Effect: Reduced energy requirements for heating, cooling, and ventilation

Substitute

Description: Substitute inefficient energy supply technologies by efficient alternatives

Example: Replace the cooling supply from a compression refrigeration system with a free-cooling system

Effect: Reduced energy requirement for the cooling supply

Cascade

Description: Cascade energy supply for efficient operation at the operating point

Example: Cascade the setup of the pump station in a cooling circuit to ensure the energy-efficient supply of coolant (quantity and pressure) for different operating points (e.g., base load and peak load)

Effect: Reduce the energy required to operate machinery and equipment

Centralize

Description: Centralize energy supply to avoid energy waste

Example: Centralize individual process cooling for machine tools and/or the respective cooling lubricant systems to avoid heat emissions to the manufacturing environment

Effect: Reduced energy requirements for air-conditioning, heating, and cooling

Decentralize

Description: Decentralized energy supply to avoid energy waste

Example: Decentralize compressed air supply

Effect: Reduced energy requirements for compressed air supply due to the elimination of hydraulic and leakage losses in widely branched piping systems

Recover

Description: Recovering useful energy through networked systems

Example: Recovery of waste heat from ventilation systems, process cooling, or compressed air supply, and reuse in heating applications (e.g., through the using of heat exchangers and/or heat pumps)

Effect: Reduced energy demand for heating due to reused waste heat

Synchronize

Description: Synchronize energy demand with energy availability

Example: Synchronize the energy requirements for process cooling or compressed air system with the availability of energy from renewable sources (e.g., from photovoltaic systems)

Effect: Reduced peak energy demand for electricity

Zone

Description: Zone manufacturing environments according to their environmental requirements

Example: Zone processing areas with high emissions (e.g., heat, oil mist) and corresponding ventilation requirements of assembly areas with narrow requirements for particle load, temperature, and humidity range

Effect: Reduced energy requirements for air-conditioning, heating, and cooling

Categories of energy flexibility measures

Measures to improve the energy flexibility of a factory should increase the responsiveness of a factory system to energy availability and market prices and thus reduce energy costs. The measures can be applied to various peripheries, such as machinery, auxiliary equipment, technical building systems, and other energy supply systems. The evaluation of energy flexibility measures is divided into four categories depending on their ability to interrupt equipment operation (e.g., to start or stop a machine), to change (e.g., switch between different energy carriers), to regulate (e.g., reduce or increase the power consumption of a process), or to store (e.g., store or release excess power). In the following, all categories are described and illustrated by a practical example (ref. Figure 5-6).

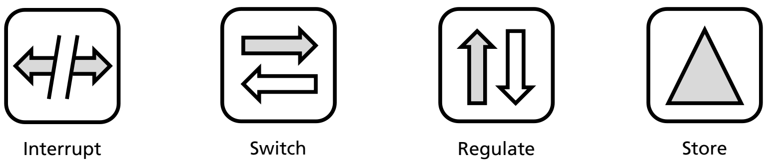


Figure 5-6 Categories of measures to improve energy flexibility (based on Weeber et al. 2017, p. 436)

Interrupt

Description: Capability to interrupt and resume power supply

Example: Suspend the operation and power supply from a combined heat and power (CHP) unit in times of low energy prices and high energy availability in the local grid

Switch

Description: Capability to switch between different energy carriers

Example: Switching the power supply of curing furnaces between gas and electricity depending on availability and energy prices for gas and electricity. Another example is the conversion of the power supply to cover the heating demand by a gas boiler, a combined heat and power (CHP) unit, geothermal probes, or resistance heating installed in a hot water storage tank.

Regulate

Description: Capability to regulate the power demand

Example: Regulate (increase/decrease) the power supply to an air-conditioning system as long as the conditions (e.g., temperature and humidity) in the factory environment are within the required ranges.

Store

Description: Capability to store and withdraw excess energy supply

Example: Store electricity, compressed air, cold and hot water in existing or new storage capacities for times of surplus or shortage of energy availability, e.g., from on-site renewable energies, or for times of low and high energy prices on the market.

The described examples of measures to increase energy flexibility in a factory environment are shown in Figure 5-7.

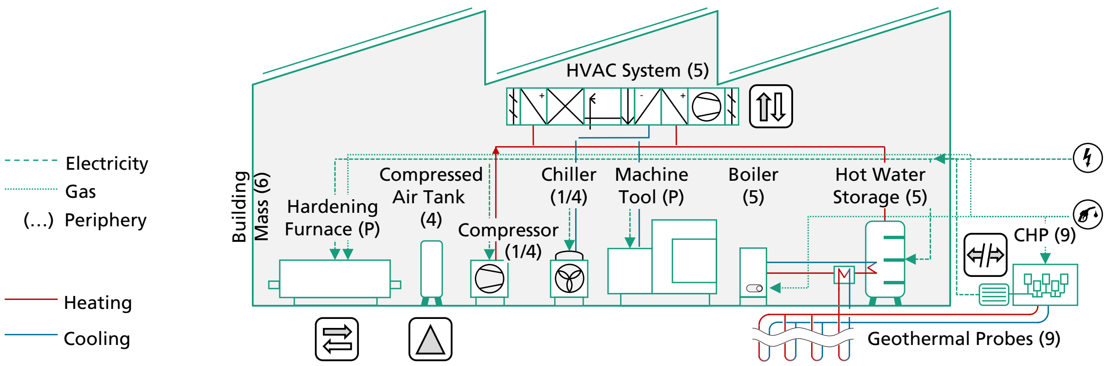


Figure 5-7 Performance metrics for energy flexibility in factories (based on Weeber et al. 2017, p. 437)

Categories of renewable energy sources

Following the implementation of various energy-saving measures, the use of renewable energy sources aims to reduce the CO_2 emissions associated with the remaining energy requirements of a factory or production site. Unlike energy efficiency and flexibility measures, the focus of on-site renewable energy use is not on reducing the energy demand but on increasing the share of energy demand that can be met by climate-friendly energy sources. Figure 5-8 introduces five categories for renewable energy sources, namely solar, wind, water, biomass, and geothermal. The individual categories are presented below, including practical examples of their use on a factory site.

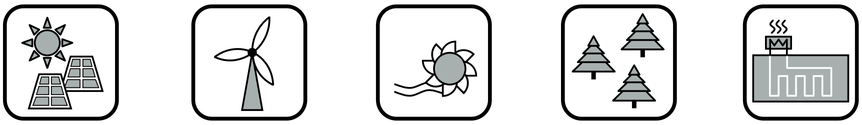


Figure 5-8 Categories of renewable energy sources that can be used in factories

Solar

Description: Technical system for the conversion of solar radiation into electrical or thermal energy

Example: Rooftop installation of a photovoltaic system

Wind

Description: Technical system for converting the kinetic energy of air movement (e.g., wind) into electrical energy

Example: Wind turbine installed on the factory site

Water

Description: Technical system for converting the kinetic energy of water into electrical energy

Example: Water turbine installed in a nearby river course

Biomass

Description: Technical system for the conversion of biomass (solids or liquids) into thermal energy

Example: Woodchip or wood pellet-fired boiler

Geothermal

Description: Technical system for obtaining thermal energy from geothermal sources

Example: Earth probe drilling and use in a heat pump system

In the context of this work, the focus is on measures that improve the use of renewable energy sources based on a site-optimized selection and a demand-oriented operation of respective technical installations for the use of renewable energy sources in the perimeters of a production site. Of course, the geographic location of the factory, as well as the local weather conditions, limit the availability of these sources. This applies in particular to solar, wind, hydro, and geothermal energy. Biomass, both in the form of solids or liquids, usually requires external suppliers. In general, the additional land use must be taken into account if the compensation of a factory's energy demand is associated with additional land use.

Although not the primary focus of the methodology presented, the reader should be aware that factories can become an integral part of local energy infrastructures, including cross-sectional energy networks. This includes the possibility of drawing energy from local energy distribution networks or nearby industry clusters and connecting the factory to decentralized energy supply infrastructures (e.g., hydroelectric or wind power farms).

Allocation and combination of measures

The matrix shown in Figure 5-9 illustrates how to summarize the identified measures according to the three fields of action (planning, controlling, retrofitting, or installing) and the periphery of a factory. It provides information on how many measures have been identified and where in the factory environment they can be assigned to. The measures collected by companies with an energy management system can be a good source for an initial pool of measures.

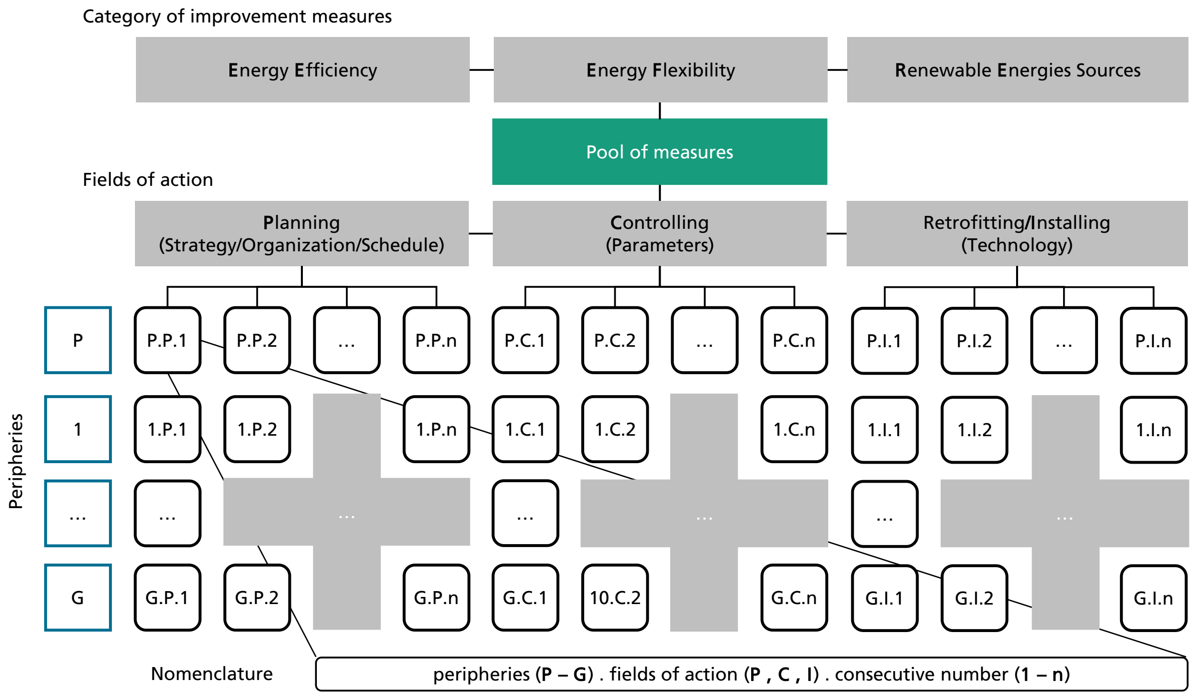


Figure 5-9 Matrix of measures assigned to the fields of action and the different peripheries of a factory

Using the nomenclatures introduced in Subsection 2.2.1 – Figure 2-8, it is also possible to graphically represent energy losses and corresponding energy efficiency countermeasures along the path of energy use within a factory. Therefore, the equipment that is responsible for energy demand is divided into four types: equipment used for the storage, distribution, conversion, and delivery of energy. Furthermore, a number is assigned to the equipment in order to allocate the equipment to the periphery where the equipment is installed. An example of this graphical representation can be found in Figure 5-10.

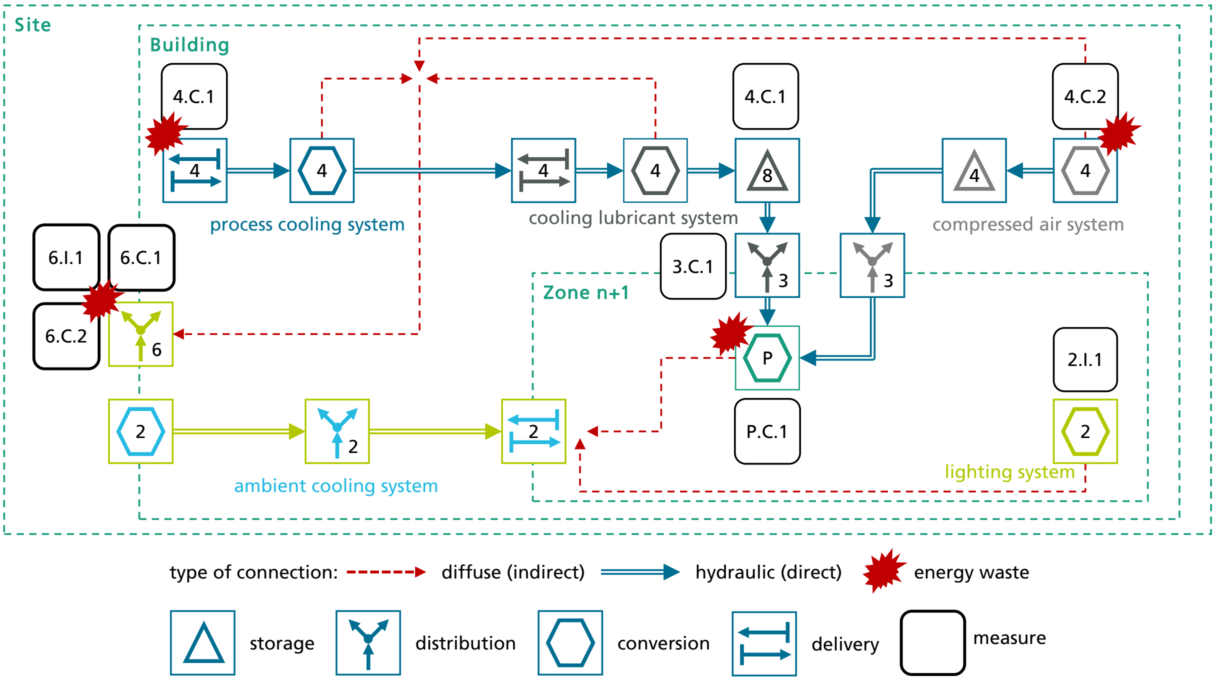


Figure 5-10 Example of the path of energy use within a factory (graphical representation)

5.3.2 Planing and design of simulation experiments

Figure 5-11 outlines the step-by-step process developed to evaluate different combinations of energy-related improvements in factory systems. Depending on the number of available measures, the project team, including company and third-party experts, first performs a pre-screening. Experts are selected based on their ability to provide the know-how relevant to the specific investigation, which in the present case is the energy assessment (Bogner and Menz 2009, p. 55). In order to allow a successful exploration of opportunities for future improvements, one selection criterion is the person's bottom-up knowledge and long-term experience with the factory's manufacturing processes, machines, and technical infrastructure, their energy demand characteristics, interconnections, past modifications, and implemented retrofits. Given the typical organizational structure of a manufacturing company, valuable knowledge carriers include production managers, shift supervisors, quality managers, technical directors, and maintenance staff. If established as functions by the company, further experts include energy and environmental officers. A valuable outside perspective can be provided by third-party experts, including, for example, lean management and energy consultants.

Furthermore, the selection of experts needs to consider hierarchies and power structures within the individual company. This is to ensure that individual interests do not lead to the exclusion of the most beneficial measures. Nevertheless, the selection needs to include management staff in order to ensure high-level support and to facilitate the roll-out and implementation of the selected measures. The use of expert knowledge generally makes it possible to focus on the most relevant measures while reducing the simulation effort. Criteria for the preselection of measures can be different for individual companies. Examples include company priorities, expected saving potentials, or potential trade-offs between measures. Supporting methods for the preselection include a multi-criteria decision analysis (MCDA) with criteria weighting based, for example, on an analytical hierarchy process (AHP) (Wang et al. 2009, pp. 2266-2276, Saaty 2008, p. 85 ff.). Following the DoE terminology, measures are referred to as factors, and their individual design characteristics are referred to as factor levels. The factor levels generally represent a technical specification, which is easily available and best characterizes the energy-related behavior of the improvement measure (e.g., insulation thickness, storage capacity, installed cooling capacity, etc.). The next step is to specify the design space based on the pool of preselected measures. In a series of iterative steps, factor levels, experimental design, and measures are defined and adjusted until a suitable fit is achieved between the number of improvement measures, factor levels, and the available experimental designs.

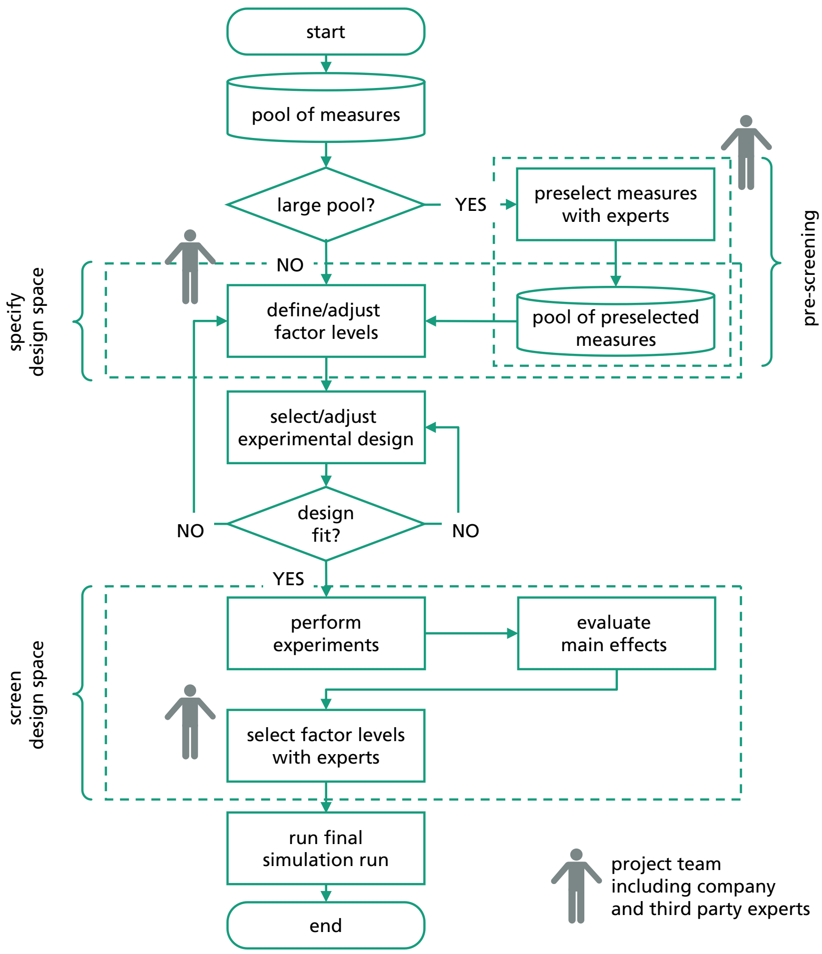


Figure 5-11 Flow chart describing the step-by-step planning and design of the simulation experiments

After adjusting the experimental design to the number of measures considered, the simulation experiments are conducted to screen the design space for the most effective measures. After completion of the number of simulation runs specified in the experimental design, the main effects of all factors and for each factor level are evaluated in relation to the performance metrics. Based on the visualization of the main effects in a main effects plot and the ranking of the individual simulation results, the project team is asked to prioritize, weigh trade-offs between performance metrics and finally select a factor level for each factor. Along with the analytic method, the importance of the expert group is emphasized because of their ability to evaluate trade-offs between individual performance metrics and the long-term strategic direction of their company. Company strategies can include addressing the growing importance of carbon pricing schemes and the facilitated access to energy flexibility markets. Finally, the selected factor levels are processed in a final simulation run. This serves to quantify the performance improvements.

Referring to the overview on experimental designs in Subsections 2.4.2 and 2.4.3, the use of orthogonal array-based matrix designs and their application within the developed methodology is presented in more detail. Table 5-2 shows how improvement measures can be translated into factors and their individual design parameters into factor levels. Using an orthogonal L_{18} array as an example, eight measures represented by the Factors A-H can be analyzed simultaneously. In this example, the design parameters for a Factor A can be specified on two levels (x_{A1}, x_{A2}) and for Factors B through H on three levels (e.g., x_{B1}, x_{B2}, x_{B3}).

Table 5-2 Example of factors and factor levels for an orthogonal L_{18} array

		1st level	2nd level	3rd level
Factors (N)	A	x_{A1}	x_{A2}	
	B	x_{B1}	x_{B2}	x_{B3}
	C	x_{C1}	x_{C2}	x_{C3}
	D	x_{D1}	x_{D2}	x_{D3}
	E	x_{E1}	x_{E2}	x_{E3}
	F	x_{F1}	x_{F2}	x_{F3}
	G	x_{G1}	x_{G2}	x_{G3}
	H	x_{H1}	x_{H2}	x_{H3}

Furthermore, orthogonal arrays can be used for the evaluation of four parameters with three levels (L_9), 11 parameters with two levels (L_{12}), three parameters with two levels, and 12 parameters with three levels (L_{36}). For an even broader overview, see Table 2-7.Preserving orthogonality, the eight factors of the example in Table 5-2 are combined so that for each pair of columns, each pair of factor level combinations occurs exactly the same number of times per row. For the example at hand, this results in a total of 18 factor-level combinations (ref. Table 5-3). In contrast, the number of round-robin trials for the same number of factors in a full factorial design would be $2^1 \times 3^7 = 4374$.

Table 5-3 L_{18} orthogonal array

	Factors									Energy performance metrics (f_n)				
	L_{18}	A	B	C	D	E	F	G	H	Energy demand	Energy costs	CO_2 emissions	…	Non-energy benefits
Simulation runs	s1	1	1	1	1	1	1	1	1	$f_{ED,s1}$	$f_{EC,s1}$	$f_{CO2,s1}$	…	$f_{NE,s1}$
	s2	1	1	2	2	2	2	2	2	$f_{ED,s2}$	$f_{EC,s2}$	$f_{CO2,s2}$	…	$f_{NE,s2}$
	s3	1	1	3	3	3	3	3	3	$f_{ED,s3}$	$f_{EC,s3}$	$f_{CO2,s3}$	…	$f_{NE,s3}$
	s4	1	2	1	1	2	2	3	3	$f_{ED,s4}$	$f_{EC,s4}$	$f_{CO2,s4}$	…	$f_{NE,s4}$
	s5	1	2	2	2	3	3	1	1	$f_{ED,s5}$	$f_{EC,s5}$	$f_{CO2,s5}$	…	$f_{NE,s5}$
	s6	1	2	3	3	1	1	2	2	$f_{ED,s6}$	$f_{EC,s6}$	$f_{CO2,s6}$	…	$f_{NE,s6}$
	s7	1	3	1	2	1	3	2	3	$f_{ED,s7}$	$f_{EC,s7}$	$f_{CO2,s7}$	…	$f_{NE,s7}$
	s8	1	3	2	3	2	1	3	1	$f_{ED,s8}$	$f_{EC,s8}$	$f_{CO2,s8}$	…	$f_{NE,s8}$
	s9	1	3	3	1	3	2	1	2	$f_{ED,s9}$	$f_{EC,s9}$	$f_{CO2,s9}$	…	$f_{NE,s9}$
	s10	2	1	1	3	3	2	2	1	$f_{ED,s10}$	$f_{EC,s10}$	$f_{CO2,s10}$	…	$f_{NE,s10}$
	s11	2	1	2	1	1	3	3	2	$f_{ED,s11}$	$f_{EC,s11}$	$f_{CO2,s11}$	…	$f_{NE,s11}$
	s12	2	1	3	2	2	1	1	3	$f_{ED,s12}$	$f_{EC,s12}$	$f_{CO2,s12}$	…	$f_{NE,s12}$
	s13	2	2	1	2	3	1	3	2	$f_{ED,s13}$	$f_{EC,s13}$	$f_{CO2,s13}$	…	$f_{NE,s13}$
	s14	2	2	2	3	1	2	1	3	$f_{ED,s14}$	$f_{EC,s14}$	$f_{CO2,s14}$	…	$f_{NE,s14}$
	s15	2	2	3	1	2	3	2	1	$f_{ED,s15}$	$f_{EC,s15}$	$f_{CO2,s15}$	…	$f_{NE,s15}$
	s16	2	3	1	3	2	3	1	2	$f_{ED,s16}$	$f_{EC,s16}$	$f_{CO2,s16}$	…	$f_{NE,s16}$
	s17	2	3	2	1	3	1	2	3	$f_{ED,s17}$	$f_{EC,s17}$	$f_{CO2,s17}$	…	$f_{NE,s17}$
	s18	2	3	3	2	1	2	3	1	$f_{ED,s18}$	$f_{EC,s18}$	$f_{CO2,s18}$	…	$f_{NE,s18}$

From the simulation runs (s), the results for each performance metric (f_n) can be quantified. The average effect $\overline{f_{n,N}}$ of each design parameter (N) (factor level) on different energy performance metrics (n) can be evaluated for all individual measures (factors). For example, the average effect of Factor C at Factor Level Two on the energy demand (ED) can be calculated according to Equation (5-8) as the average effect of the results from the simulation runs s2, s5, s8, s11, s14, s17.

$$\overline{f_{ED,C2}} = \frac{f_{n,s2} + f_{n,s5} + f_{n,s8} + f_{n,s11} + f_{n,s14} + f_{n,s17}}{6} \tag{5-8}$$

$\overline{f_{n,Nx}}$	Average effect of factor N at factor level x on performance metrics n
n	Individual performance metric

Within the scope of the developed methodology, intermediate results are presented using various visualization techniques. These are presented in the following subsection.

5.3.3 Visualization and evaluation of simulation results

Various types of visualization are used to present intermediate and final results in order to actively support the user of the methodology in decision-making. With reference to the flowchart in Figure 5-11, a thorough evaluation of the main effects is crucial to arrive at near-optimal solutions. Figure 5-12 shows the five visualization techniques used in the evaluation of the simulation results. The main effects plot (A) is used to illustrate the average effect and trend the design characteristic (factor level) of an improvement measure (factor) has on different performance metrics. Main effects plots are also used to identify the measures that achieve the highest relative improvements and the highest performing factor levels (highlighted by white squares) with respect to individual performance metrics. Multi-dimensional plots (B) are used to visualize how each factor level combination performs in the simulation runs with respect to multiple performance metrics. This is used to identify trade-offs between individual simulation runs and the best factor-level combinations with respect to multiple performance metrics. C shows how the ranking of all simulation runs is visualized, starting with the worst performance on the left and ending with the best performance on the right. Again, all performance metrics are considered. D is the excerpt from C showing only the performance of worst (w), median (m), best (b), and selected (s) factor level combinations. “Selected" refers to the factor level combination chosen by the project team. Finally, pie charts (E) are used to illustrate the relative improvements per performance metric.

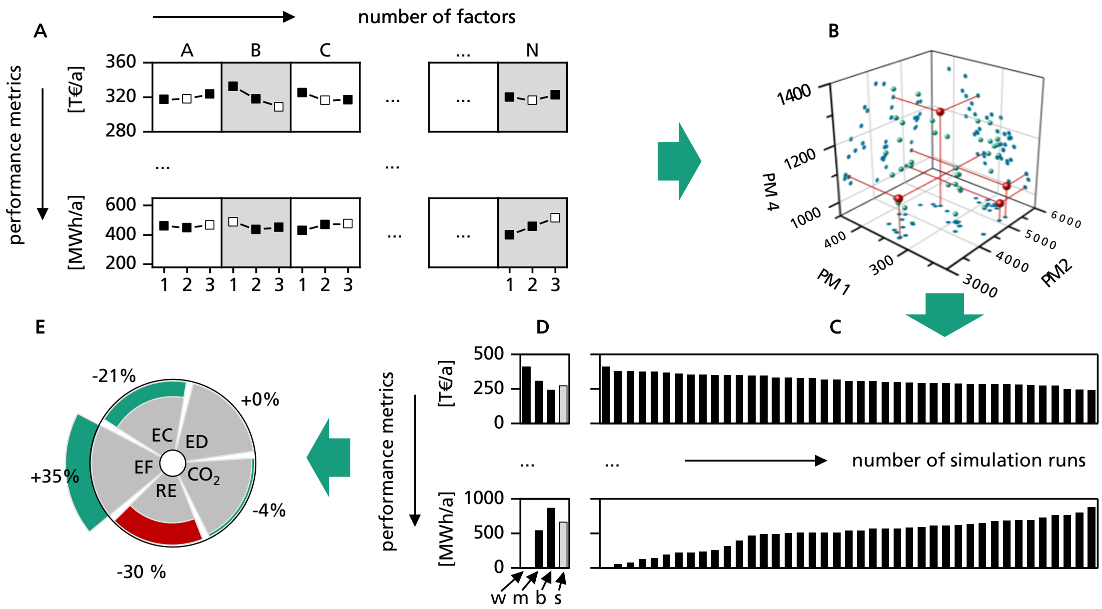


Figure 5-12 Visualization techniques used in the evaluation and presentation of the simulation results. (A) main effects plots; (B) multi-dimensional plot, (C) ranking of simulation results per performance metric, (D) worst (w), median (m), best (b), and selected (s) simulation results per performance metric; (E) pie chart showing relative improvements per performance metric, energy costs (EC), energy demand (ED), CO_2 emissions (CO_2), renewable energy share (RE), and energy flexibility (EF)

These pie charts are often referred to as Coxcomb, polar area charts, or Nightingale Rose Diagrams. Each wedge of the pie chart is measured from the center of the chart. The median performance (baseline) is referenced by the black edges of the outer circle. Either green or red wedges mark improvements or deteriorations within each dimension of the performance metrics.

5.4 Development of a Factory Simulation Model

This section presents the development of the factory simulation model. Figure 5-13 outlines the different peripheries of the factory represented in the model, its submodels and interconnections. The submodels are specified in Subsections 5.4.1, 5.4.2, and 5.4.3. Subsection 5.4.4 concludes the model development and specifies how the factory model is implemented, coupled, and verified. The general model condition is that during each time step power demand and supply are balanced for each carrier of useful energy (e.g., electricity, compressed air, warm/cold media etc.) (ref. Equation 5-9)

$$\sum_{1}^{i} P_{demand,i}(t) = \sum_{1}^{j} P_{supply,j}(t) \quad and \quad \sum_{1}^{i} \dot{Q}_{demand,i}(t) = \sum_{1}^{j} \dot{Q}_{supply,j}(t) \tag{5-9}$$

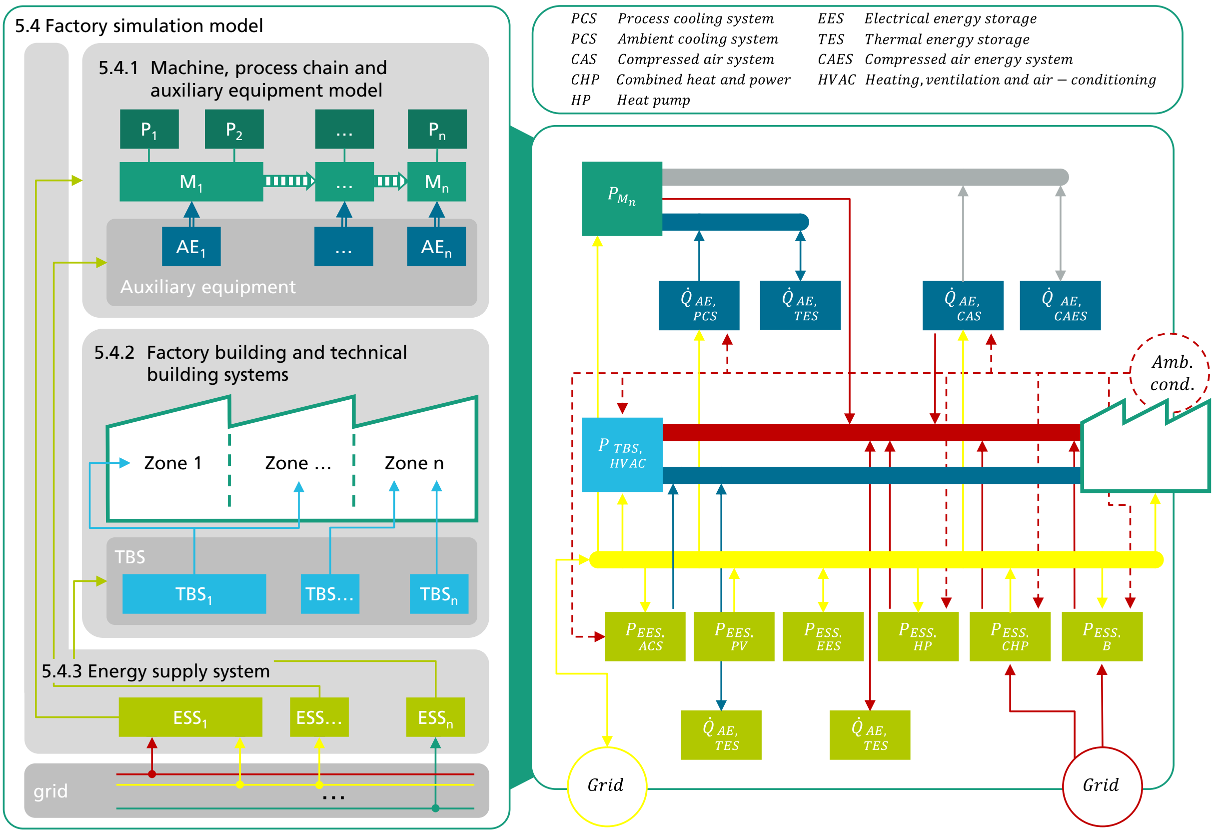


Figure 5-13 Overview of the factory simulation model, submodels and interconnections

5.4.1 Machine, process chain, and auxiliary equipment model

Machine model

Machines and other energy-consuming equipment perform a variety of manufacturing processes. On individual machines ($M_1 - M_n$), either single or multiple processes ($P_{n.1} - P_{n.m}$) are executed, which convert useful energy as input energy resources ($I_{ER.n.1} - I_{ER.n.i}$) into useful energy services (ref. Figure 5-14). These energy services are capable of performing value-added and non-value-added tasks while changing their state or condition. Energy conversion in machines produces output energy resources ($O_{ER.n.1} - O_{ER.n.j}$) with different qualities and varying reusability. Output energy resources with limited reusability are commonly designated as “energy losses” or “waste of energy”. A concrete example is heat emissions caused by friction losses. Due to their influence on heating, ventilation, and cooling demand, these output energy resources need to be given special consideration in the proposed factory building model. A model to account for heat emissions from machinery is proposed in the next paragraph.

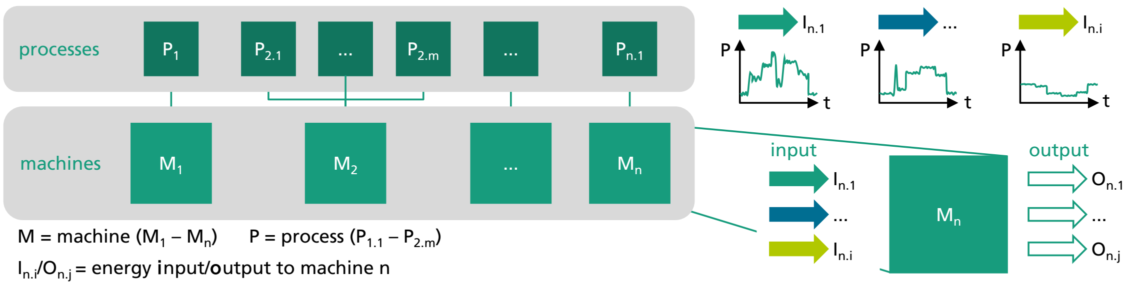


Figure 5-14 Framework for process and machine model

The power demand $P_{M_1}(t)$ is characterized for all machines M_1 to M_n by temporal or continuous power measurements that take into account each input of useful energy ($I_{ER.n.1}$ to $I_{ER.n.i}$) supplied to the machine (ref. Equation 5-10). The average power demand of all individual energy resources is either assigned to different operating states, as described in Subsection 2.2.3, or specified in look-up tables for different batch sets.

$$P_{M_1}(t) = \sum_{1}^{i} P_{I_{M1.i}}(t) \tag{5-10}$$

Heat emissions from machine operation

The demand-oriented design and efficient operations of technical building systems in factories require a detailed representation of the production processes within the plant. Compared to other non-residential buildings, information on internal heat gains is crucial to improve the accuracy of simulation results for industrial buildings (Katunsky et al. 2013, p. 143).

Among the main parameters linking technical building systems to the manufacturing process in terms of energy use are the heat emissions from the process.

For example, most (75-95%) of the electrical energy demand of a machine tool is dissipated as heat to the factory environment. This heat dissipation is caused by friction and power losses in mechanical and electrical components. Only small amounts of energy are transferred and stored in the workpiece. (Bleicher et al. 2014, p. 443)

Simple approaches do not consider specific operating times of machinery and equipment but look at the sum of process and miscellaneous gains divided by the square meter size of the floor area of the zone in which the equipment is operated. For example, Moynihan and Triantafillu consider an average value of 60 W/m² for heat dissipation to the manufacturing environment (Moynihan and Triantafillu 2012, p. 76).

The VDI standard 3082 suggests the consideration of surface thermal loads between 50 – 250 W/m² for machining processes. Depending on the design and location of the cooling system (centralized or decentralized), 30 – 70% of these heat emissions are dissipated by the cooling lubricant and the swarf. For cold and warm forming processes, it is recommended to consider surface-related values between 100 – 300 W/m² or 15% – 20% of the installed power of the machine as heat gains from machine operation. (VDI 3802, p. 27 f.)

Table 5-4 shows the guideline of a machine tool manufacturer for the approximate determination of the internal heat gains from the operation of machine tools under consideration of different operating states.

Table 5-4 Guideline for heat dissipation from machine operations as % of the installed load (Deckel Maho Seebach GmbH 2014, p. 35)

State of machine	**Example**	**Heat dissipation as % of installed load**
Machine standby	Main switch turned on	5%
Machine ready	Ready for operation	10%
Machine operation	Temporary max. load	20%

In summary, there is a wide variety of recommendations on how to account for heat gains from manufacturing processes. However, there is a lack of precise methods to represent the thermal properties of machines, such as inertia and the resulting heat gains, in a time-discrete manner. The specification of heat emissions by higher temporal resolutions aims at an improved simulation accuracy.

Given the limitations of existing approaches, Schlüter et al. proposed a nodal model to characterize the heat emissions from manufacturing processes. The model simplifies the complex geometry of a machine tool by representing different parts as heat-emitting basic geometries (e.g., spheres or cylinders) with different layers. The heat transfer between the inner layers, the outermost layer, and the environment is described based on energy-, power- and mass balances. The differential equations connecting the different layers are solved by numerical methods. The model was validated for an injection modeling machine at constant operating conditions. (Schlüter et al. 2011, Schäfer et al. 2012, Martin et al. 2012, p. 103 ff.).

The presented modeling approach requires an informed user experience to choose the right structure of nodes, layers, and parameters. Therefore, the effort for model setup, tuning, and adoption is high. Moreover, the verification of the individual model representations of a machine is difficult to realize in practice.Taking into account an appropriate relationship between modeling effort and model accuracy, two different model representations for heat emissions from manufacturing operations are proposed.

The first case represents a structure suitable for machine tools connected to auxiliary equipment and is used to support either one or more machines simultaneously (ref. Figure 5-15). The model assumes that the electrical power consumption of a manufacturing process is dissipated as heat to the ambient zone of the factory building. Equation (5-11) describes the heat emissions $\dot{Q}_{HE}$ from the operation of a machine as a function of its electrical power $P_{el.}$ demand. Furthermore, Schönemann suggests the use of an efficiency factor η ($0 < \eta < 1$) to quantify heat emissions relative to its electricity demand (Schönemann 2017, p. 85). The term $\dot{Q}_{AE}$ is added to represent auxiliary equipment used to either cool (-) or heat (+) the machine.

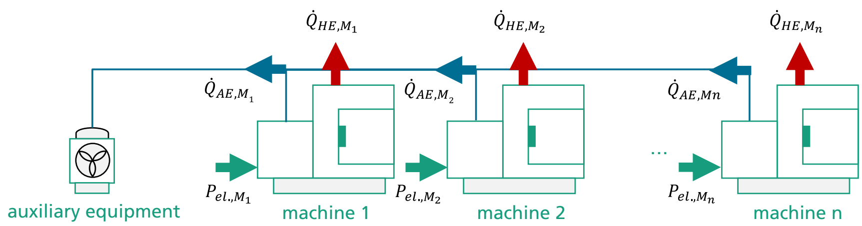


Figure 5-15 Case 1: Machine tool with attached auxiliary equipment

$$\dot{Q}_{HE,M_n}(t) = P_{el.,M_n}(t) \cdot (1 - \eta) + \dot{Q}_{AE,M_n}(t) \qquad (5\text{-}11)$$

The second case is suitable for the representation of heat emissions from thermal processes (e.g., hardening or curing furnaces), which are operated either continuously or in batches. Since process temperatures are the main operating parameters and generally show good data availability, they can be used to simulate heat emissions using a substitute thermodynamic model of the process.

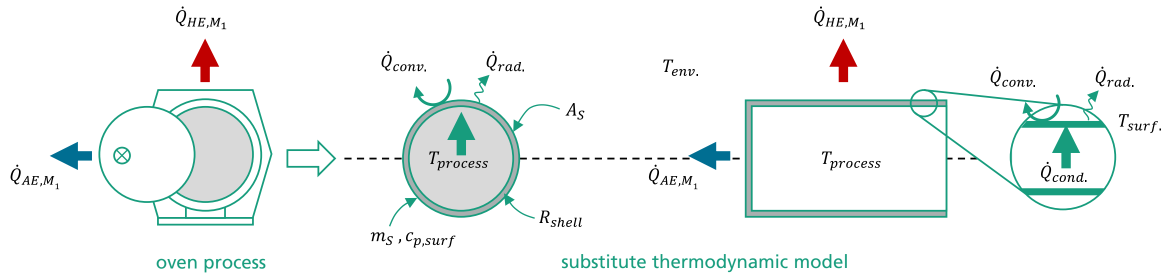


Figure 5-16 Case 2: Substitute thermodynamic model for the representation of heat emissions from thermal processes

With additional information on the machine geometries and material characteristics, the energy balance at the machine surface can be represented by Equation (5-12), where the heat emission $\dot{Q}_{HE}$ is equal to the amount of heat dissipated by the process taking place within the machine core $\dot{Q}_{cond.}$ and the amount of heat supplied (+) or dissipated (-) by auxiliary equipment $\dot{Q}_{AE}$, minus the amount of heat $\dot{Q}_{surf.}$ causing the change in machine surface temperature $T_{surf.}$. The heat given off by the surface of the machine body to the factory environment $\dot{Q}_{HE}$ can be further described as the sum of convection $\dot{Q}_{conv.}$ and radiation $\dot{Q}_{rad.}$ (ref. Equations (5-13), (5-14) and the heat absorbed by the machine surface $\dot{Q}_{surf}$ as a function of its mass, heat capacity, and incremental change in surface temperature (Equation 5-15). The temperature gradient between the process $T_{process}$ and surface temperature $T_{surf.}$ divided by the thermal resistance R_{shell} is referred to as conduction (ref. Equation 5-16).

$$\dot{Q}_{HE}(t) = \dot{Q}_{cond.}(t) + \dot{Q}_{AE}(t) - \dot{Q}_{surf.}(t) \tag{5-12}$$

$$\dot{Q}_{HE}(t) = \dot{Q}_{conv.}(t) + \dot{Q}_{rad}(t) \tag{5-13}$$

$$\dot{Q}_{HE}(t) = \alpha \cdot A_{surf} \cdot \left(T_{surf.}(t) - T_{env.}\right) + \varepsilon \cdot \sigma \cdot A_{surf} \cdot \left(T_{surf.}(t)^4 - T_{env.}{}^4\right) \tag{5-14}$$

$$\dot{Q}_{surf.}(t) = m_s \cdot c_{p,surf.} \cdot \frac{dT_{surf.}(t)}{dt} \tag{5-15}$$

$$\dot{Q}_{cond.}(t) = \frac{T_{process}(t) - T_{surf.}(t)}{R_{shell}} \tag{5-16}$$

It is assumed that the material-specific parameters c_p (heat capacity), α (convective heat transfer factor) and the ε (emission factor) are constant and homogenous without temperature dependence on $T_{surf.}$. Furthermore, the model is simplified by assuming that the temperature of the surrounding zone $T_{env.}$ is constant.

The differential equation derived from using Equation (5-12) with Equations (5-14), (5-15), and (5-16) can be approximated by Equation (5-17) and solved for different time steps Δt.

$$T_{surf.}(t + \Delta t) = T_{surf.}(t) + \frac{dT_{surf.}(t)}{dt} \cdot \Delta t \quad (5\text{-}17)$$

The individual sources of heat emissions from machine operation are assigned to the respective zones within the factory building model. Due to the effects of thermal inertia and to improve simulation performance, heat emissions are implemented as one-hour averages. The feasibility of using lower temporal resolutions for certain energetic observations has already been recognized by Bleicher et al. (2014, p. 443). The example presented in Figure 5-17 shows the resulting heat emissions from a model representation of a furnace process.

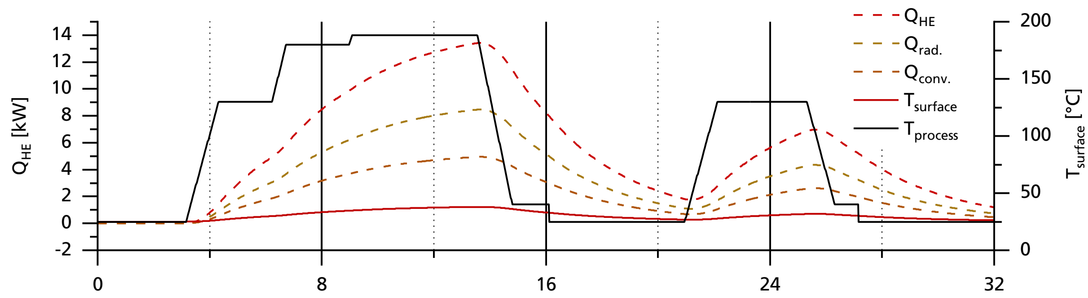


Figure 5-17 Example of heat emissions from a furnace process

Process chain model

According to VDI 2221 , a process chain refers to an arrangement of various successive manufacturing steps. A process chain can also be understood as a controlled sequence of individual processes "with the objective of transforming certain items from an input state into a conformable output state" (Henjes 2014, p. 976). In a factory setup, the individual processes are usually carried out by a certain number of machines and/or manual labor, which are linked together in a process chain by manual or automated logistics operations. A process chain model is characterized by a set of general (e.g., customer demand, shift calendar, number of products variants, respective batch sizes) and process- or machine-specific (e.g., process, setup, and cycle time) information.

The specifics of production planning and scheduling, including machine availability and the product mix processed by each machine, are capture by both enterprise resource planning systems (ERP) and manufacturing executing systems (MES). The information available in these systems can be used to parameterize the process chain model. The value stream method presented in 2.2.2 also offers a standardized way to gather the information required to characterize the process chain within the factory model. Figure 5-18 outlines a process chain model which processes a material flow across a specific number of machines and buffers. Each machine performs a defined number of processes.

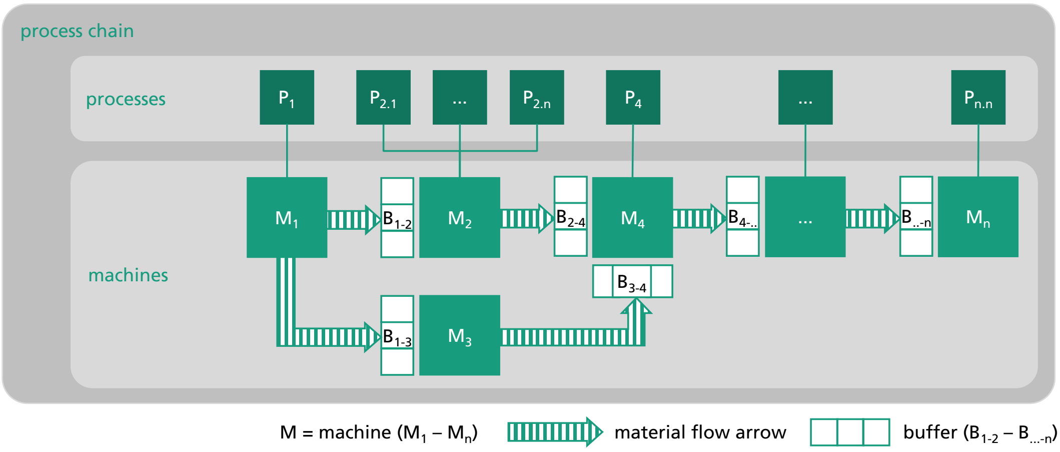


Figure 5-18 Framework for process chain model

Auxiliary equipment model

Auxiliary equipment includes technical installations to supply the manufacturing processes with further resources, in particular process media. Their operation results in an additional energy requirement. Examples include compressed air and vacuum, process cooling and heating as well as all types of process gases. In addition to supplying resources that are used directly in the process, auxiliary equipment also includes installations that enable the proper functioning of process-related machinery and equipment. An example of such a support function is the supply of compressed air to the airlock of a machine tool, which prevents dirt and dust from entering the inside of the spindle.

Auxiliary equipment either provides individual resources to multiple machines at different conditions (e.g., volume flow, pressure level, temperature) or individual resources to singular machines with uniform conditions (ref. Figure 5-19).

Depending on the quantitative and qualitative requirements, auxiliary equipment is installed either centrally (e.g., in a powerhouse) or decentralized (e.g., close to the process and machine). Apart from these considerations, the location and the auxiliary equipment installations at a production site are influenced by the boundary conditions and constraints imposed by the factory building and its historical development.

Within the factory simulation, the energy demand of auxiliary equipment is represented by a black-box model. This model sets the quantity of the resource supplied (e.g., m³ of compressed air) in relation to the power requirement for the operation of the auxiliary equipment (e.g., kW electric load for compressor operation). The model may evolve in accuracy depending on data availability and measurement effort. Figure 5-20 illustrates a step-by-step procedure to developing model accuracy according to data availability and measurement effort.

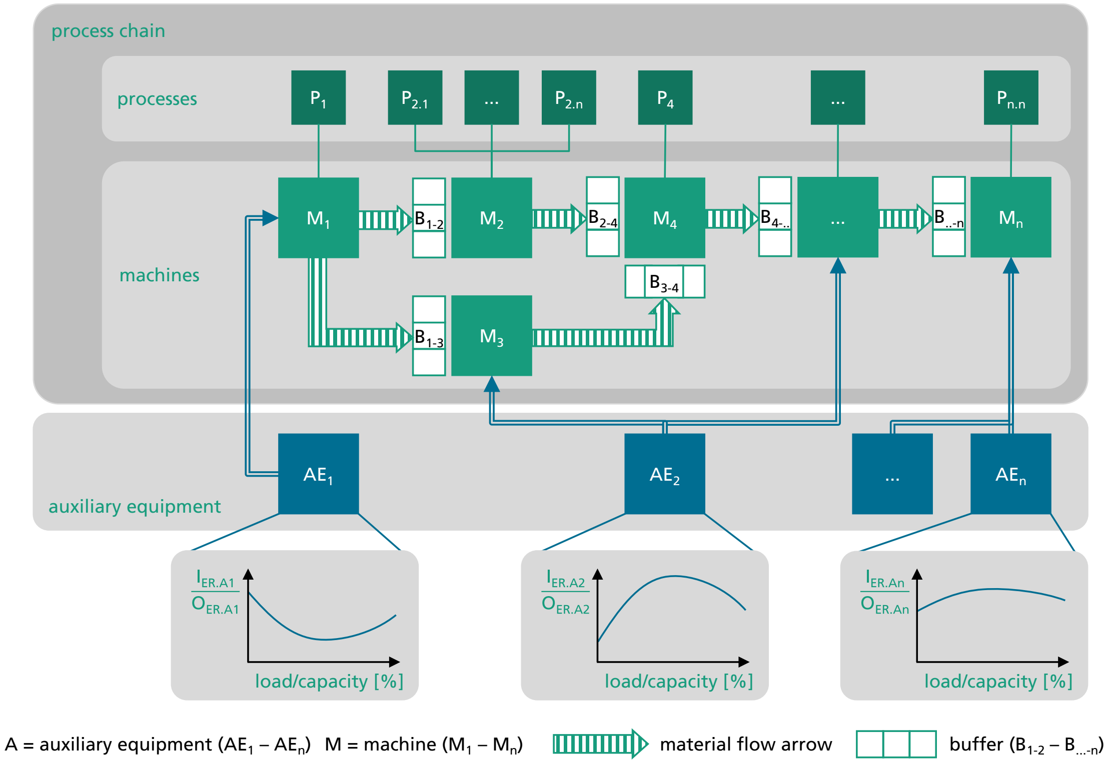


Figure 5-19 Framework for auxiliary equipment model

In the first step, a physical model (1) is fitted by available information from equipment manufacturer data sheets (2). In a subsequent step, two-dimensional regression models (3) and n-dimensional look-up tables (4) are implied into the model, based on one-time measurements conducted in the field.

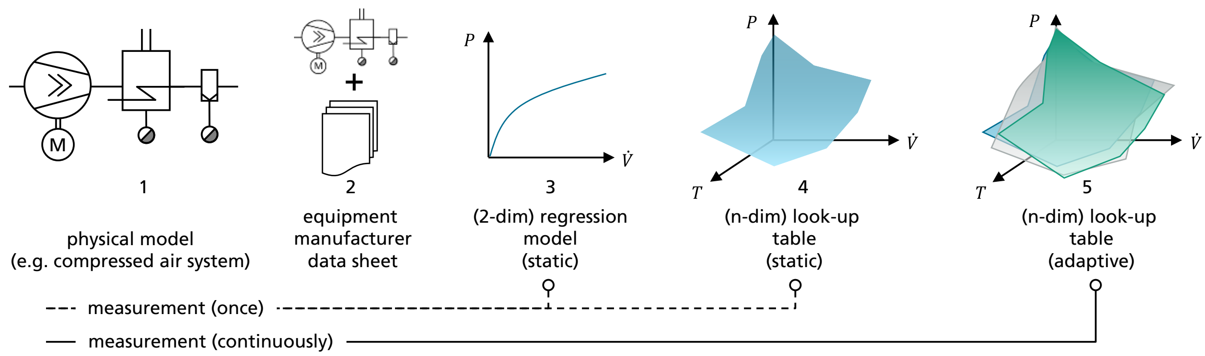


Figure 5-20 Step-by-step procedure to evolve model accuracy

If continuous measurement data are available (e.g., from a process monitoring system), the model may include an adaptive look-up table (5) to represent changing operating conditions. In this way, the system response of a physical asset can be matched with its model representation, thus increasing model accuracy.

This general modeling approach is further illustrated with representative auxiliary equipment used in a factory environment and described in the next paragraph.

Model of a compressed air system

A compressed air system, including the components for conversion, storage, distribution, and delivery, is shown in Figure 5-21. The power requirement of an air compressor can be described by a physical (thermodynamic) model and expressed by the mass flow $\dot{m}$ multiplied by the specific compression work required to compress one m³ of air (Equation 5-18).

$$P_{CAS}(t) = \dot{m}(t) \cdot w_{T,1\to 2}(t) \tag{5-18}$$

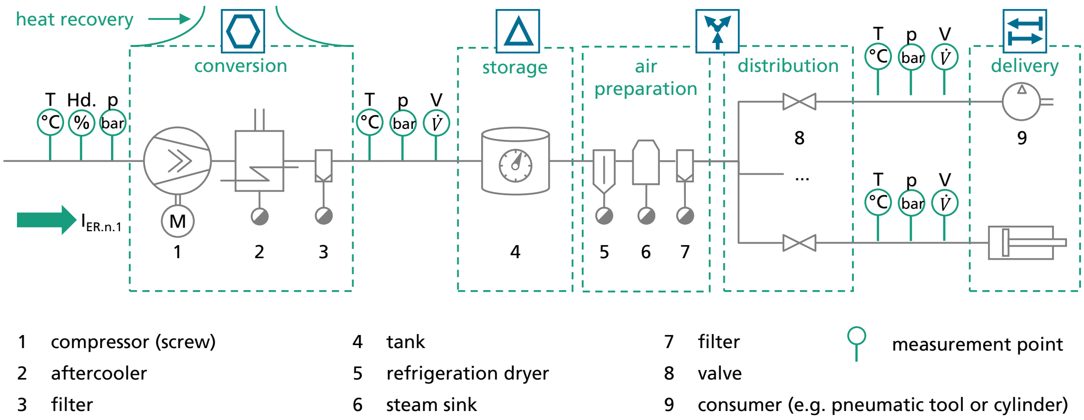


Figure 5-21 Auxiliary equipment model (example of a compressed air system)

In order to specify the compression work, it is necessary to establish the energy balance for the air compressor according to the first law of thermodynamics for open systems (Equation 5-19). Depending on the system boundaries, the change in kinetic energy in a gaseous fluid is insignificant and can be neglected. Due to its low dead weight, this also applies to the change in potential energy. (Langeheinecke et al. 2017, p. 89)

$$\Delta h_{1\to 2} + e_{kin.\ 1\to 2} + e_{pot.\ 1\to 2} = q_{1\to 2} + w_{T,1\to 2} \tag{5-19}$$

A thermodynamic transformation at isothermal conditions assumes that there is no temperature change ($\Delta T = 0$) and that all the heat generated by the work $w_{T,1\to 2}$ is completely dissipated as heat $-q_{1\to 2}$ by the environment. This can be realized if the thermodynamic transformation is carried out very slowly. A thermodynamic transformation at adiabatic conditions represents the other extreme case. In this scenario, there is no heat exchange with the environment ($-q_{1\to2}$ = 0), which can only be realized if the thermodynamic transformation is carried out very quickly. Since there are no friction losses, the adiabatic process is reversible and is referred to as isentropic. Isothermal and isentropic processes represent ideal cases that cannot be realized in technical applications. A thermodynamic transformation at polytrophic conditions best represents the physical behavior of a compressor. In this case, heat is exchanged with the environment during the compression work. Equation (5-19) is therefore reduced to Equation (5-20). The difference in model behavior considering isothermal, polytropic, or isotropic assumptions is illustrated in Figure 5-22.

$$w_{T,1\to2.poly} = \Delta h_{1\to2} - q_{1\to2} \qquad (5\text{-}20)$$

The value of $w_{T,1\to2}$ can be calculated considering the general gas equation under ideal gas conditions and the relation of the specific gas constant, the polytropic coefficient, and the specific heat capacities (Hering et al. 2016, pp. 179-185). Together with Equation (5-18) and the Poisson equation, the power for compression can be described according to Equation (2-21).

$$P_{CAS}(t) = \frac{n}{(n-1)} \cdot p_1 \cdot \dot{V}_1(t) \cdot \left[\left(\frac{p_2(t)}{p_1}\right)^{\frac{n-1}{n}} - 1\right] \qquad (5\text{-}21)$$

For more details on physical models for compressed air systems, see also Pohl et al. (2012, p. 738 f.) and Thiede (2012, pp. 108-114).

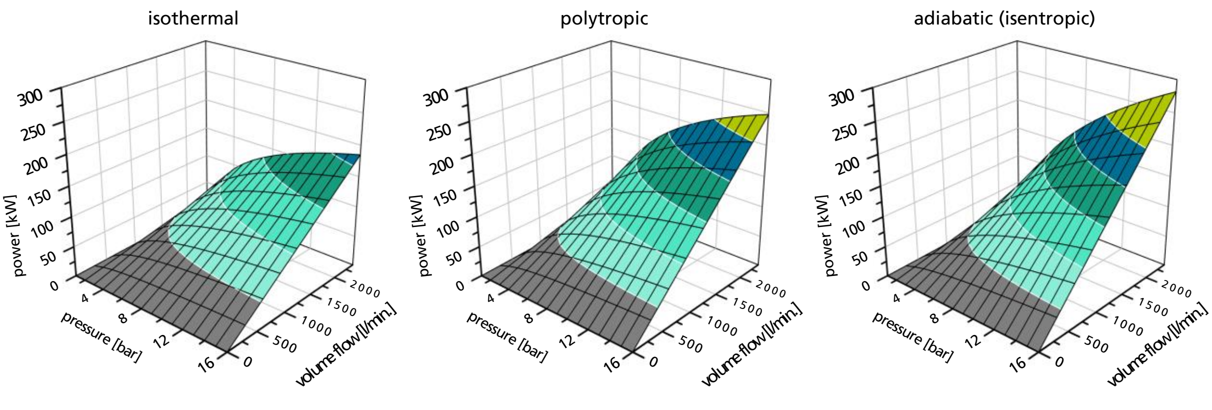


Figure 5-22 Power demand of compressed air systems considering volume flow and pressure rise at isothermal, polytrophic, and isentropic conditions

In order to further develop the physical model, measuring points for pressure, temperature, humidity, and volume flow are further given in Figure 5-21. According to ISO 1217, these measurement points can be used to characterize the compressed air system and relate its electrical energy demand to the compressed air flow provided (ISO 1217 , ISO 1217 AMD 1). Compared to a physical modeling approach, measurement-based black-box models can provide a more realistic representation of the energy consumption characteristics of a compressed air system. Based on the measurement setup, the model can also include the effects of subcomponents such as filters and coolers. Equation (5-22) summarizes the relevant measurement point for a black-box model, includes the humidity ratio x_1 and x_1, the actual mass of water vapor present in moist supply, and return air. The results can be implemented in a model using look-up table (LUT).

$$P_{CAS} = LUT(p_1, p_2, T_1, T_2, x_1, x_2, \dot{V}_1) \tag{5-22}$$

Model of a process cooling system

To meet the cooling demand of a process within a factory, a cooling system is required. A cooling system generally consists of technical components for the conversion, storage, distribution, and delivery (ref. Figure 5-23). The heart of a cooling system setup is a refrigeration unit or chiller. Its respective energy balance is described in Equation (5-23). A medium with the flow rate $\dot{m}_E$ and the heat capacity $c_{p,E}$ that requires cooling from $T_{E,in}$ to $T_{E,out}$ exchanges the heat flow $\dot{Q}_{PCS}$ through a heat exchanger and evaporates the refrigerant (e.g., R410A) inside the chiller by dissipating the heat $\dot{Q}_E$ (ref. Equation 5-24).

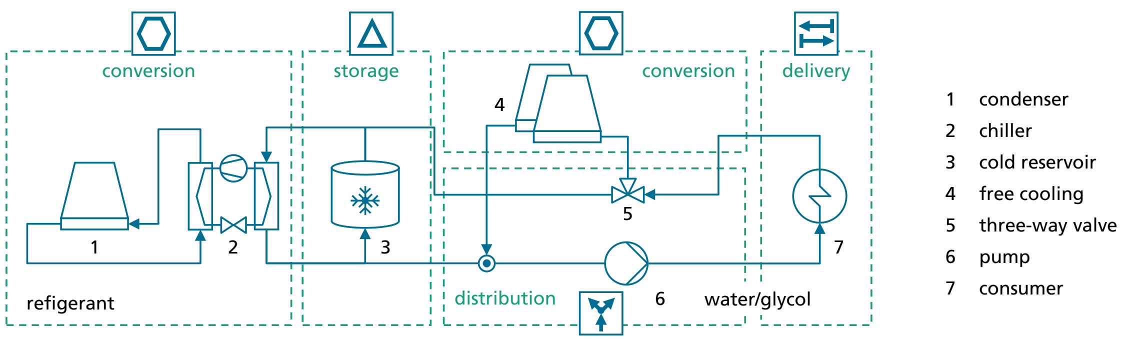


Figure 5-23 Model of auxiliary equipment (example of a process cooling system with free cooling)

Electrical power $P_{comp.,el.}$ is required to compress the evaporated refrigerant with the mass flow $\dot{m}_C$ to higher pressures. In the next step, the refrigerant at higher pressure is passed through a second air- or water-cooled heat exchanger. While exchanging the heat flow $\dot{Q}_c$ with a heat sink (e.g., air or water-glycol-mixtures), the refrigerant with the heat capacity $c_{p,C}$ condenses (ref. Equation 5-25). An expansion valve closes the thermodynamic circuit while reducing pressure and temperature of the refrigerant.

$$\dot{Q}_E + P_{comp.,el.} + \dot{Q}_c = 0 \quad (5\text{-}23)$$

$$\dot{Q}_{PCS} = \dot{Q}_E = \dot{m}_E \cdot c_{p,E} \cdot (T_{E,out} - T_{E,in}) \quad (5\text{-}24)$$

$$\dot{Q}_c = \dot{m}_c \cdot c_{p,C} \cdot (T_{c,out} - T_{c,in}) \quad (5\text{-}25)$$

The Energy Efficiency Ratio (EER) of a cooling system describes the ratio between the available cooling power and the electrical power demand of the cooling system (Equation 5-26). Based on measurement campaigns conducted in the field, the EER can be quantified for specific cooling system configurations and ambient conditions. To improve the model accuracy, EER can also be implemented in the cooling system model as a look-up table (LUT). Depending on whether the condenser is air- or water-cooled, the look-up table relates the measured values for $\dot{Q}_{PCS} = f(\dot{m}_E, T_{E,out}, T_{E,in})$, $P_{comp.,el.}$ and the inlet temperature $T_{c,in}$ of air or water (ref. Figure 5-24 A).

$$EER = \frac{\dot{Q}_{PCS}}{P_{comp.,el.}} = LUT(\dot{Q}_{PCS}, P_{comp.,el.}, T_{c,in}) \quad (5\text{-}26)$$

Free cooling is an important measure for reducing the energy demand of cooling systems in general and process cooling systems in particular. A free cooling system uses the temperature difference between supply temperature $T_{E,out}$ and ambient temperature. This is especially true for factories that operate manufacturing processes with constant cooling requirements and that are located in temperate or cold climates. Figure 5-24 B shows the example of a cooling system design with free cooling and supply temperature requirement of 16 °C. The figure shows that at a temperature difference of 10 °C or outdoor temperatures below 6 °C, respectively, free cooling can cover 100 % of the cooling demand. With the annual temperature distribution (green curve), free cooling can cover the entire cooling demand 45 % of the time. For 85% of the time, it can at least partially help reduce the cooling demand provided by the cooling system.

Further details on the part-load performance of air-cooled chillers can be found in Yu and Chan (2007, p. 3824 f.). For more information on modeling cooling systems, including storage and free cooling, see Puls et al. (2015, p. 168 f.) and Puls et al. (2019, p. 1873 ff.).

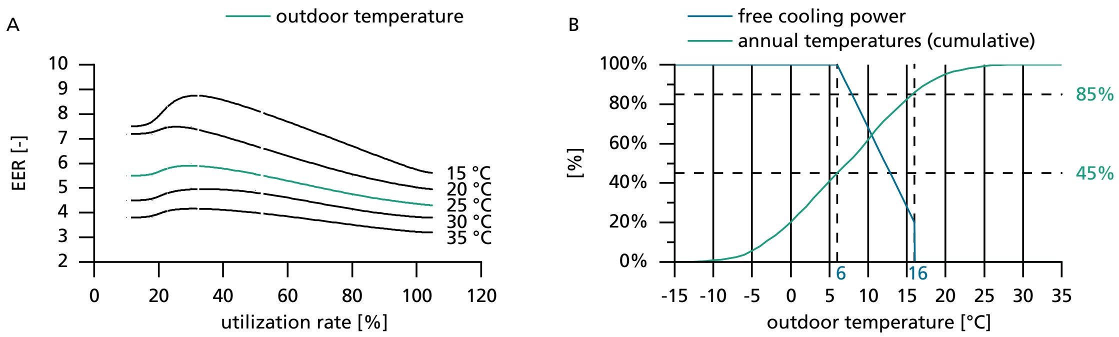


Figure 5-24 (A) Characteristic efficiency of a chiller at partial load for different outdoor temperatures and utilization rates of maximum cooling power (Mitsubishi 2020); (B) Example of available free cooling capacity as a function of outdoor temperature (supply temperature 16 °C, cooling demand covered 100% by free cooling at outdoor temperatures below 6 °C)

5.4.2 Model of the factory building and technical building systems

Model of a factory building

The factory building model describes the characteristics of the building envelope, including walls, roofs, and floors. All parts of the envelope are described in terms of geometry and material composition. Furthermore, the number and dimensions of all openings, windows, doors, leakages, and thermal bridges are characterized. The factory building model further specifies how the interior spaces are divided into zones and how these zones are composed and interconnected. Each individual zone includes information on temperature, humidity, and ventilation requirements. In addition, the equipment installations for lighting, heating, ventilation, and air-conditioning are defined and assigned to each zone. All building zones take into account internal heat gains from equipment operation and staff occupancy. Heat emissions from machinery and auxiliary equipment are quantified according to the models developed in Subsection 5.4.1. The factory building model also takes into account the thermal inertia caused by the mass and material composition of the building envelope and equipment installations. Also included are submodels describing manual and automated control strategies for shading devices and window openings designed to prevent excessive heating and take advantage of natural lighting and ventilation.

Figure 5-25 illustrates the different energy flows within a factory building, including heat gains and losses from radiation ($\dot{Q}_{rad.}$), convection ($\dot{Q}_{con.}$), and conduction ($\dot{Q}_{cond.}$), heat dissipation from internal heat sources ($\dot{Q}_{HE}$) and the heating and cooling controlled by heating, ventilation, and air-conditioning systems ($\dot{Q}_{HVAC.}$). Furthermore, ventilation ($\dot{Q}_{vent.}$), transmission ($\dot{Q}_{trans.}$), and leakage losses ($\dot{Q}_{leak.}$) are taken into account. Assuming stationary conditions ($\sum_j \dot{m}_{in,j} = \sum_j \dot{m}_{out,k}$), the factory building model must satisfy the energy balance equation given in Equation (5-27) to maintain the indoor environment at a constant level ($\frac{dE_{building}}{dt} = 0$). The heat exchange within the individual building zones consists of the heat transfer between the building and the surrounding environment, the heat emissions $\dot{Q}_{HE}$ from the activities of the employees $\dot{Q}_{HE,E}$, the lighting $\dot{Q}_{HE,L}$, and the operation of machines $\dot{Q}_{HE,M}$ and auxiliary equipment $\dot{Q}_{HE,AE}$ as well as the heating and cooling by technical building systems (Equations 5-28) and 5-29).

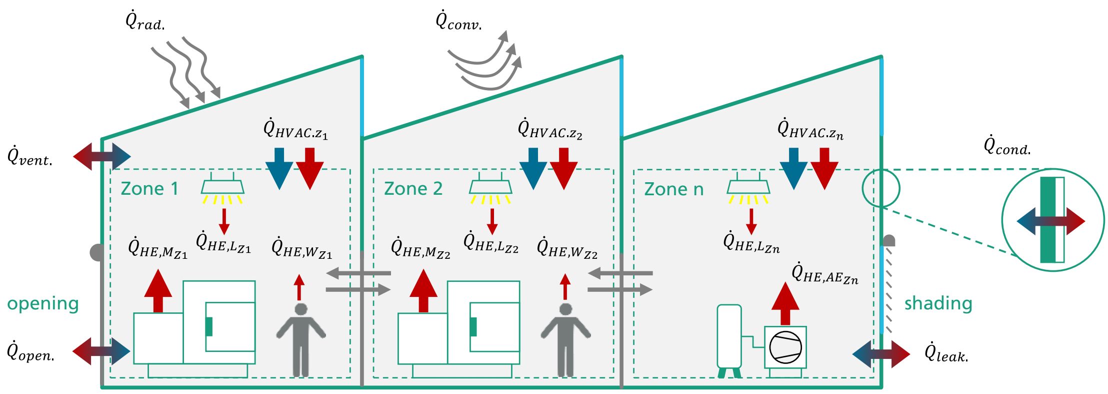


Figure 5-25 Building model (M = machinery; AE = auxiliary equipment)

Equation (5-30) adds heat exchange as a result of mass transfer through openings $\dot{Q}_{open.}$, leakages $\dot{Q}_{leak.}$, and ventilation systems $\dot{Q}_{vent.}$.

$$\frac{dE_{building}}{dt} = \sum_{Z1}^{n} \sum_{i} \dot{Q}_i(t) + \sum_{Z1}^{n} \sum_{j} \dot{m}_{in,j}(t) \cdot h_j(t) - \sum_{Z1}^{n} \sum_{k} \dot{m}_{out,k}(t) \cdot h_k(t) = 0 \qquad (5\text{-}27)$$

$$\sum_{Z1}^{n} \sum_{i} \dot{Q}_i(t) = \dot{Q}_{cond.}(t) + \dot{Q}_{rad.}(t) + \dot{Q}_{conv.}(t) + \dot{Q}_{HE}(t) + \dot{Q}_{HVAC}(t) \qquad (5\text{-}28)$$

$$\dot{Q}_{HE}(t) = \dot{Q}_{HE,E}(t) + \dot{Q}_{HE,L}(t) + \dot{Q}_{HE,M}(t) + \dot{Q}_{HE,AE}(t) \qquad (5\text{-}29)$$

$$\sum_{Z1}^{n} \sum_{j} \dot{m}_{in,j} \cdot (h_j - h_k) = \dot{Q}_{open.}(t) + \dot{Q}_{leak.}(t) + \dot{Q}_{vent.}(t) \qquad (5\text{-}30)$$

There is a wide range of software tools available to help engineers assess the energy demand and comfort performance of buildings. These tools usually come from the research fields of architecture and civil engineering. Depending on the particular application and the availability of information, these software tools allow the description of physical phenomena at different levels of detail. The models are based on either a white-box, black-box, or combined gray-box modeling approach (Amara et al. 2015, pp. 98-101). Apart from the energy consumption of a building, modern building simulation software can be used to define gradients and distribution of pressure, humidity, and temperature within individual building zones. In general, numerical methods are used to solve the differential equations describing the physical behavior (heat flux, heat transfer, and heat storage) of a building (Wetter 2009, pp. 144-146).

Among the tested and commercially available software tools for energy analysis of buildings are EnergyPlus, TRNSYS, and IDA ICE. Detailed comparisons between the different software tools can be found in Crawley et al. (2008, p. 666 ff.) and Jarić et al. (2013, p. 107 ff.).

Technical building systems model

According to DIN EN ISO 16484-2, technical building systems comprise the technical equipment distributed in the infrastructure of a building. This includes installations for electricity, gas, heating, water, and communication systems (DIN EN ISO 164842, p. 14). In addition to this definition, the presented factory simulation model further distinguishes between technical systems of the building infrastructure, auxiliary equipment used for the supply of manufacturing processes, and energy supply systems for the handling and transformation of the final energy demand between the grid and intermediate energy carriers. Considering the building infrastructure, the detailed representation of heating, ventilation, and air-conditioning (HVAC) systems is crucial for an accurate representation of the building behavior in the model in terms of energy consumption (Kramer et al. 2017, p. 287 f., Shin and Haberl 2019, p. 9 f.). HVAC systems that incorporate the four functions, heating, cooling, humidifying, and de-humidifying, are commonly referred to as 'full air-conditioning systems'. If only a selected number of functions are installed, the systems are referred to as 'partial air-conditioning systems' (Wiendahl et al. 2015, p. 294).

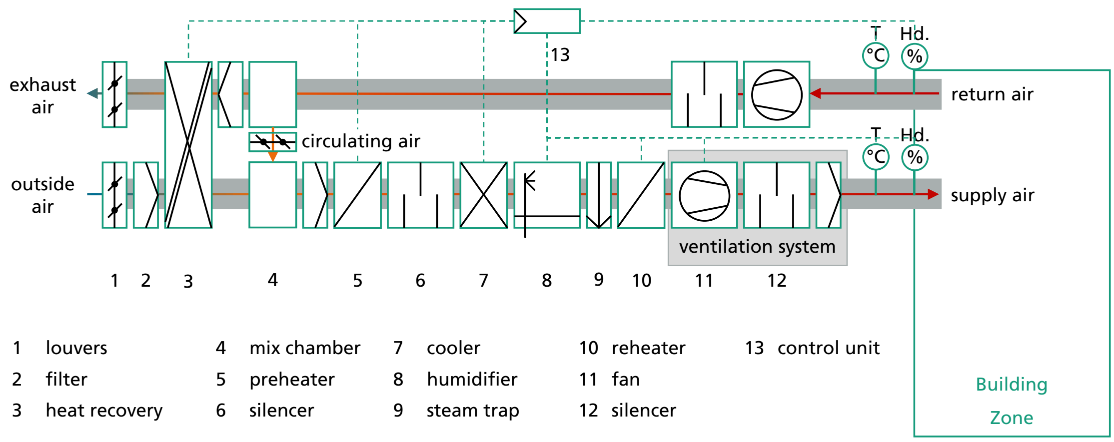


Figure 5-26 Heating, ventilation, and air-conditioning system (HVAC) (own representation based on Wiendahl et al. 2015, p. 294, with symbols according to Siemens 1999)

Figure 5-26 shows an example setup for a centralized HVAC system. When the louvers (1) are open in this setup, outside air is filtered (2) and passes through a heat recovery unit (3) to either preheat or precool the incoming air using the temperature and humidity difference between return airflow and outside air conditions. Heat recovery units generally use a cross-flow or rotary heat exchanger. The proportion of fresh air and recirculated air can be adjusted in the mixing chamber (4). The supplied air is then passed through a series of preheating (5), silencing (6), cooling (7), humidifying (8), and reheating (10) units to adjust the supply air to the desired conditions. Before reaching the respective building zone(s), the ventilation section, consisting of a fan (11), a silencer and filter, applies the required pressure difference to compensate for the pressure losses in the distribution system (e.g., ventilation pipes and openings). In addition to the described system setup, there are many variations. In decentralized setups, for example, preconditioned air from a central ventilation system is used, while heating, cooling, and (de-)humidification are implemented decentrally (Wiendahl et al. 2015, p. 294). Modular system setups increase flexibility. For example, if manufacturing activities change or if different ambient air conditions are required in different parts of the factory building, the system can be taken over or partially switched off, while the rest of the building can continue to be air-conditioned as required in an energy-efficient manner.

In addition to the HVAC system setup, the system controls have a major impact on energy consumption and indoor air quality. Therefore, a thorough representation of the control strategy in the factory simulation model is required.

In the system setup shown in Figure 5-26, the control unit (13) compares the temperature and humidity measured in the zone or the return airflow with the temperature and humidity present in the thermostat and hygrostat of the control unit. If the temperature and humidity deviate from the preset values, the valves supplying the heating or cooling coils and/or the (de)humidifiers are controlled accordingly. If a heat recovery unit is part of the HVAC system setup, the control unit can adjust the speed of the rotary heat exchanger to change the degree of heat recovery. The proportion of recirculated air increases proportionally to the decrease in outside air temperature. The minimum fresh air supply is preset. In addition to heat recovery and air recirculation, there are other ways to improve energy efficiency through individual control strategies. These are, for example, predictive control functions that take into account external factors such as changing weather conditions or changes in internal gains (Oldewurtel et al. 2012, p. 16).

The VDI 3802 Part 1 standard generally distinguishes between four different types of air-conditioning project frameworks: (1) construction in a new hall, (2) the modernization of air-conditioning in an existing hall, (3) the conversion of an air-conditioning system due to changed loads, and (4) the retrofitting an air-conditioning system in an existing facility (VDI 3802, p. 10). The requirements for collection, supply, and exhaust airflow requirements in factories must be designed in accordance with the occupational exposure limits for substances summarized in the standard. Empirical values for area-related supply airflows are summarized in Table 5-5.

In addition, the standard also recommends the use of laboratory tests and CFD simulations to improve the accuracy of the design results (VDI 3802, pp. 57, 70). Besides, the room temperature, humidity, CO_2 concentrations, and airflow must comply with the occupational health and safety standards according to BGI 7003, ASR A3.5, ASR A3.6, and DIN EN 16798 (DGUV 2010, BAuA 2010, BAuA 2012, DIN EN 16798-3).

Table 5-5 Empirical values for area-related supply airflows (extract from VDI 3802, p. 71, DIN 18599-10, p. 55)

State of machine	**Area-related supply airflows [m³/(h·m³)]**
Foundry	50 – 200
Mechanical manufacturing	20 – 75
Forming	20 – 50
Assembly	20 – 30

Table 5-6 gives examples of values for minimum air temperatures in working spaces, which are specified according to work intensities. Also, the maximum air temperatures should not exceed +26 °C (BAuA 2010, p. 4).

Table 5-6 Minimum air temperature in workspaces (BAuA 2010, p. 4)

Predominant posture		**Work intensity**	
	Light	Moderate	heavy
Sitting	20 °C	19 °C	-
Standing, walking	19 °C	17 °C	12 °C

Climate zones and weather data

The location of the factory building has a major influence on the design of the technical building systems and its energy consumption. In addition, the location defines the types and quantities of renewable energy sources that can be used on-site.

According to the Köppen-Geiger climate classification, the world climate can be divided into five different zones, tropical (mega-thermal) climates, arid and semiarid climates, temperate (mesothermal) climates, continental (microthermal) climates, polar and alpine (montane) climates (Rubel and Kottek 2010, p. 136 f. and Beck et al. 2018, p. 3). Each climate zone and local weather condition presents unique possibilities and constraints for the designs of a factory's energy system. Therefore they require a corresponding representation in the factory simulation model.

Historical time series and hourly weather data on temperature, humidity, global radiation, precipitation, and wind speed are available from various institutional organizations and commercial providers, including Deutscher Wetterdienst (DWD), ASHRAE, and Meteotest (DWD 2020, ASHRAE 2020, Meteotest AG 2020). An example time series for the Munich site is shown in Figure 5-27.

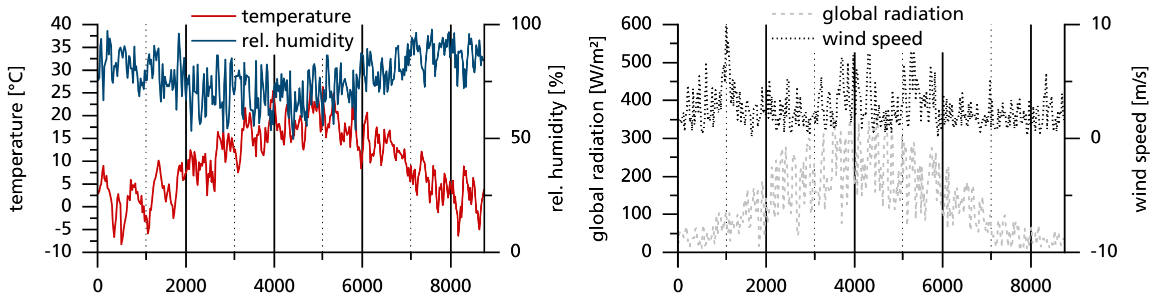


Figure 5-27 Example weather data time series with temperature, relative humidity, global radiation, and wind speed (hourly values for Munich obtained from Meteonorm 7)

Validation of the factory building and technical building systems model

Before the simulation experiments are carried out, the building model must be validated. In general, the quality of a model representation from a real-world system is verified by comparing simulation results with measured data taken from the field. For example, the energy consumption of the modeled factory can be compared to the measured energy consumption of the real-world factory. Another example is the comparison between simulated indoor temperature and measured indoor temperature. Depending on the application scenario and modeling objective, other parameters can also be used.

Two different statistical performance metrics and corresponding acceptance criteria for model calibration are reported in the literature: Mean Bias Error (MBE) (Equation 5-31) and Coefficient of Root Mean Square Error (CVRMSE) (Equation 5-32). Further guidance on building energy simulation and model calibration can be found in Coakley et al. (2014).

$$MBE\ [\%] = \frac{\sum_{i=1}^{N_p}(m_i - s_i)}{\sum_{i=1}^{N_p}(m_i)} \tag{5-31}$$

MBE is a dimensionless bias measure that calculates the average deviation between measured in simulated values. A low MBE indicates a small deviation between the values derived from the model and the measured values.

Here m_i and s_i represent measured and simulated values for each model instance i. N_p is the number of data points between interval p. For monthly values, N_p is equal to 12 and for hourly values, N_p is equal to 8760.

MBE is a good measure to evaluate the overall bias of the model, but the positive bias compensates for negative bias. This is called the cancellation effect and requires an additional measure to quantify the model error. CVRMSE does not suffer from the cancellation effect and allows the assessment of the model fit between measured and simulated data. The CVRMSE is obtained by dividing the root mean square error (RMSE) by the average value of all measurement values $\bar{m}$.

$$CVRMSE\,[\%] = \frac{RMSE}{\bar{m}} = \frac{\sqrt{\left(\sum_{i=1}^{N_p}(m_i - s_i)^2\right) / N_p}}{\bar{m}} \tag{5-32}$$

The RMSE indicates the variability between measured and simulated data. For the RMSE values, the difference between each pair of measured m_i and simulated s_i values are squared, and the sum of all squares within the interval p is divided by the respective number of data points N_p of the same interval.

After calculating the deviation and variability between modeled and measured data, the quality of the simulation results must meet the acceptance criteria specified in standards (ref. Table 5-7). For example, ASHRAE Guideline 14 and the U.S. Department of Energy define the most stringent requirement for the monthly evaluation. When considering hourly values, the Energy Valuation Organization allows a maximum MBE of 5% and a CVRMSE of 20%.

Table 5-7 Acceptance criteria for calibration of models (Coakley et al. 2014, p. 126)

Standard/guideline	**Monthly criteria (%)** $N = 12$		**Hourly criteria (%)** $N = 8760$	
	MBE	CV RMSE	MBE	CV RMSE
ASHRAE Guideline 14 (2002)	5	15	10	30
Efficiency Valuation Organization (2002)	20	-	5	20
U.S. Department of Energy (2015)	5	15	10	30

If the initial model calibration does not meet the defined acceptance criteria, refinements must be considered. Based on the findings of Lam and Hui (1996, p. 36), Table 5-8 provides an overview of different building model components and their influence on model accuracy. Further measures to refine the simulation models can be achieved by adjusting air exchange rates and thermal storage masses (Schramek and Recknagel 2011, p. 591).

Table 5-8 Building model components and their influence on model accuracy

Model component	**Influence on model accuracy**
Heating, ventilation, and air-conditioning (HVAC) setpoints	high
Occupant density, lighting and equipment load	high
Building envelope specifications	medium

5.4.3 Energy supply system models

It is noted that the conceptual synthesis of an energy supply system model is responsible for determining much of the total costs of the system (Voll et al. 2015, p. 447). In order to arrive at a demand-oriented design that takes into account both the specifics of the underlying manufacturing processes and the specifics of the factory location, additional submodels are introduced (ref. Figure 5-28). These models are used to describe the consumption characteristics of the energy supply system.

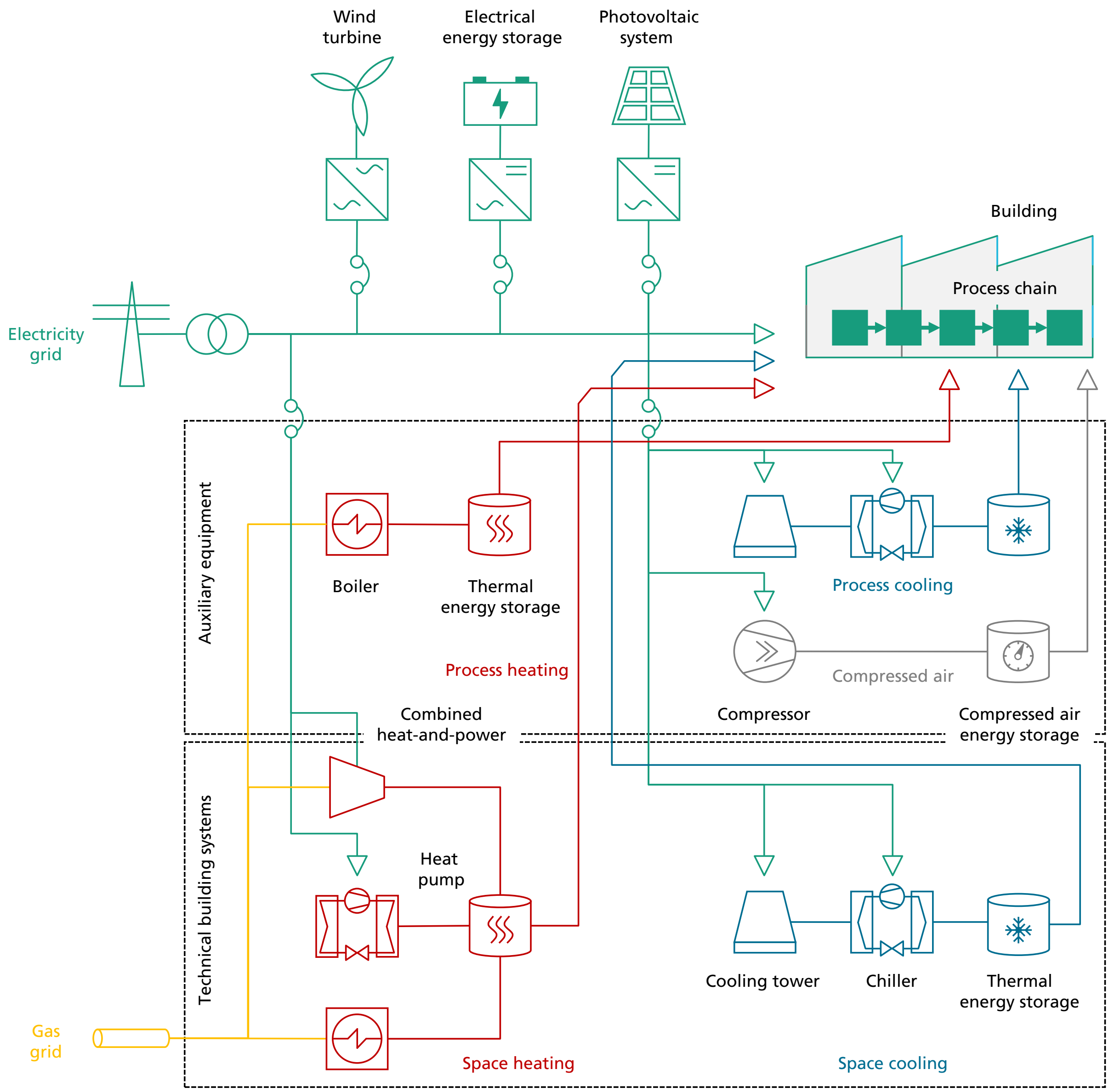


Figure 5-28 Overview of components in a typical energy supply system for industry

The energy supply system model represents the interaction of auxiliary equipment, technical building systems, and other installations used to meet the required energy demand (e.g., renewable energy systems). It further takes into account the connection to both electricity and gas grids but also represents other local grid infrastructures. It also sets energy price tariffs, including the remuneration schemes for the feed-in of energy from renewable sources and demand-side management.

Figure 5-28 shows the energy supply system model with its submodels and interconnections. The figure shows the different subcategories, namely technical building systems, including equipment installations for space heating and cooling, auxiliary equipment for the provision of process-related energy demand, including compressed air, process heating, and cooling as well as installations for the production of energy from on-site renewable sources. When considering the energy path with storage, distribution, conversion, and delivery, a special focus is put on the different energy storage submodels.

Models of the space heating and cooling systems

A wide range of technical systems can provide the space heating requirements, including boilers, heat pumps, and combined heat and power (CHP) systems. Depending on the specific demand characteristics, the design of the supply system may include different technologies. Figure 5-29 A shows an example of a load duration curve. Three supply technologies are also indicated with their respective operating ranges. In this setup, a combined heat and power plant (CHP) with flexible operating ranges is used to provide the baseload heating demand. A heat pump (HP) is used for intermediate loads. Finally, a combination of boiler and heating storage is used to cover peak loads.

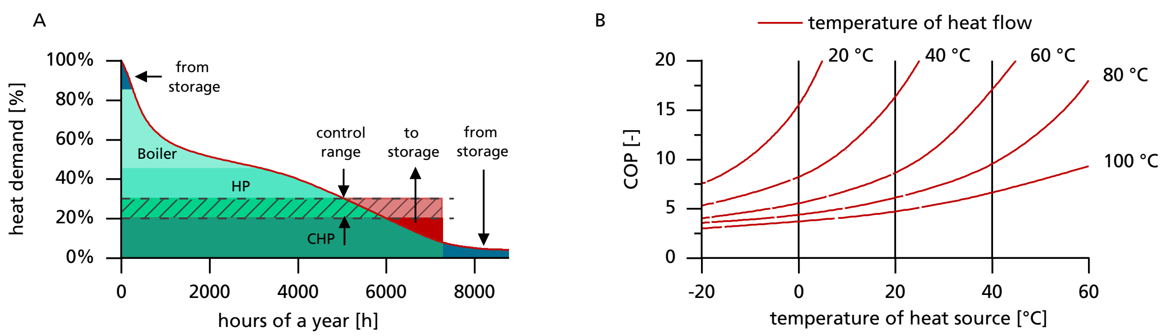


Figure 5-29 A: Example of a load duration curve for heating demand; B: Example of the characteristic relationship between heat source, heat flow, and COP for high-temperature heat pumps with delta T = 40 K (Rieberer et al. 2015, p. 88)

The electrical and thermal efficiency of CHP plants is between 25-35% and 55-65%, respectively, while the overall efficiency is approximately 85% (Schramek and Recknagel 2011, p. 782). Equation (5-33) relates the electrical and thermal power obtained from a CHP plant to the efficiencies $\eta_{electr./therm.}$, the fuel demand $\dot{m}_{fuel}$, and the calorific value H_i of the fuel. The maximum installed heating capacity of a CHP plant is usually chosen to be 50% of the peak heating demand (Schramek and Recknagel 2011, p. 784).

$$P_{CHP,electr.}(t) + \dot{Q}_{CHP,therm.}(t) = (\eta_{electr.} + \eta_{therm.}) \cdot \dot{m}_{fuel}(t) \cdot H_i \tag{5-33}$$

Figure 5-29 B shows the individual performance characteristics of a heat pump, expressed by the coefficient of performance (COP) and depending on the heat source and the flow temperature. The COP puts the electrical power requirement of a heat pump in relation to the thermal power provided. In general, high temperature differences between the heat source and flow lead to lower COP values. Based on Schramek and Recknagel (2011, p. 720), the COP of a heat pump is described by Equation (5-34). With this relationship in Equation (5-35), the heat supply from a heat pump can be calculated with $\dot{Q}_0$, the power capacity of the evaporator, $\eta_{comp.}$ the efficiency of compression, and $P_{comp.}$ the power demand of the compressor.

$$COP_{HP}(t) = \frac{\dot{Q}_0(t) + \eta_{comp.} \cdot P_{comp.}(t)}{P_{comp.}(t)} \tag{5-34}$$

$$\dot{Q}_{HP}(t) = \dot{Q}_0(t) + \eta_{comp.} \cdot P_{comp.}(t) = \dot{Q}_0(t) \cdot \left(1 + \frac{\eta_{comp.}}{COP_{HP}(t) - \eta_{comp.}}\right) \tag{5-35}$$

The boiler model is described in Equation (5-36) and takes into account the efficiency η_B of the boiler operation, the fuel demand $\dot{m}_{fuel}$, and its heating value H_i. The lower heating value H_i represents the usable heat within a certain fuel quantity. Unlike the higher heating values H_s, the enthalpy stored in the vapor of the combustion products is not taken into account here.

$$\dot{Q}_B(t) = \eta_B \cdot \dot{m}_{fuel}(t) \cdot H_i \tag{5-36}$$

The model used to characterize the energy demand for space cooling is identical to the model presented in Subsection 5.4.1 to describe the energy demand for process cooling. Therefore, no further description of space cooling is given in this section.

Energy storage system models

Three types of energy storage systems are considered in the energy supply system model, namely thermal, compressed air, and electrical energy storage systems. Table 5-9 gives an overview of the parameters used in the model.

The energy storage capacity of a thermal energy storage system can be described according to Equation (5-37), where $m_{storage}$ is the mass in the storage system, c_p the heat capacity for the storage medium (e.g., air, water, thermal oil), and $(T(t) - T_{min.})$ is the difference between the current and the minimum permissible temperatures in the storage system. The charging and discharging capacity of a thermal energy storage system is limited by the mass flow of the heat transfer medium, the difference between the temperature of the heat transfer medium and the current temperature in the storage tank, and the size of the heat exchanger surface. Within the model, these parameters are set according to the manufacturer's specifications and supplemented by a term representing the losses of the system (Equation 5-38). The boundary conditions include the footprint or the space required for installing the system $V_{TES.max.}$ and the maximum and minimum permissible temperatures $T_{TES.max.}$ / $T_{TES.min.}$ in the storage system.

Table 5-9 Overview of energy storage systems and their parameters

	Thermodynamic		Electrochemical
	Thermal energy storage	**Compressed air energy storage**	**Electrical energy storage**
Symbol	 **heat**  **cold**		
Storage capacity	Q_{TES}	U_{CAES}	W_{EES}
Maximum charge	$\dot{Q}_{TES.in.max.}$	$\dot{V}_{CAES.in.nom.max.}$	$P_{EES.in.max.}$
Minimum discharge	$\dot{Q}_{TES.out.min.}$	$\dot{V}_{CAES.out.nom.min.}$	$P_{EES.out.min.}$
Boundary conditions	$V_{TES.max.}$ $T_{TES.max.}$ / $T_{TES.min.}$	$V_{CAES.max.}$ $p_{CAES.max.}$ / $p_{CAES.min.}$	$V_{EES.max.}$ $W_{EES.max.}$ / $W_{EES.min.}$

$$Q_{TES}(t) = m_{TES} \cdot c_p \cdot (T_{TES}(t) - T_{TES.min.}) \quad (5\text{-}37)$$

$$\frac{dQ_{TES}(t)}{dt} = \dot{Q}_{TES.in}(t) - \dot{Q}_{TES.out}(t) - \dot{Q}_{TES.loss}(t) \quad (5\text{-}38)$$

Unlike incompressible storage media such as water, air can be used to store energy through compression. According to the ideal gas law, the compressed air energy storage is modeled as a system with isothermal behavior (Equation 5-39). The assumption of isothermal behavior is only valid if the change of state during compression and expansion is sufficiently slow and the heat dissipation sufficiently quickly. Compressed air systems use aftercoolers to reduce the air temperature after compression (ref. Figure 5-21). The charging and discharging is described by the mass flow of compressed air injected and withdrawn from the storage system according to Equations (5-40) and (5-41). The maximum charging $\dot{V}_{CAES.in.nominal.max.}$ and discharging volume flow $\dot{V}_{CAES.out.nominal.max.}$, as well as upper and lower pressure limits $p_{CAES.min.}$ and $p_{CAES.max.}$, are set as parameters within the air compressor model. Taking conservation of mass into account, the relationship between the volume flow at nominal conditions and after compression can be described by the mass balance according to Equation (5-42). Assuming isothermal conditions, the energy contained in a compressed air storage system is described by Equation (5-43).

$$p(t) \cdot V_{const.} = m_{CAES}(t) \cdot R_{air} \cdot T_{CAES} \tag{5-39}$$

$$m_{CAES}(t) = m_{CAES.0} + \int \dot{m}_{in}\, dt - \int \dot{m}_{out}\, dt \tag{5-40}$$

$$m_{CAES}(t) = m_{CAES.0} + \rho_{air.in} \cdot \int \dot{V}_{CAES.in}(t)\, dt - \rho_{air.out} \cdot \int \dot{V}_{CAES.out}(t)\, dt \tag{5-41}$$

$$\dot{m}_{CAES.in/out} = const. \Rightarrow \; \rho_{air.in/out} \cdot \dot{V}_{CAES.in/out}(t) = \rho_{air.nominal} \cdot \dot{V}_{in/out.nominal}(t) \tag{5-42}$$

$$U_{CAES}(t) = m_{CAES}(t) \cdot c_V \cdot T_{CAES} \tag{5-43}$$

The use of compressed air for energy storage only makes sense if there is a corresponding demand for heat, the byproduct of air compression. Depending on the desired storage pressure, gradual compression with intermediate cooling is required, which further increases the total energy required to store compressed air. Combining a compressed air energy storage system with a thermal energy storage system is another way to increase the cycle efficiency of this type of energy storage system. In this case, the heat generated during air compression is stored and returned to the compressed air during expansion.

The electrical energy storage systems model considers the maximum charging and discharging rates $P_{EES.max.}$ and $P_{EES.min.}$ as well as the maximum and minimum storage capacities $W_{EES.min.}$ and $W_{EES.min.}$. Injection and withdrawal from the electrical energy storage are described according to Equations (5-44) and (5-45). The current energy content W_{EES} is given in Equation (5-46).

$$\frac{dW_{EES,in}}{dt} = \eta_{in} \cdot P_{EES.in}(t) \quad with \quad P_{EES.in} < \; P_{EES.in,max.} \tag{5-44}$$

$$\frac{dW_{EES,out}}{dt} = \eta_{out} \cdot P_{EES.out}(t) \quad with \quad P_{EES.out} < \; P_{EES.out,max.} \tag{5-45}$$

$$W_{EES} = W_{EES,0} + \eta_{in} \cdot \int P_{EES.in}(t) \cdot dt - \eta_{out} \cdot \int P_{EES.out}(t) \cdot dt \tag{5-46}$$

$$with \quad W_{EES,min.} < W_{EES} < W_{EES,max.}$$

The initial storage capacity for each energy carrier is defined based on its desired peak balancing capability. The specific values can be obtained from a load duration curve that takes into account a one-year measurement period (ref. Figure 5-29). The derived dimensions of the storage systems are checked for their feasibility by comparing storage volume and footprint with the technical characteristics of storage systems available on the market.

Renewable energy system models

To improve solar yield and reduce shading losses, the panels of a photovoltaic system are usually installed in an inclined position with spacing between each row of panels. Quaschning and Hanitsch (1998, p. 3 f.) consider representative utilization rates of 50 % for a given roof size and for panels with angles of inclination between 10° and 30° degrees.

In general and with reference to Wagner (2015, p. 135), the yield $P_{PV}(t)$ of the photovoltaic system at each time step can be calculated according to Equation (5-47). In this equation P_{peak} represents the installed peak power of the photovoltaic system, $G(t)$ the temporally resolved global radiation data on an inclined surface data for a specific factory location, PR_0 is the performance ratio that relates the actual and the theoretical power outputs of the photovoltaic system. Additional losses i within the system setup (e.g., inverter loses, loses due to the coverage of the panel surface, etc.) can be represented through multiplication with $\prod_i \eta_i$. E_0 represents the irradiation data under standard test conditions (STC) according to DIN EN IEC 60904-3 (2020).

$$P_{PV}(t) = \frac{P_{peak} \cdot G(t) \cdot PR_o \cdot \prod_i \eta_i}{E_0} \tag{5-47}$$

Although north-south orientation generates higher maximum power outputs, the use of dual-tilt east-west orientated arrays with low tilt angles (generally between 5° - 10°) increases the packing density for a given roof size. This can increase maximum energy yield and decrease power peaks around midday. Taking into account the individual characteristics of a factory site, a more even distribution of energy generation from a photovoltaic system can be beneficial to improve self-consumption and energy flexibility.

Figure 5-30 shows the power and energy yield for different tilt-angels and panel orientations for an exemplary site in southern Germany. Although north-south oriented systems with an inclination of 30° achieve the highest power and energy yields for a given number of installed panels, the packing density can increase for east-west oriented setups, which in turn allows more energy to be generated throughout the year.

Today, photovoltaic systems are the most common source of renewable energy on a factory site. Nevertheless, other forms of energy supply with wind, water, biomass, or geothermal heat as an energy source can also be considered as part of the energy supply system model.

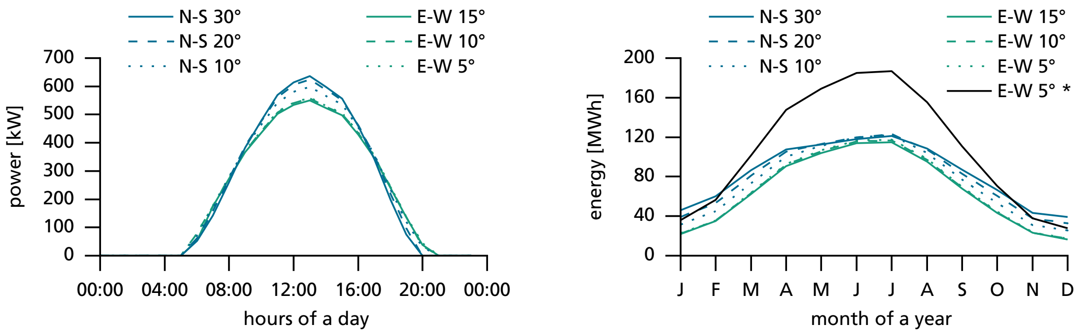


Figure 5-30 Power (exemplary day in July) and energy (per month) yield at different orientations and tilt angles. (* increased packing density by 30%) (own calculation based on hourly irradiation data for Munich taken from Meteonorm 7)

5.4.4 Model implementation, coupling, and validation

Implementation

The hierarchy of the factory simulation model is shown in Figure 5-31, along with the corresponding software tools used in the implementation. The process, machine, and respective process chain models are realized in the modeling and simulation environment of Tecnomatix Plant Simulation 14. Following a value stream approach, demand and supply for all input and output energy resources for each energy-consuming equipment (e.g., machines) are specified individually. Based on measurements in the field, the energy requirements of each machine are determined either for different operating states or individual batches using look-up tables. Tecnomatix Plant Simulation 14 is based on the principles of discrete event simulation presented in Subsection 2.3.2. This allows the software to map the characteristic workflows and operating procedures in a manufacturing environment. The output of the process chain model is a number of individual time series that quantifies the energy demand for different energy resources according to a user-defined temporal resolution.

In this work, the modeling and simulation of the factory building and the associated technical building systems are carried out using EQUA IDA ICE 4.8.

There are several different software tools for assessing the energy performance of buildings. A comparative review of several existing building energy performance simulations (BEPS) was conducted by Crawley et al. (2008, p. 662 ff.). IDA ICE was selected for its good validation, superior simulation performance, user-friendly graphical interface, and its wide application in industrial use cases (Kropf and Zweifel 2001, p. 1, Nageler et al. 2018, p. 53).

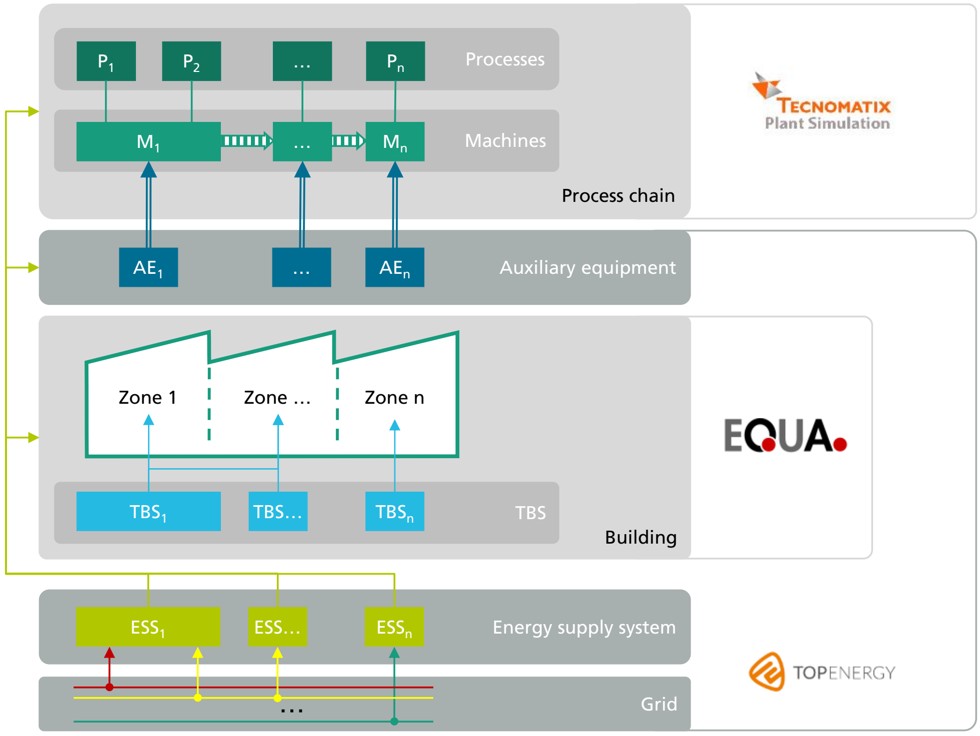


Figure 5-31 Outline of the factory simulation model

IDA ICE offers three user interfaces with the respective level of detail. The wizard level is designed to guide the user through all the modeling steps required to define a building in terms of its energy demand behavior. The standard level allows for the implementation of detailed multi-zone and advanced heating, cooling, and air-conditioning (HVAC) systems. The extended level allows the user to change the individual equations, variables, and parameters of the underlying mathematical models. (Sahlin et al. 2004, p. 950) As part of recent software improvements, programming interfaces to Python, Matlab, Excel, C++, and Java have been developed as well as an import function for Building Information Models (BIM) (EQUA 2020). IDA ICE implies an equation-based modeling approach using both the Neutral Model Format (NMF) and Modelica simulation languages (Crawley et al. 2008, p. 665). The software is composed of various submodels for flow networks, control principles, and dynamics, long- and short-wave radiation, convection, solid-state heat transfer, and thermal storage (Sahlin et al. 2004, p. 952). Detailed and simplified zone models are available for both in-depth analyses of individual models and for the runtime-optimized execution of simulation experiments with numerous variants. The flow network satisfies mass balance equations and takes into account supply and exhaust airflows from air-handling units. Airflows through openings and leaks are also implemented based on pressure-loss equations. (Hilliaho et al. 2015, p. 113)

Simulation in IDA ICE is performed by simultaneously solving a system of differential-algebraic equations (DAE) with a variable time step solver. These differential equations are generated from the equation-based submodels in the last paragraph. (Wetter 2005, p. 1086).

The output of simulations performed in IDA ICE represents the energy demand for the operation of the building and its technical building systems. In addition, non-energy benefits such as comfort criteria can also be quantified.

The energy supply system model, which also contains the auxiliary equipment, is built up in the modeling and simulation environment of TOP-Energy 2.10. TOP-Energy is a software developed to support the analysis and optimization of energy supply systems considering the prevailing conditions and restrictions in energy consulting projects. These include limited data availability and tight time schedules as well as budget restriction on project implementation (Augenstein et al. 2004, pp. 4, 7, Augenstein et al. 2005, p. 5). The software provides a graphical editor with which the network-like structure of an energy supply system, consisting of nodes (equipment installations) and edges (distribution systems), can be implemented. In addition, a library of various predefined models for energy conversion units is available to facilitate rapid build-up and parameterization of the energy supply system model. In TOP-Energy, the energy supply system is composed of individual component models using a system of algebraic equations. These equations describe the mass and energy flow within the network. They also propagate constant parameters through the system (Augenstein et al. 2005, p. 5). The Process Modeling Language (PML), which originated in Modelica, is used to specify stationary and/or quasi-stationary nonlinear models (Kirschbaum et al. 2008, p. 3). The mass flow and energy balances are solved for each time step using a combination of Mixed Integer Linear Programming (MILP) and evolutionary algorithm (Augenstein et al. 2005, p. 6). The continuous decision variables represent flow rates, equipment sizing, etc. The discrete decision variables model the (non-)existence and on/off status of the energy-consuming equipment within the energy supply system (Voll et al. 2015, p. 447). TOP-Energy operates within the boundary conditions of the energy market, environmental conditions (e.g., local climate and ambient weather conditions), and the demand profiles of energy end-users quantified in the process chain, building, and technical building systems model (Augenstein et al. 2005, p. 3). The output of the energy supply system simulation presents results on the total energy demand, cost, and CO_2 emissions of the factory operation considering individual energy supply system designs.

Coupling

The different simulation environments are coupled offline. The exchange of data is shown in Figure 5-32 and takes place in a total of five steps. First, the process chain model is simulated for one year. Second, the results from the simulation of the process chain simulation are transferred to the building and the associated technical building system model. Third, the energy demand of the building and the associated technical building system model is assessed, taking into account both heat emissions from the process chain model and the site-specific weather data from the Meteonorm 7 database. Fourth, the results from the process chain, building, and technical building systems models are transferred as input data to the energy supply system model. Last, the auxiliary equipment and energy supply system model is simulated to quantify the impact of the different system setups and configurations on the total energy demand and cost of factory operation.

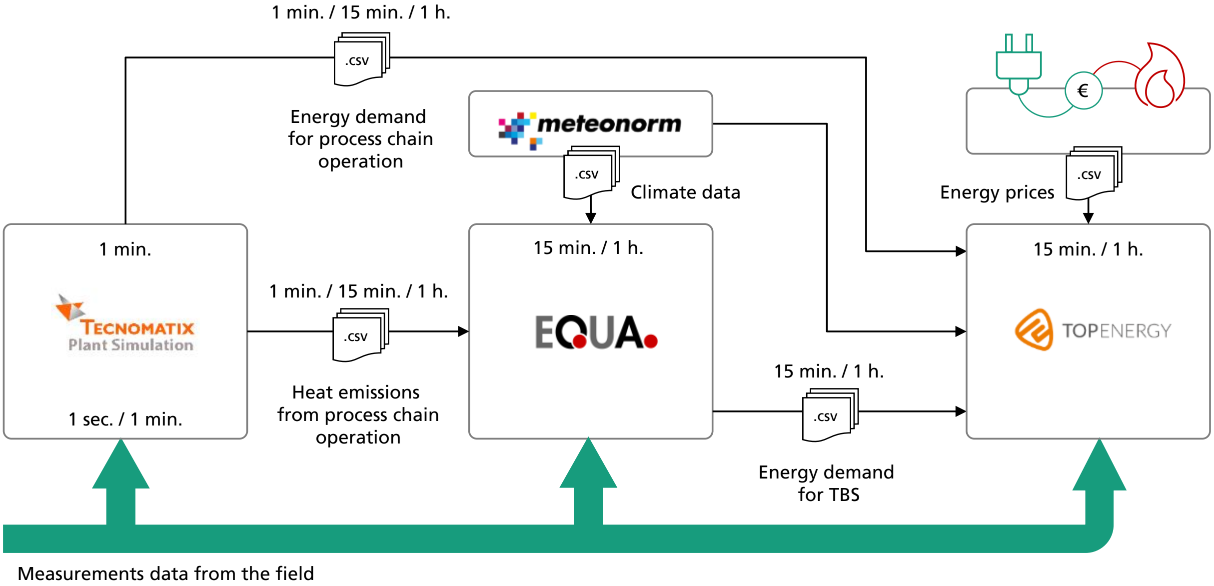


Figure 5-32 Outline of the coupling between the proprietary simulation environments

In general, a simulation period of one year is chosen in order to be able to take into account the seasonal fluctuations in energy demand. However, the analysis of user-defined and time-limited periods of a full year is possible. The temporal resolution used in the simulation is variable, with time steps usually ranging from one second to one hour. While resolutions of one second or one minute are common for process chain simulations, building and energy supply system simulations usually work with intervals of 15 minutes or one hour. This is to improve the numerical stability of the simulation and reduce the computing time (Bleicher et al. 2014, p. 443). When data with higher resolution is transferred and processed within a simulation environment that uses lower resolution, the simulation data is compressed using a moving average.

Measurement data from the field are used to characterize the resource requirements of the underlying manufacturing process as well as to parametrize the various submodels.

Validation

With reference to 2.3.2 and the taxonomy introduced by Balci (1998b, pp. 354-379), different techniques are applied to validate the behavior accuracy of the individual submodels of the factory simulation model. Dynamic testing techniques and more specifically, special input testing based on boundary values or extreme input values are used to test the machine and process chain model. As presented in Subsection 5.4.2, statistical techniques using Mean Bias Error (MBE) and Coefficient of Root Mean Square

Error (CVRMSE) are used to validate the building and technical building system model by relating model outputs and measurement values. Wherever the availability of measurement data allows, visualization techniques are used to compare graphs of measurement data with the graphs of respective simulation results. Assertion checking is used to compare whether certain common-sense assumptions of the modeler hold true and can be represented in the simulation results after model execution.

Table 5-10 presents an overview of the applied techniques with reference to the individual submodels. Apart from the examples provided in Table 5-10, individual use cases require individual validation strategies depending on the availability of measurement data and accessible measurement points.

Table 5-10 Verification and validation techniques used for the individual submodels

Submodel	**Validation technique**	**Testing (examples)**
Machine model – case 1	visualization	the graph of the simulation results is compared to graphs of the measured data
Machine model – case 2	statistical technique	CVRMSE between measured and simulated machine surface temperature
Process chain model	assertion checking	e.g., processing 10 orders results in 10 times the energy demand for the process chain operation
Auxiliary equipment model – compressed air system	special input testing – extrem input testing	for $p_1 = p_2 \Rightarrow V_0$ is zero
Auxiliary equipment model – process cooling system	special input testing – extrem input testing	for EER=1 t $\Rightarrow \dot{Q}_{PCS} = P_{comp.,el.}$
Factory building and technical building systems model	statistical technique	CVRMSE between measured and simulated indoor temperature
Models of space heating and cooling system	statistical technique	regression analysis between power demand of cooling/heating and outside temperature for both measured and simulated values
Energy storage system models	special input testing – boundary values	No energy storage is possible if energy storage capacity is set to zero
Renewable energy system model	special input testing – boundary values	energy from a photovoltaic system is zero if the collector surface is set to zero

5.5 Summary

Chapter 5 documents the development of a new methodology that aims to extend the scope of existing factory simulation models while also increasing the comprehensiveness and generalizability of the associated assessment procedures.

Section 5.1 outlines the methodology, which consists of three main elements, namely the extended energy performance metrics, the assessment procedure, and the factory simulation model. Section 5.2 addresses the extension of existing energy-related performance metrics that summarize energy demand, energy costs, CO_2 emissions with non-energy benefits. The non-energy benefits are divided into six categories: improved occupational safety, improved product quality, reduced production waste, improved capacity utilization, improved security of supply, and reduced maintenance costs.

Section 5.3 describes an extension of the peripheral factory model that merges the manufacturing and architectural perspective on factory systems. The new model includes a total of twelve peripheries, from processes (P) (inner periphery) to grid (G) (outer periphery). The aim is to improve transparency and facilitate the identification and categorization of improvement measures in complex manufacturing systems. It then specifies the different categories of improvement measures, including energy efficiency, energy flexibility, and measures to improve the use of renewable energy sources. Each category is formally introduced and illustrated by practical examples. The improvement measures are further classified according to their focus (planning, controlling, retrofitting/installing) and with reference to the different peripheries of a factory system. The subsection concludes with a graphical representation called the "path of energy use". The general assessment procedure is indicated in the flow chart in Figure 5-11. It involves a step-by-step process for selecting and jointly evaluating improvement measures within a factory simulation model using a combination of expert knowledge together with a Design of Simulation Experiments (DoSE) approach. The DoSE included in the procedure model is based on an orthogonal array-based matrix design. A selection of visualization techniques to support the decision-making processes along the assessment procedure concludes Section 5.3.

Section 5.4 contains a detailed description of the individual submodels and their relationships within the overall factory simulation model. Subsection 5.4.1 presents the machine, process chain, and auxiliary equipment models. This includes submodels for the consideration of heat emissions from machine operation and specific auxiliary equipment models for compressed air and process cooling systems. Subsection 5.4.2 specifies the factory building model and its technical building systems, before Subsection 5.4.3 outlines the energy supply system models (including those for space heating and cooling systems, energy storage, and renewable energy systems). Subsection 5.4.4 describes the implementation of the factory simulation model by coupling the software environments Tecnomatix Plant Simulation 14, EQUA IDA ICE 4.8, and TOP-Energy 2.10 and concludes by outlining the different techniques used to verify and validate individual submodels of the factory simulation model.

6 Application of the Methodology

The methodology proposed in Chapter 5 was applied to a case study conducted in the aerospace composite industry. Within the case study, all steps of the methodology were carried out to test both its validity and transferability.

6.1 Analysis of the Initial Situation and Definition of Objectives

In the manufacture of aerospace composites, semi-finished products, namely pre-impregnated woven fabrics (prepregs) made from carbon fiber reinforced plastics (CFRP) and activated resin (epoxy and hardener), are processed using a combination of semi-automated and manual processes. Due to the specific material properties (high strength, low weight), the manufactured parts are used within various aerospace applications to improve the fuel efficiency or the productivity delivered per unit of fuel consumption (Hileman et al. 2008, p. 2 f.). The manufactured products are characterized by high-quality requirements, while the manufacturing process chain has only limited possibilities for automation. Furthermore, the individual manufacturing processes require high amounts of energy, which are either fed directly into the process or are taken from auxiliary equipment (e.g., compressed air systems, vacuum systems, and process cooling).

The overview presented in Figure 6-1 summarizes the value stream within aerospace composite manufacturing. First, prepreg plies are cut and trimmed with an automatic knife cutter according to the geometric requirements. Alternatively, the individual layers of a product can be preassembled automatically using a tape-laying machine. Tape-laying machines can automatically preassemble different layers of pre-impregnated tapes which come at standardized widths. This process enables layers with local reinforcements or individual fiber orientations according to the mechanical requirements of the designed composite component.

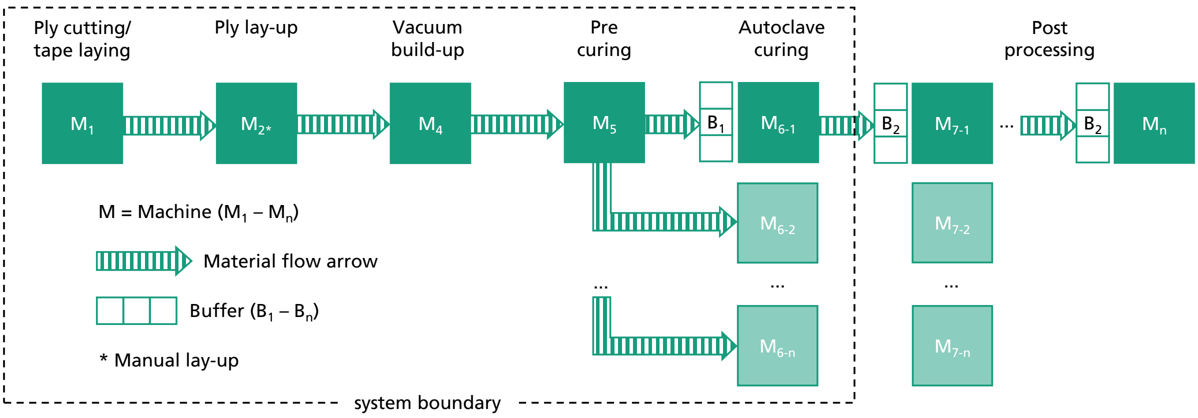


Figure 6-1 Value stream in the manufacture of composite parts in the aerospace industry (extract)

After the plies are cut, they are placed into molds that define the geometric properties of the composite part. After the plies are placed, the structure is wrapped in a vacuum bag, and a vacuum is applied to stabilize the structure and prevent air pockets. The assembly is then transferred to a workstation that uses radiant heaters to activate the reaction of the activated resin. This step is performed to pre-cure the composite part, identify possible manufacturing defects, and add further stability to the structure. Pre-curing is followed by curing in an autoclave. The autoclaves are loaded with several parts that require identical curing conditions. During autoclave operation, temperature, pressure, heating and cooling ramps, as well as holding times, can be controlled.

After curing in the autoclave, the composite part is demolded and the mold cleaned. Curing is followed by finishing, including milling and sanding operations, which are performed on CNC-based (Computerized Numerical Control) machine tools. These processes are used to remove protrusions and excess resin and to functionalize the geometric properties of the composite part.

Curing and the associated manufacturing process steps, as well as the conditioning of the factory building, dominate the energy demand in the production of composite parts. Due to their low energy demand and the fact that the finishing operations are located in another factory building, their energy demand is not considered in this case study. Figure 6-2 characterizes the factory layout, including the building geometry, the positioning of the auxiliary equipment, and its connection to the autoclave process and the technical building systems.

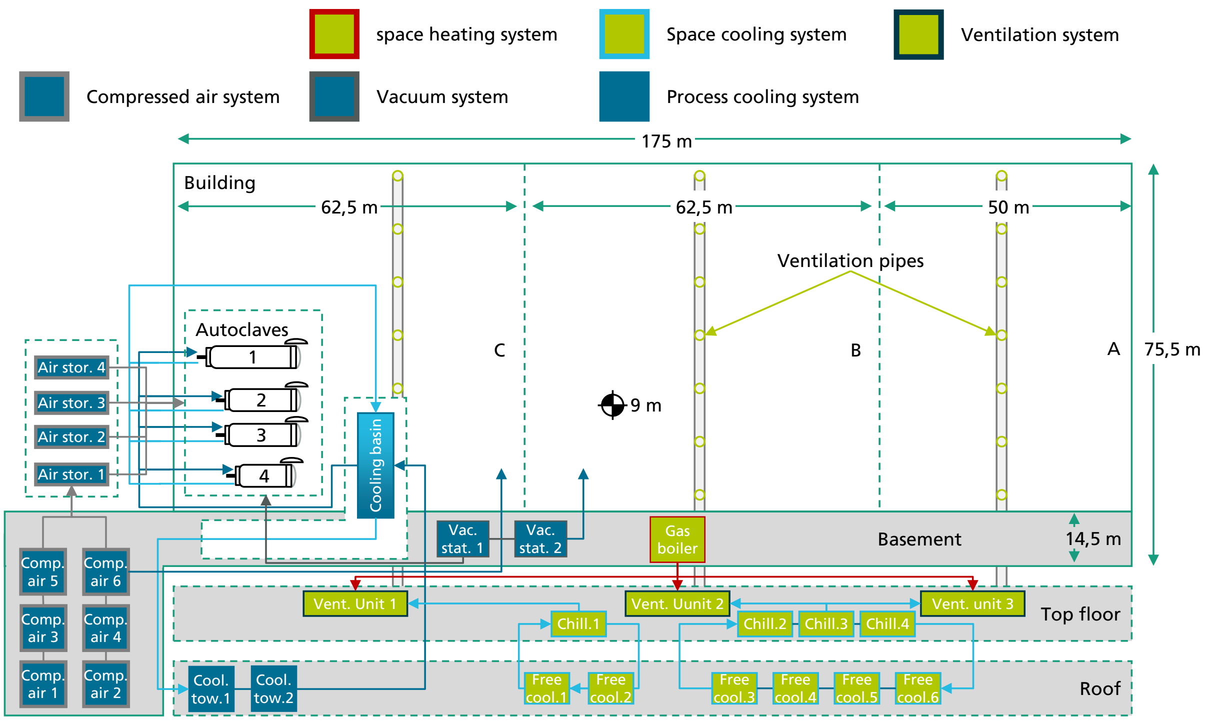


Figure 6-2 Factory layout of a manufacturer of composite aerospace parts including auxilary equipment and technical building systems

Several processes in the manufacture of composite parts require the use of air in a conditioned form. This includes vacuum, compressed air, and nitrogen.

A vacuum is used during the cutting of plies and laying of the tapes, during the preparation of the molds, and during the various curing processes. In the present case study, vacuum is generated both centrally (feeding into a vacuum grid) and decentrally (at the process or as part of the manufacturing equipment) by using vacuum pumps.

Compressed air is supplied to the factory in general and the autoclave process in particular. Pressure levels vary between 8 and 16 bars, and the demand is met by a number of compressors with different flow capacities and installed power. In many autoclave applications, the vessel is pressurized with nitrogen instead of air. Therefore, the compressed air system setup is further complemented with air compressors specified for nitrogen conditioning. The absence of air and the use of inert media reduce the risk of fire when processing composite parts in high-pressure and high-temperature environments. The corresponding equipment setup includes primary compressors, a nitrogen plant, booster compressors, and storage tanks. The booster compressor raises the pressure level of nitrogen to 17-22 bar. The high pressure differences between tank and autoclave allow high pressurization rates of up to 2 bar/min. Nitrogen storage tanks are usually sized to deliver 2.5 times the storage volume of the autoclave at operating pressure. (Upadhya et al. 2011, p. 5).

The operation of an autoclave also requires the use of auxiliary equipment for process cooling. Autoclaves must be connected to a process cooling system in order to cool the autoclave van and to realize cycle time-optimized cooling ramps at the end of a curing cycle.

Material properties of the material to be processed, occupational safety regulations and product quality requirements demand that the climatic conditions in the factory (temperature and humidity) are kept within narrow limits. In the present case, the technical building systems consist of heating, ventilation, and air-conditioning (HVAC) units.

The objective of conducting an energy assessment at an existing site of a composite parts manufacturer was twofold. The first objective was to identify various energy-related improvement measures in the different peripheries of the factory system and to quantify their combined potential for reducing energy demand, cost, and emissions. Non-energy benefits were also considered in the quantification.

Based on the derived energy-saving potential, the second objective was to design an adequate energy supply system for the production site, taking into account different design principles, technology options, and the integration of on-site renewable energies.

The simulation-based approach was chosen to complement measurement data and enable an efficient and safe evaluation of combined energy-related improvement measures. The simulation-based evaluation strategy considers a multi-criteria planning environment and recognizes interdependencies and potential trade-offs between individual improvement measures.

The evaluation results should be used to derive the best combination of energy-related improvement measures and an energy system design that reflects customer-specific planning preferences, including non-energy benefits. Focusing on optimized use of energy resources, the application of the developed methodology was proposed to support decision-making during the optimization of the manufacturing system in order to mitigate investment risks, avoid unnecessary operating costs and associated CO_2 emissions.

6.2 Selection of Improvement Measures

The selection of improvement measures was based on the findings from a review of existing documentation, on-site visits, an inspection of the technical facilities, and subsequent workshops with the company's responsible persons and experts.

In order to support transparency and help the project team in the selection process, a graphical representation of the main energy flows inside the factory building was created according to the terminology presented in Subsection 5.3.1 – Figure 5-10. In this representation, the energy-consuming equipment, including its connections, is assigned to different peripheries according to the classification presented in Subsection 5.3.1 – Table 5-1. Improvement measures are also assigned to the respective equipment and periphery. The individual measures are presented and explained in detail in Section 6.4.

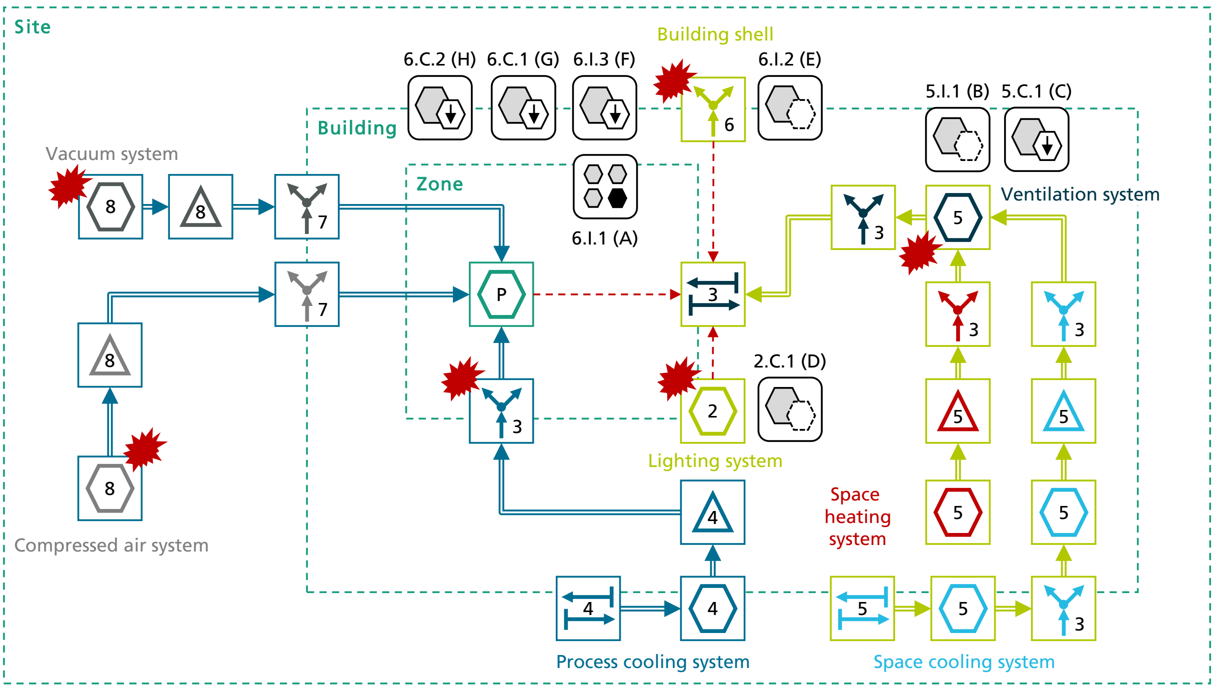


Figure 6-3 Graphical representation of energy use within an aerospace composite parts manufacturing factory, including selected improvement measures

6.3 Application of the Factory Simulation Model

In this section, the application of the factory simulation model is demonstrated. The model used to characterize the behavior of the case study factory in terms of energy demand was based on, and verified against, data from extensive measurement campaigns conducted at the aerospace composite parts manufacturer's site. In accordance with the principles of model-building presented in Section 5.4, the factory simulation model was built starting with the machine model of the autoclave process. Subsequently, the machine model was transferred to the process chain model, which represents the characteristics of production planning and scheduling in the factory under consideration. As a preliminary result, the process-specific energy demand could be determined for a period of one year, taking into account various input and output energy resources (electrical energy, compressed air, process cooling, heat emissions, etc.). Next, auxiliary equipment models were defined for the compressed air system and the process cooling system to represent the behavior of installed equipment. Subsequently, the factory building and the technical building systems were modeled and connected to the process chain model. It was possible to take into account the effects of the building envelope, the climatic conditions on the factory site, and the effects of the process chain-related heat emissions on the factory environment. By linking the different models, it was possible to derive a characteristic energy demand for the operation of the process chain, the auxiliary equipment, and the factory building. The energy demand was given for the individual energy resources, namely electricity, compressed air, process cooling, space heating, and space cooling. Last, the energy supply system model was set up to evaluate different energy supply system designs.

Machine model

The energy characteristics of the autoclave process were derived from batch protocols (time duration of the curing program, operating temperature, and operating pressure) and power measurements (electrical energy demand) performed in the field (ref. Figure 6-4). In order to take into account the varying operating conditions and different batch programs within the autoclave model, a measurement period of two weeks was chosen.

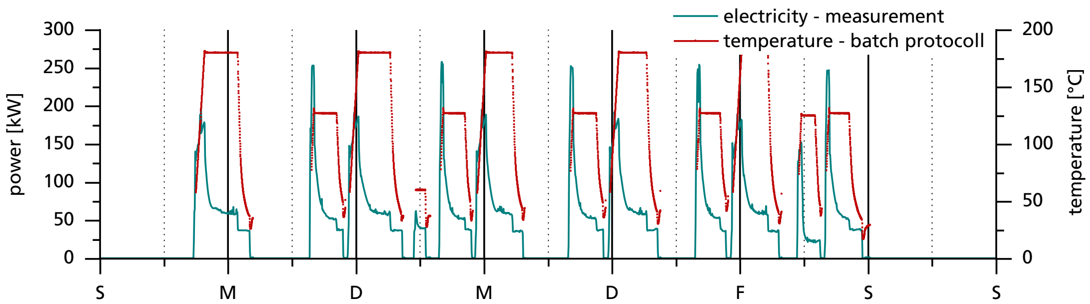


Figure 6-4 Measurement of electrical power consumption and operating temperature for Autoclave 2 (one week extract)

Subsequently, individual autoclave models and production programs were implemented for Autoclaves 1 to 4. The heat emissions of the autoclaves were modeled individually based on the technical specifications of Autoclaves 1 to 4 and according to the thermodynamic substitute model presented in Subsection 5.4.1, Equation (5-12), and following. Due to lack of accessibility, it was not possible to measure the compressed air flow rate and process cooling requirements individually for the different autoclaves. Therefore, the compressed air flow rate and the process cooling requirement were also derived from the thermodynamic substitute model and specified for the different autoclaves and batch protocols.

Figure 6-5 shows the combined results of measurement and simulation using the example of Autoclave 2. The top portion of Figure 6-5 (A) characterizes an individual curing cycle that begins at 6:00 pm and lasts until 7:00 am. The temperature is raised to 135 °C within one hour. After holding this temperature for about five hours, the temperature is further increased to 180 °C and held for another four and a half hours.

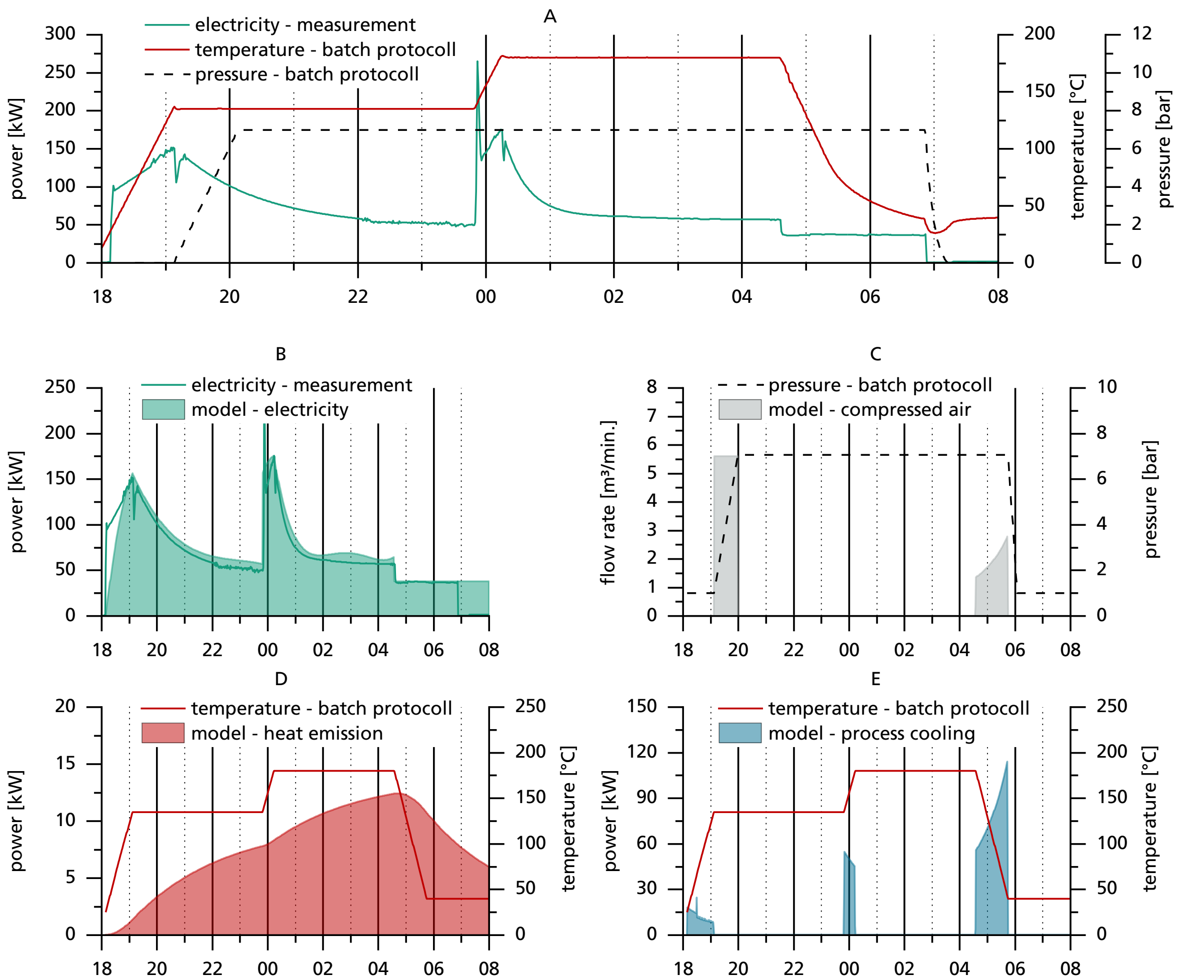


Figure 6-5 Autoclave 2 measurement and batch protocol data – electrical power demand, temperature, and pressure (A); Model representation of Autoclave 2 – electrical power demand (B), compressed air (C), heat emission (D), and process cooling (E)

The dashed curve shows the pressure curve inside the autoclave. In this particular batch protocol, the pressure is increased to seven bars after the autoclave has reached its first temperature plateau at 135 °C. The pressure is then kept constant for the entire duration of the curing cycle. The temperature is lowered before the pressure release from the autoclave is initiated. The process cooling system connected to the autoclave actively cools the system and supports the ramp-down of the system. Once the ambient temperature has been reached, the autoclave can be opened and the part removed from the autoclave. The results for the different input and output energy resources are shown in the lower part of Figure 6-5 (B-E). With the available pressure and temperature measurements, it was possible to model the airflow (C) and process cooling demand (E) based on the ideal gas law. A snapshot of the autoclaves 1-4 is shown in Figure 6-6.

Figure 6-6 Autoclaves 1-4 in the factory environment

Process chain model

In order to simulate the energy demand for a year-round factory operation, the machine models of Autoclaves 1-4 were implemented within the process chain model using look-up tables. The look-up tables contain the autoclave-specific and batch-specific information on heat dissipation to the factory environment as well as the electricity, compressed air, and process cooling requirements. The process chain model represents the composite manufacturing process, focusing on the autoclave process. The cutting and laying of the plies, as well as the procurement, were not considered in this case study. The reduction of the modeling effort to the autoclave was justified because curing in the autoclave has the greatest influence on the total process-specific energy demand. The process chain model was created in Tecnomatix Plant Simulation 14 and takes into account parameters such as the factory's operating hours (number of shifts, working days, and national holidays) as well as variations in the start times for processing each batch in the autoclaves (ref. Figure 6-7).

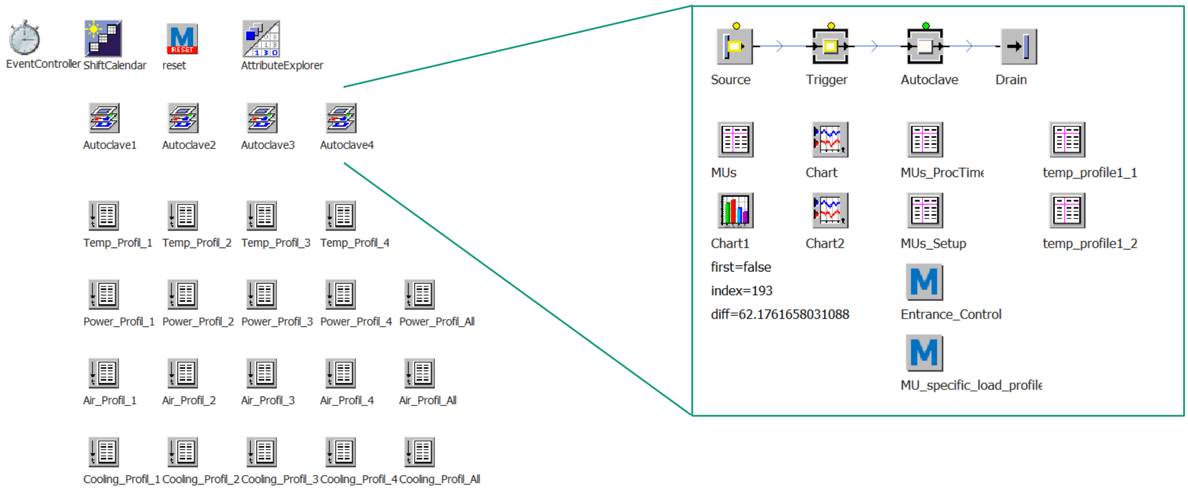


Figure 6-7 Process chain model in Tecnomatix Plant Simulation 14

The results of the process chain model are shown in Figure 6-8. The extract shows which different batch protocols were operated on Autoclaves 1 to 4. In the course of a day, two individual batches were usually operated on one autoclave. The left side of Figure 6-8 specifies the individual batch protocols by characteristic temperature profiles. The right-hand side of Figure 6-8 outlines the operation of Autoclaves 1 to 4 over a period of one week, also taking into account statistical variations in the start time of individual batches. With regard to the measurement period, no autoclaves were operated on Sundays. The right-hand side of Figure 6-8 also shows the individual heat emissions of Autoclaves 1 to 4 with maximum values reaching approximately 25 kW.

Figure 6-9 shows the energy demand for the operation of the process chain considering a representative period of one week. The four different diagrams in the figure indicate the demand characteristics of the different input and output energy resources, namely electrical energy (input), compressed air (input), heat emissions (output), and process cooling (input). The peak demand shows 530 kW for electrical power, 40 m³/min. for compressed air flow rate, 70 kW for heat dissipation, and 1460 kW for process cooling.

Compressed air and process cooling show the greatest fluctuations in demand. On the contrary, the heat emissions from the autoclaves are relatively uniform due to the effects of thermal inertia.

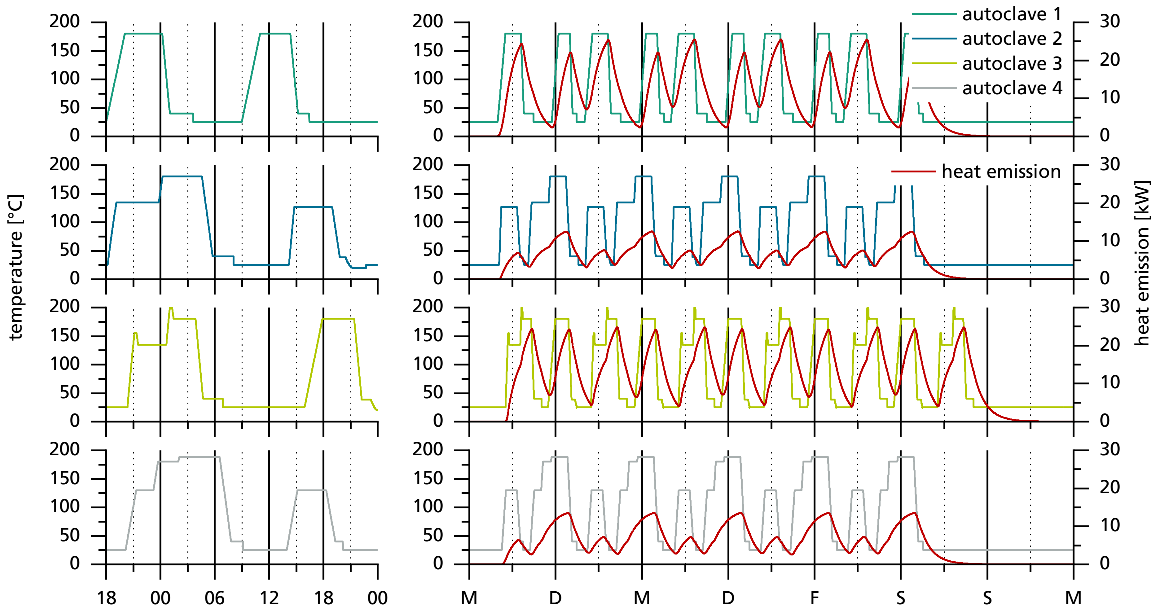


Figure 6-8 (Left) Temperature batch protocols for Autoclaves 1-4 for (one-day extract); (right) Simulation results – individual temperature profiles and heat emissions from Autoclaves 1 to 4 (one-week extract)

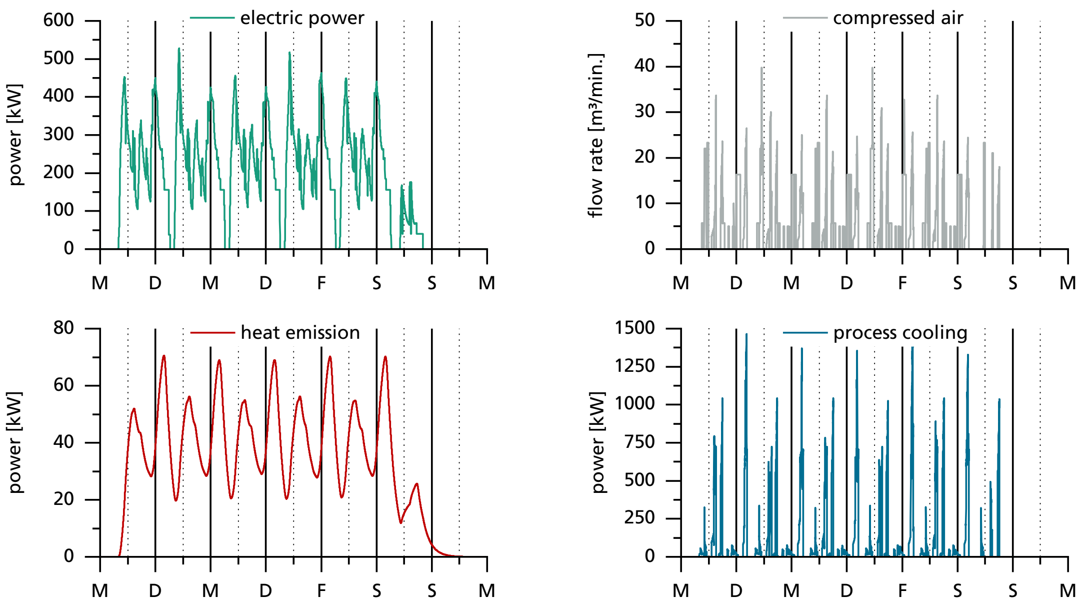


Figure 6-9 Example simulation results of the process chain (one-week extract) – power demand profile for electrical power, compressed air, heat dissipation to the factory environment (heat emissions from all autoclaves, and process cooling

Auxiliary equipment model

The modeling of auxiliary equipment in this case study included the compressed air system and the process cooling system. The demand for compressed air, which was derived from the machine and process chain models and quantified in terms of flow rate, was used to determine the electrical power required for the operation of the compressors according to the model presented in Subsection 5.4.1. The model is parameterized with the information on the electronic nameplate and the information provided by the manufacturer of the compressed air equipment. No power measurements could be made on the compressed air system on-site.

The cooling demand derived from the process chain model was verified with the measurement concept for fluid-bound energy carriers presented in Subsection 2.2.2. To measure the combined process cooling demand for Autoclaves 1 to 4, an ultrasonic flowmeter was installed on the central cooling circuit together with temperature sensors on the supply and return pipes. The measurement covered two weeks of factory operation.

While they have similar demand characteristics, higher maximum and mean values were found. The higher average values can be explained by the cooling requirement for the autoclave fans, which was not taken into account in the thermodynamic substitute model of the autoclaves. The occurrence of coincident cooling phases explained higher maximum values when running the different batch programs for Autoclaves 1 to 4.

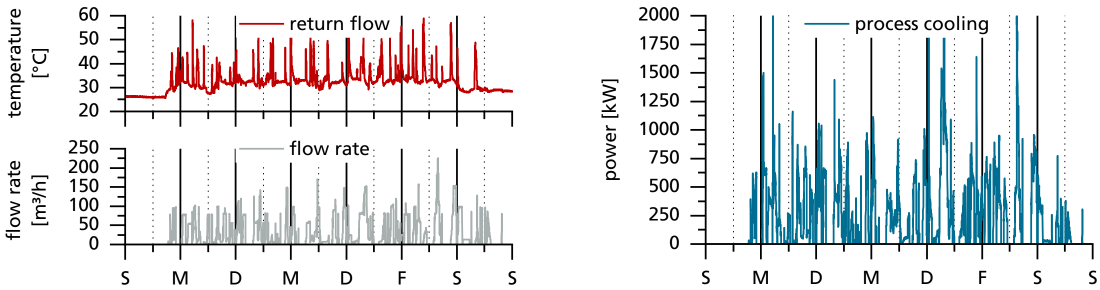


Figure 6-10 Measurement of return temperature, volume flow rate (top), and total cooling demand (bottom) for Autoclaves 1-4 (one-week extract)

The process cooling demand derived from the process chain model and checked for plausibility by measurements were then used to quantify the electrical energy demand of the equipment installations for the process cooling equipment used on-site. The process cooling system setup was implemented according to the model presented in Subsection 5.4.1 and parameterized using the available technical documentation.

Both the compressor and process cooling models were implemented in TOP-Energy 2.10 according to the outline shown in Subsection 5.4.4 Figure 5-31.

Building and technical building systems model

The energy demand for the operation of the factory building with its technical building systems was quantified using the modeling concept presented in Subsection 5.4.2. The software EQUA IDA ICE 4.8 was used to characterize the physical building infrastructure and equipment installations, including lighting systems and air-handling units. The orientation and wall and roof structure of the building envelope were specified in the building model. Openings, including windows, doors, and skylights were considered and implemented according to their individual size and orientation. The 3D model of the factory realized in EQUA IDA ICE 4.8 is shown in Figure 6-11. In addition, the division of the building into different floors and zones (floor plan) was used in the model. Furthermore, the number of employees (occupancy) and electrical appliances (e.g., computers, monitors, printers) were quantified and assigned to the various building zones. Finally, the heat emissions quantified in the process chain model were coupled with the building model and considered as heat gains within the respective building zone.

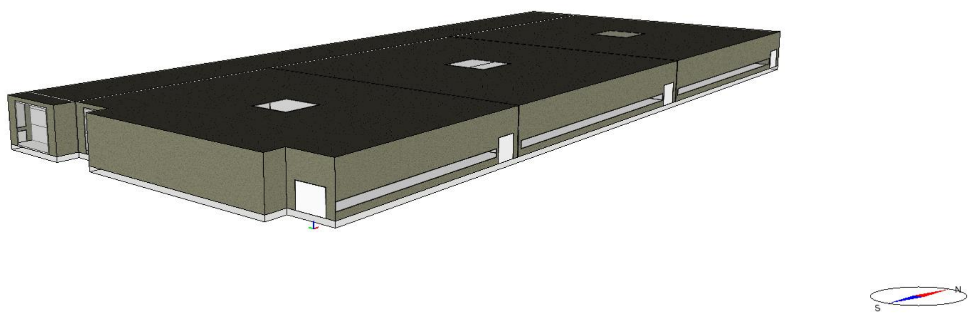


Figure 6-11 Factory building model in EQUA IDA ICE 4.8

In order to specify the characteristics of the technical building, air exchange rates and setpoints for temperature and humidity were defined for each zone of the factory. Representative of the air-handling units, two different heating, ventilation, and air-conditioning systems were implemented, assigned to both the administrative and manufacturing areas of the factory.

The ambient conditions at the factory locations were determined using statistical weather data from the Meteonorm 7 database. The datasets include profiles for representative one-year periods, including temperatures, global radiation, and wind speed.

The coupling between the building model, process chain model, and weather data was realized according to the procedure presented in Subsection 5.4.4 Figure 5-32.

Exemplary simulation results of the building and technical building systems models are shown in Figure 6-12. The building electricity demand is composed of the demand for lighting and ventilation systems but also takes into account other electric appliances. The peak electricity demand for the building operation was estimated at 85 kW, with a significant contribution due to the operation of the lighting system. The air-handling units provide for the space heating and cooling requirements of the different building zones and maintain the defined temperature and humidity limits. The peak demand was calculated at 235 kW and 865 kW, respectively.

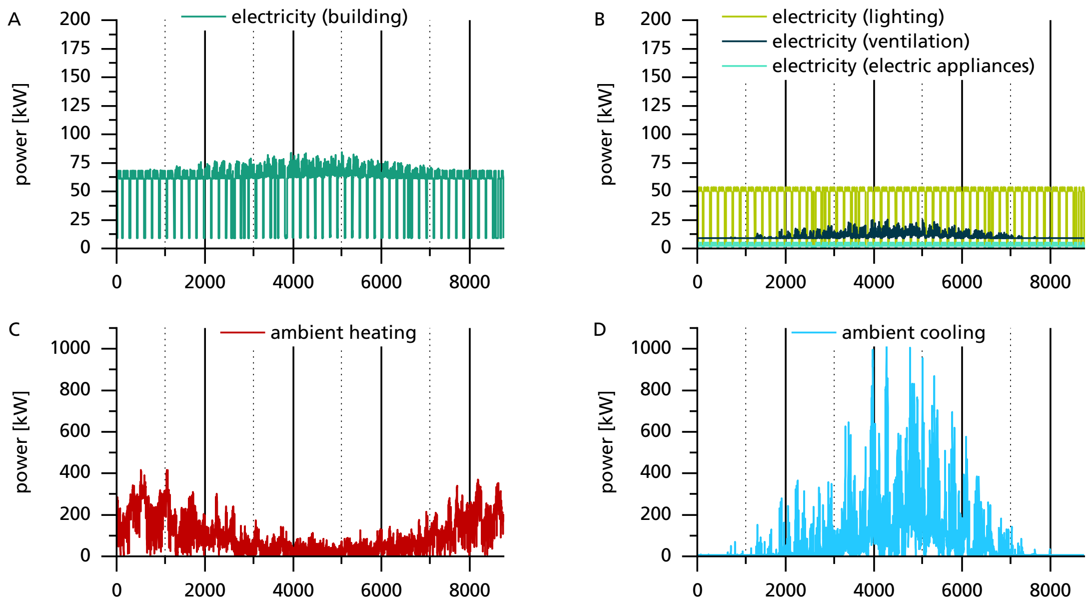


Figure 6-12 Exemplary simulation results of building and technical building systems models for a period of one year. The electricity demand of building operation (A), consisting of the electrical energy demand for lighting, ventilation, and other appliances (B), space heating demand (C), and space cooling demand (D)

The building and technical building system model was verified according to the Mean Bias Error (MBE) and Coefficient of Root Mean Square Error (CVRMSE) acceptance criteria presented in Subsection 5.4.2 – Table 5-7. The excerpt shown in Figure 6-13 compares the simulation values for temperature and relative humidity from EQUA IDA ICE 4.8 with measurement data recorded in the production areas A to C. The MBE for relative humidity and temperature were calculated to 9% and 5%, respectively. The CVRMSE was calculated with 14% and 8%, respectively. Both performance criteria are within the suggested ranges, indicating adequate model quality.

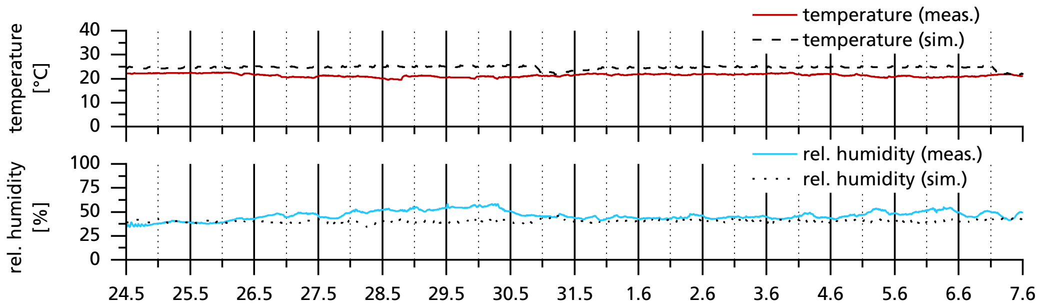


Figure 6-13 Comparison between simulation and measurement for temperature and relative humidity

Figure 6-14 shows the results from the process chain, building, and technical building systems models (A, B, C, D). It also includes cooling and compressed air demand (E-F).

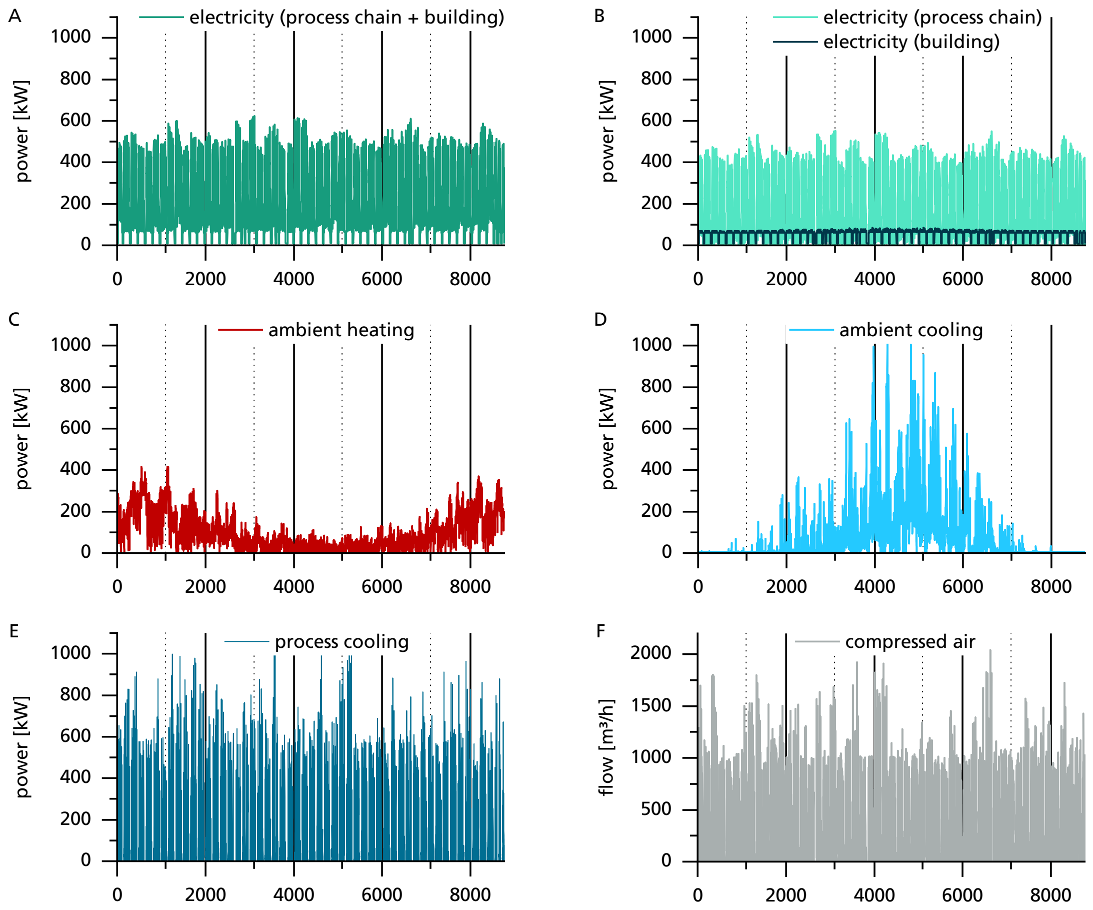


Figure 6-14 Example simulation results consisting of the electricity demand for the operation of the process chain and building (A, B), the demand for space heating and cooling which has to be provided by the technical building systems (C, D), and the demand for process cooling and compressed air, which has to be provided by the auxiliary equipment (E, F) (one-year period)

In the case study presented, the modeling procedure was able to quantify the energy demand of a factory operation in a bottom-up approach. It starts with quantifying the energy demand of the manufacturing process and then adds the energy demand for operating the factory building and its technical building systems. However, at this stage, the model does not capture the characteristics of the energy supply system setup at the manufacturer's site. For this reason, the results of the process chain, building, and technical building systems models are further transferred into an energy supply system model.

Energy supply system model

The energy supply system model was implemented according to the modeling procedure presented in Subsection 5.4.3 and used to represent the individual and site-specific characteristics of all equipment installations used for providing the various energy requirements. In this case study, the implementation of the energy supply system model included auxiliary equipment models for compressed air and process cooling systems, as well as technical building systems models for space heating and cooling. Furthermore, combined heat and power installations and equipment to generate energy from renewable sources were considered. This included a cogeneration unit, a photovoltaic system, and a geothermal heating system. In addition, various energy storage technologies for electricity, heat, cold and compressed air were used. The entire energy supply system model was built within the TOP-Energy 2.10 simulation environment. Figure 6-15 shows a snapshot of an example model configuration.

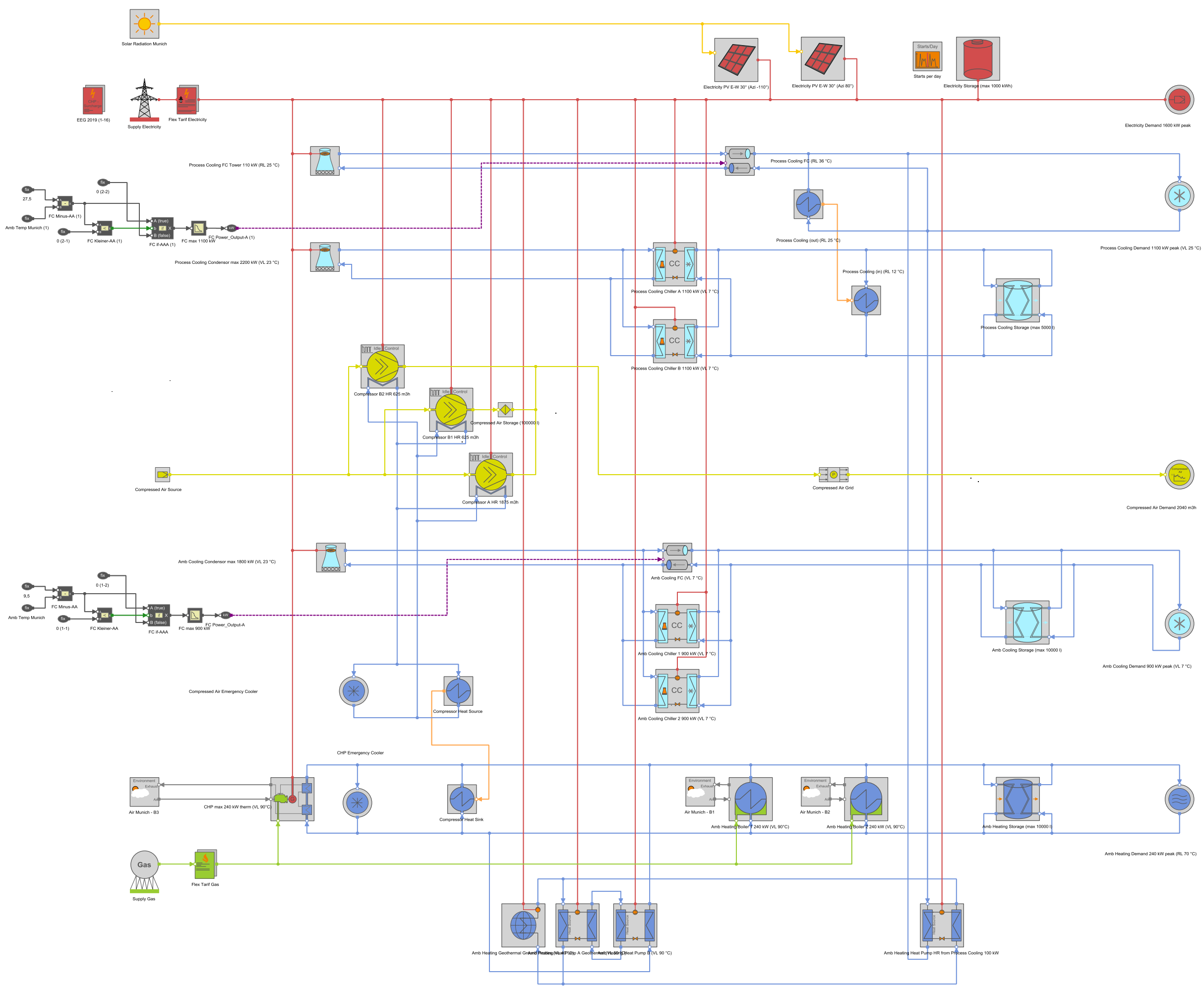


Figure 6-15 Energy supply system model in TOP-Energy 2.10

The weather data used in the energy supply system model was identical to the weather data used in the building and technical building systems models.

The energy tariffs for electricity and gas considered in the model follow the German pricing scheme for industry customers. In addition, a flexible energy tariff was implemented to enable an evaluation of energy flexibility measures according to Subsection 5.3.1. The flexible energy tariff used in this case study combined the relative energy price fluctuations in 2019 (ref. Figure 6-16 – B) with the average market price for electricity and gas in 2019 (ref. Figure 6-16 – A), resulting in a representative flexible energy tariff as shown in Figure 6-16 – C.

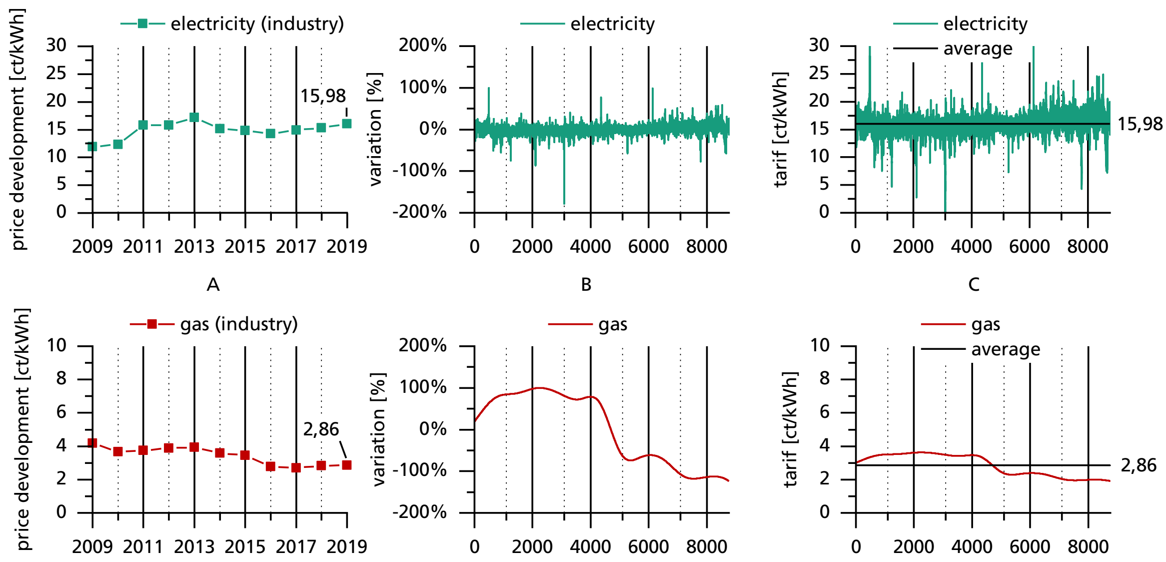


Figure 6-16 Top row: Electricity; bottom row: Gas; A: Development of energy prices in the industry (Bundesnetzagentur 2019, pp. 287 f., 460 f.), B: Representative energy price fluctuations around the average price, C: Representative flexible energy tariff for one year

Further, the energy price specifications implemented in the case study included the tariff schemes according to the Renewable Energy Act (EEG) for the on-site operation of CHP plants and photovoltaic systems. The Renewable Energy Sources Act (EEG) surcharge subsidizes the feed-in of electricity from CHP plants with five ct/kWh (for CHP plants with a size of max. 250 kW_{el}) (BAFA 2019). Photovoltaic systems also benefit from subsidized feed-in tariffs of approximately eight ct/kWh (Bundesnetzagentur 2020a). Furthermore, self-consumption of electricity from CHP plants and photovoltaic systems is charged with 40% of the current EEG levy of 6.7560 ct/kWh (Bundesnetzagentur 2020b). Additional remuneration for energy-intensive companies is not taken into account in the model.

Individual subcomponents of the energy supply system model were verified if the accessibility allowed the temporary installation of a metering system. A major limiting factor was the heterogeneity of the technical installations found on-site. The energy supply system analyzed in this case study is a complex composition of old and new equipment that has grown over many years of factory operation. Nevertheless, measurements were carried out to verify the parameter setup of the room cooling and ventilation system. Figure 6-17 shows the composite results obtained from six energy metering systems during a two-week period in May. The figure correlates outside temperature with the power demand of the air-handling units and the chillers of the space cooling systems. Depending on the outside temperature, the power demand varies between a minimum of 150 kW and a maximum of 550 kW and shows a linear correlation. The results of the simulation show good agreement with the measured data.

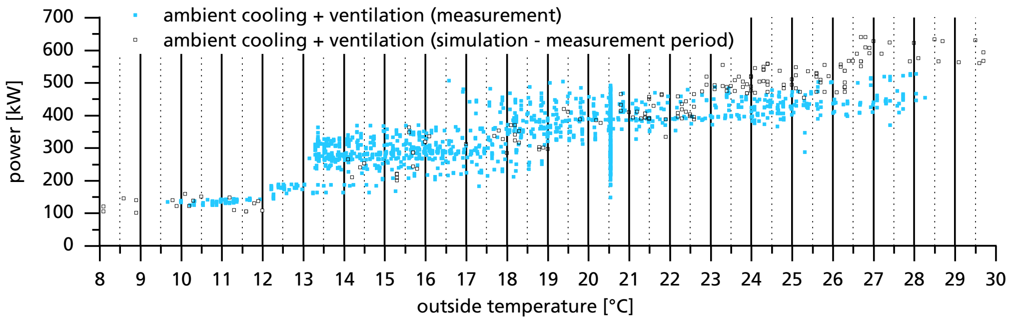


Figure 6-17 Correlation between outside temperature and power demand for air-handling units and chillers; Comparison between measurements and simulation results (measurements 10-min. intervals; simulation one-hour intervals)

As a result of applying the modeling procedure from Section 5.4 to the case study, it was possible to represent the current energy demand characteristics of the factory in a simulation model.

Subsequently, the simulation model was used to evaluate different improvement measures by generating variants of the model. With the aim of reducing the modeling effort and the number of simulation runs required, an approach based on the design of simulation experiments was adopted in accordance with the method presented in Subsection 5.3.2.

6.4 Planning and Design of Simulation Experiments

The energy efficiency measures identified at the building and technical building systems levels are summarized in Table 6-1. The measures focused on equipment installations, control strategies as well as technical features and design characteristics of the building. Within the matrix experiment, the measures are referred to as design parameters or factors. The measures implemented only take into account the manufacturing area and not the areas where the factory's administration is located.

Factor A was chosen to assess the impact of separating Building Zone C from Zones B and A using drywall construction. This measure was intended to stabilize the room climatic conditions (temperature and humidity) in the manufacturing area and to limit the heat emissions of the autoclaves to Building Zone C. It was also expected that the measure would reduce the total energy demand for ventilation and space cooling. Factor B examined different technical setups for the air-handling unit (AHU) used to air-condition the room climate of the manufacturing area. To control room temperature and humidity, AHU Setup 1 uses heating and cooling coils and a steam humidifier. Alternatively, humidification in AHU Setup 2 is implemented by an adiabatic evaporative humidifier, which also uses an improved control strategy. AHU Setup 3 uses direct evaporation cooling on the supply air side, limited by relative humidity and discharge air temperature. Furthermore, indirect evaporation cooling on the return side of AHU 3 is limited by the ambient temperature. Due to product quality requirements, the temperature and humidity setpoints in the assembly area (Zones A and B) must be maintained in narrow ranges. However, the curing zone (Zone C) can be operated within less restrictive limits. Therefore, Factor C is used to assess the effect of adjusting the setpoints in the zones to individual temperature and humidity ranges.

Table 6-1 Summary of measures at the building and technical building systems levels and design of the matrix experiment

Measures	**Design parameters/factors (Building and TBS)**	**Levels**		
		L1	**L2**	**L3**
	A. Constructional separation	n/a	wall with opening	-
	B. AHU	AHU1	AHU2	AHU3
	C. Setpoints (Ø Hd. [%] / T [°C])	Zone A: 25-45/18-24 Zone B: 25-45/18-24 Zone C: 25-45/18-24	Zone A: 25-45/18-24 Zone B: 25-45/18-24 Zone C: 25-60/18-24	Zone A: 25-45/18-24 Zone B: 25-45/18-24 Zone C: 20-70/15-27
	D. Lighting	incandescent (500 W)	glow-discharge lamp (400 W)	LED (130 W)
	E. Windows glazing	1 glaze	2 glazes	3 glazes
	F. Insulation	low wall: 80 mm roof: 100 mm	medium wall: 100 mm roof: 120 mm	high wall: 120 mm roof: 150 mm
	G. Window shading control	n/a	manual control	sun and schedule control
	H. Window opening control	n/a	manual control	temperature and schedule control

Changes to the lighting systems were addressed in Factor D. While maintaining a luminous flux of 7000 lm and the number of lamp sockets, the effect of changing the setup of the lighting system between incandescent, glow-discharge, and LED lamps was tested. The lamps have a rated wattage per unit of 500 W, 400 W, and 130 W, respectively. Factor E evaluated the impact of installing windows with one, two, or three glazes. Furthermore, the effect of improved insulation of the roof and the exterior walls was tested with Factor F. Factor G was used to assess the energy-saving potentials of window shades in conjunction with various manual and automated control strategies. Last, Factor H was set to evaluate the effect of natural ventilation and its combination with a manual or an automatic opening control strategy for the windows.

Due to the number of factors and the respective factor levels, an L_{18} orthogonal array was chosen from Subsection 2.4.2 – Table 2-7. L_{18} includes one factor with two levels and seven factors with three levels each, resulting in 18 simulation runs (ref. Table 8-2).

After completion of all simulation runs with different factor level combinations, the average impact of all factor levels on the selected performance metrics was evaluated according to the calculation method presented in Subsection 5.3.2 Equation (5-8).

The assessment at the building and technical building systems levels was carried out in order to improve the performance-metric energy demand. Non-energy benefits related to building operations were also considered. In accordance with the categories introduced in Subsection 5.3.1, improved occupational safety was assessed using thermal comfort indices, namely the predicted percentage of dissatisfied (PPD). The improved product quality was quantified by measuring the stability of the indoor climate conditions. PPD quantifies the relative number of people dissatisfied with the thermal conditions within a building based on their predicted mean vote (PMV). PMV is calculated by an analytic equation with information on clothing conditions, metabolic rate, air temperature, relative humidity, among others. In our calculation, the metabolic metabolic equivalent of task (MET) for the occupants was estimated to be 2 MET, representing activities such as movement, walking, lifting heavy loads, or operating machinery. Please refer to DIN EN ISO 7730 (p. 8 f.) and Dentel and Dietrich (2013, p. 25 f.) for further information on thermal comfort. In the next step, the factor levels with the best average performance with respect to the selected performance metrics were used in a final simulation run.

Based on the assessment results, a second assessment was carried out at the building and technical building systems levels. The second assessment focused on improving the design of the energy supply system in terms of energy costs, CO_2 emissions, use of renewable energy, and energy flexibility. Table 6-2 summarizes the 16 preselected measures that were evaluated under the energy supply system model. The measures were identified during the expert workshop that was held. Each measure was categorized according to the portfolio of measures introduced in Subsection 5.3.1.

Factors A to C were used to describe the design parameters of alternative process cooling setups, including the number of individual chillers and their installed capacity (A), the availability of free cooling and its capacity (B) as well as the storage size of the cold reservoir (C). Factors D and E focused on the design of the compressed air system. Again, the effects of cascading the capacity and operation of the compressors were analyzed (D) as well as the influence of variation of the size, max. feed-in and withdrawal of equipment for compressed air storage (E). Factors F through H were used to evaluate various equipment setups for space cooling. The space cooling evaluation scheme used the same design parameters used in the process cooling setup evaluation, namely the number of equipment installations and capacity as well as free cooling and storage capacity. Factor I analyzed different heating technologies (including boilers and heat pumps) and their mutual combination.

Table 6-2 Summary of the measures at the energy supply system level and design of matrix experiment

Measures	Design parameters/factors (energy supply system)		Levels L1	L2	L3	Reference
	A. Cooling (process)	C 1	100%	75%	50%	% of peak cooling demand
		C 2	0%	25%	50%	
		~~Ab(d). C~~	0%	0%	0%	
	B. Free cooling (process)	FC (C)	0%	100%	150%	% of peak cooling demand
	C. Cold reservoir (process)		5%	10%	15%	% of peak cooling demand
		In/out	54 kW	108 kW	162 kW	max. feed-in
		out	54 kW	108 kW	162 kW	max. withdrawal
	D. Compressed air	CA 1	100%	75%	50%	% of peak compressed air demand
		CA 2	0%	25%	50%	
	E. Compressed air storage		5%	10%	15%	% of peak compressed air demand
		in	204 m³/h	204 m³/h	204 m³/h	max. feed-in
		out	204 m³/h	204 m³/h	204 m³/h	max. withdrawal
	F. Cooling (building)	C 1	100%	75%	50%	% of peak cooling demand
		C 2	0%	25%	50%	
	G. Free cooling (building)	FC (A)	No	yes		% of peak cooling demand
	H. Cold reservoir (building)		5%	10%	15%	% of peak cooling demand
		in	45 kW	90 kW	135 kW	max. feed-in
		out	45 kW	90 kW	135 kW	max. withdrawal
	I. Heating (building)	B 1	75%	25%	25%	% of peak heating demand
		B 2	0%	25%	0%	
		HP 1	25%	50%	75%	
		~~HP 2~~	0%	0%	0%	
	J. HP-Heating source		Air	Water	Geotherm.	
	K. Heat recovery	A-HR	0%	100%		% of max. recoverable heat
		D-HR	0%	100%		
	L. Heat reservoir (building)		5%	10%	15%	% of peak heating demand
		in	12 kW	24 kW	36 kW	max. feed-in
		out	12 kW	24 kW	36 kW	max. withdrawal
	M. Cogeneration	CHP	0%	50%	100%	% of peak heating demand
	N. PV-orientation		N-S	E-W		
	O. Renewables	PV	10%	20%	30%	tilt angle
	P. Electrical energy storage		5%	10%	15%	% of peak electrical power demand
		in	32 kW	64 kW	96 kW	max. feed-in
		out	32 kW	64 kW	96 kW	max. withdrawal

Factor J varies between the three different heat sources available for heat pump technologies: air, water, and geothermal. The heat recovery was evaluated with Factor K at two levels. Level one represented an energy supply system setup without heat recovery. Level 2 embodies the setup that takes full advantage of all heat recovery opportunities in the system, including direct heat recovery from the operation of the air compressors and heat recovery at the return flow of the chiller using heat pump technology. Factor L was used to assess the influence of different heat storage capacities. The influence of using a cogeneration unit was represented by Factor M. Its capacities varied between 0% and 100% of the maximum space heating demand of the factory. Finally, the use of on-site renewable energy sources was evaluated. Factors N to P include the orientation of a photovoltaic system (N) and the angle of inclination (O). Factor P concluded the summary of measures. It was used to evaluate the impact of an electrical energy storage system on the operation performance of the energy supply system. All the storage equipment evaluated in this case study was dimensioned using the method presented in Subsection 5.4.3. The identified measures were assigned to 16 factors. Each factor was evaluated in a maximum of three levels. An L_{36} orthogonal array was selected from Subsection 2.4.2 – Table 2-7, which can evaluate 13 factors with three levels and three factors with two levels, giving a total of 36 simulation runs.

6.5 Visualization and Evaluation of Simulation Results

In this section, the results of the matrix experiments and the corresponding simulation runs are presented.

Results of matrix experiment at building and technical building systems levels

Figure 6-18 shows the factor charts resulting from evaluating the 18 simulation runs of the matrix experiment and the factors given according to Table 6-1. The highest average effect considering the performance metrics energy demand was achieved by Factor H (window opening control) at Level 1. This was followed by Factor D (lighting) at Level 3 and Factor B (air handling unit) at Level 2.

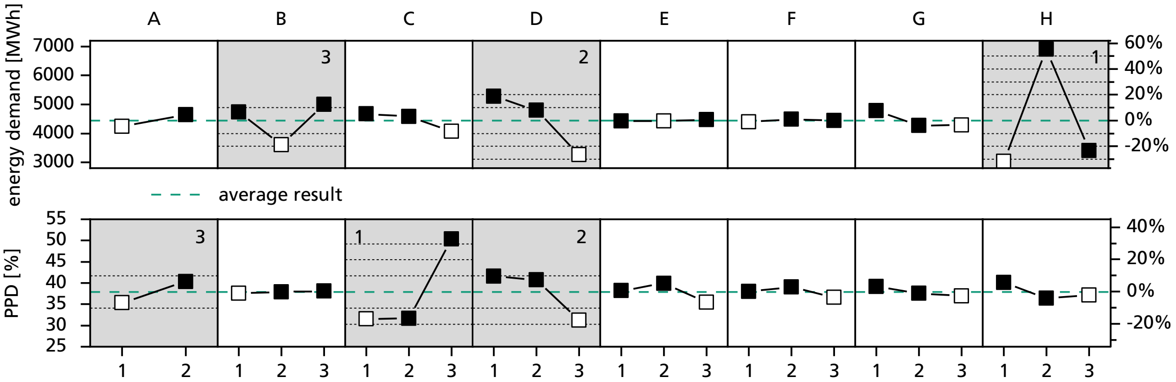


Figure 6-18 Main effects plot at the building and technical building systems levels

The results show that neither manual nor temperature-specific control strategies can help to reduce the energy demand of the building operation. Manual control can even have a highly counterproductive effect and significantly increase the energy demand of the building and its associated heating, ventilation, and air-conditioning system. Not surprisingly, changing the lamps in the lighting system from glow-discharge (Factor D Level 2) to LED (Factor D Level 3) can reduce the energy demand by 32%. The 20% energy-saving potential of the air-handling unit at Factor Level 2 compared to Factor Level 3 can be explained by the higher energy efficiency of the adiabatic evaporative humidifier compared to the steam humidifier. Factors E (window glazing) at Level 2, Factor F (insulation) at Level 3, and Factor G (window shading control) at Level 3 show further energy-saving potentials, but their average effect is comparatively low. By separating Building Zone A from B and C (Factor A), no great effect can be achieved. Adjusting the temperature and humidity setpoints (Factor C) also failed to achieve any significant energy savings. The explanation is that the transfer of composite parts between zones requires frequent opening and closing of gates between zones. This subsequently affects the climate in the individual building zones.

The simulation results were compared with the performance metric for thermal comfort. This evaluation showed that Factor C at Level 3 not only had a small effect on improving the energy demand but also potentially increased the predicted percentage of dissatisfied occupants by about 60%. Factor D at Level 3 was rated as meeting both the goal of reducing the energy demand of the factory building and the predicted percentage of dissatisfied occupants. Considering the different performance metrics, further trade-offs had to be evaluated for Factors B, E, and H. The AHU (B) had the best performance at Factor Level 2, while PPD is lowest at Factor Level 1. Energy demand was lowest for window glazing (Factor E) at Level 2 with two glazings, while PPD was lowest with three glazings. Automatic window opening control (Factor H) performed best in terms of PPD at Level 3, while energy demand is lowest at Factor Level 1.

The relationship between the improvement measures and product quality was evaluated in terms of temperature and humidity stability within the manufacturing environment. Figure 6-19 shows the variation of humidity and temperature levels in Building Zone B.

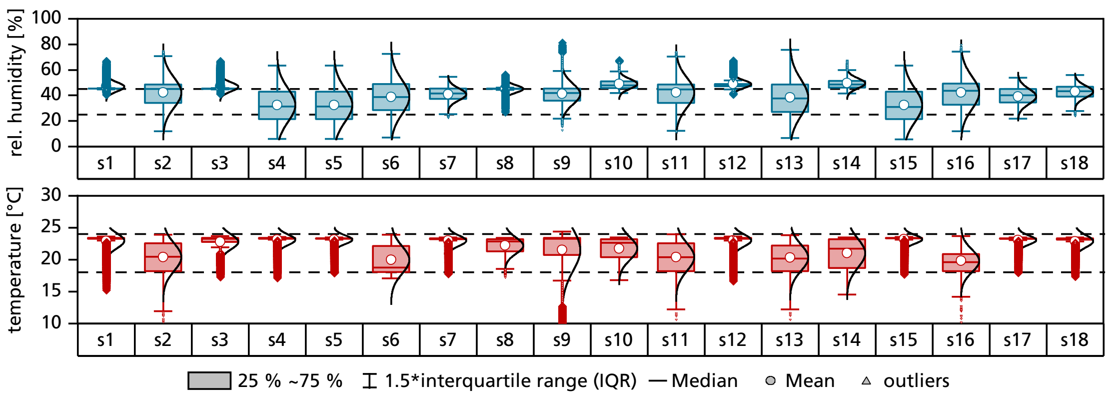


Figure 6-19 Humidity and temperature variations for matrix experiments s1 to s18 for Building Zone B

The boxplot was obtained from running Simulations s1 to s18. As a result, the variation of humidity levels was evaluated higher than the variation of temperature levels. Figure 6-20 shows the percentage of humidity and temperature values outside the predefined ranges (ref. Table 6-1). The most important effects are highlighted by gray boxes. The figure shows that Factors A, B, D, and H significantly affect the percentage of humidity and temperature values outside the predefined ranges.

Contrary to expert estimates, the separating wall between Building Zones B and C was evaluated as detrimental to the stability of indoor climate conditions. AHU Setting 3 was evaluated to best support stable indoor climate conditions.

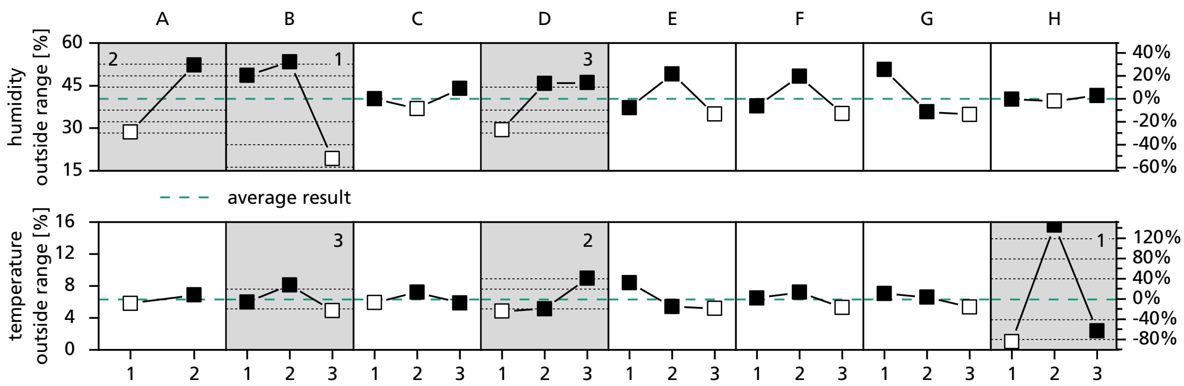


Figure 6-20 Main effects plot for the percentage of humidity and temperature levels outside the predefined ranges

Figure 6-21 shows the ranking of all simulation runs with respect to the different performance metrics. When considering energy demand, major improvements can be achieved by combining the factor levels in Simulations s17 and s4 (Figure 6-21 A). With respect to the PPM, humidity, and temperature limits, the combination of factor levels in Simulations s6 (for PPM), s5, and s3 (for the humidity range), as well as s16 and s10 (for the temperature ranges), allowed significant performance improvements (Figure 6-21 B, C, and D). The simulation result combining the best performing factor levels in terms of energy demand is shown in Figure 6-21 by a shaded bar with “energy” marked.

Considering the various trade-offs that emerged from the main factor plots, the project team decided on the following selection of factor levels in the final simulation run (A-L1; B-L3; C-L2; D-L3; E-L3; F-L1; G-L3; H-L1). The selection was primarily based on energy demand, followed by the stability of temperature and humidity levels and thermal comfort. The result of this simulation run is shown as a gray bar in Figure 6-21 and is marked with the term “selected”.

This combination of the “selected” factor levels reduces energy demand by 49% and PPM by 17% compared to the median from all simulation runs. At the cost of a 9% increase in energy demand, PPM improves by 26%, and the stability of the indoor climate conditions improves by 25% for humidity and 121% for temperature.

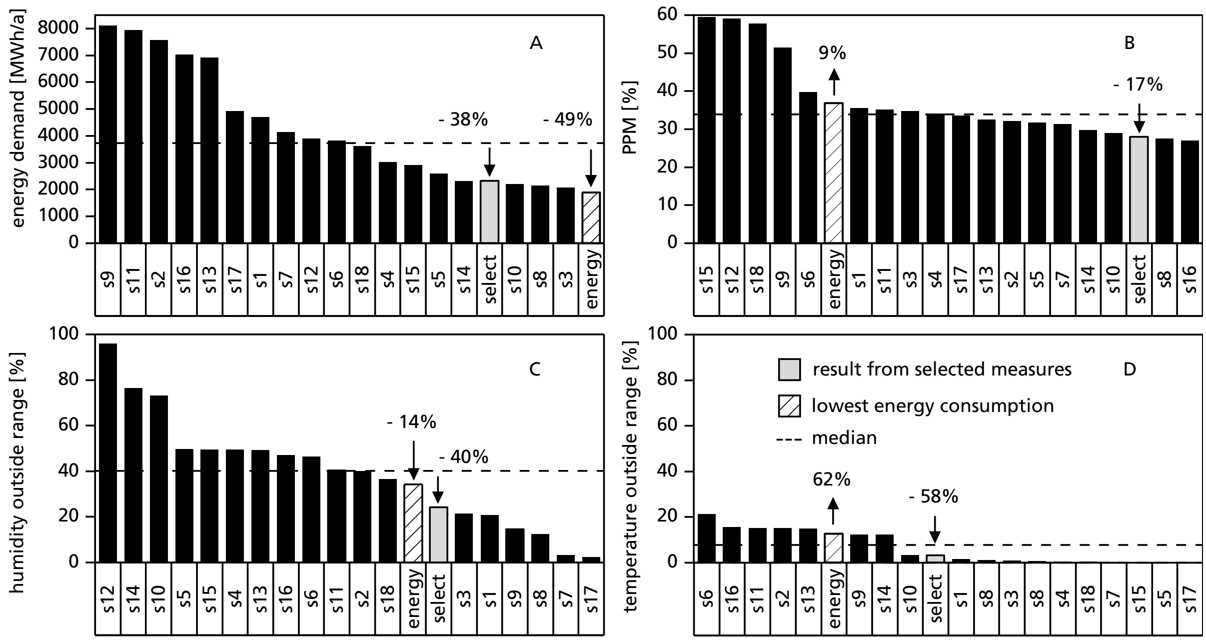


Figure 6-21 Ranking of simulation results according to different performance metrics

Results of matrix experiment on the energy supply system level

In this paragraph, the results of the matrix experiment at the energy supply system level are presented. Figure 6-22 and Figure 6-23 illustrate the simulation results using a main effects plot. Using these mappings, the project team was able to characterize the main effects and factor interactions, including their characteristic behavior across the design space. These figures were also used to identify main effects and to characterize the average impact of all individual factors on the various performance metrics of the energy supply system setup. In general, Factors B (free cooling in the process cooling setup), D (compressed air system setup), I (heating system setup), M (cogeneration), and P (electrical energy storage) were found to have a significant effect on the performance metrics, energy demand, energy cost, CO_2 emissions, renewable energy share, and energy flexibility.

The following is a discussion of each factor in relation to the various performance metrics.

A – Process cooling setup

Though the differences between the design options demonstrated to be minor, a combination of baseload and peak load chillers proved to be the most cost, energy-efficient, and climate-friendly way to provide process cooling (Factor A). Given the demand characteristics for process cooling (high peaks, high fluctuations) and the part-load characteristics of the chiller, a 50% / 50% (Factor Level 3) split of the installed cooling capacity between the baseload and peak-load chillers could meet the process cooling demand at the most efficient operating point. No significant impacts on energy demand and energy flexibility of the energy supply system were identified.

B – Free cooling in the process cooling setup

The use of free cooling (Factor B) within the process cooling setup has been shown to reduce energy costs in proportion to the installed free cooling capacity. It performed best at Factor Level 3. The energy demand and CO_2 emissions showed the same performance characteristics. The use of free cooling in the system setup showed no improvement in the system setup in terms of its energy flexibility capabilities.

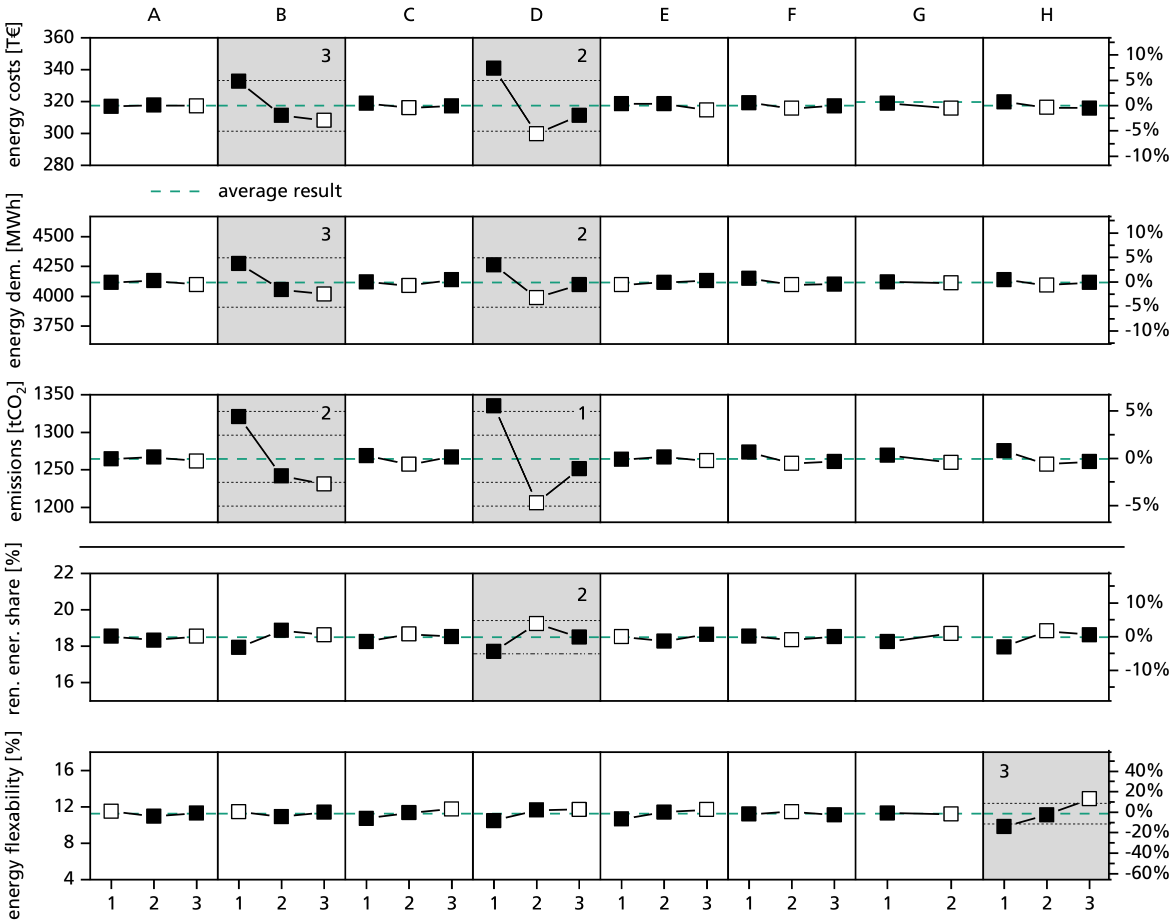


Figure 6-22 Main effects plot (Factors A – H) on energy cost, energy demand, CO_2 emissions, and energy flexibility (the strongest effects are highlighted by gray boxes, and the numbers indicate the order of significance)

C – Cold reservoir for process cooling

Increasing the size of the cold reservoir (Factor C) in the process cooling setup together with the maximum charging and discharging power has shown that the energy costs can be reduced. The highest reduction was found for Factor Level 2. Energy demand and the associated CO_2 emissions show the same trend. The ability of the setup to absorb fluctuating energy demand increases with larger storage sizes.

D – Compressed air system setup

In this case study, the operation of the compressed air system (Factor D) was found to have a significant impact on the total energy costs of the factory. It is demonstrated how baseload and peak load compressors can be cascaded to achieve the most efficient average operating point. The best match between the fluctuating compressed air demand required to operate the autoclaves (pressure ramps – high demand, pressure hold – no demand) and the efficiency characteristics of the individual compressors (larger compressors - higher average efficiency; smaller compressors - lower average efficiency) was determined with a 75% / 25% split between the compressor units (Factor Level 2). Energy demand, CO_2 emissions, and renewables share followed the same performance characteristics. For Factor D, only a minor improvement of the system's energy flexibility was found.

E – Compressed air storage

In contrast to the other factors, the increase in the capacity of the compressed air storage tank in combination with the maximum charging and discharging power (Factor E) showed little effect on the evaluated performance metrics. The lowest energy demand and highest renewables share were identified for minimum storage capacities (Factor Level 1). CO_2 emissions and energy flexibility increased proportionally to the tank size and were highest at Factor Level 3.

F – Space cooling setup

Based on the demand characteristics for space cooling, it was shown that the chiller setup (Factor F) operates most economically at Factor Level 2. The combination of a baseload and a peak load chiller with a 75% / 25% distribution of the installed cooling capacity between the chiller units showed superior performance. Taking into account the CO_2 emissions, the simulation results also recommended covering the cooling demand with several chillers and splitting it according to Factor Level 2. Although the advantage is minor, the performance in terms of energy demand is also best at Factor Level 2. Again, no significant effect on the energy flexibility characteristics was found.

G - Free cooling in the space cooling setup

In the space cooling setup, free cooling (Factor G) only needs to be evaluated on two levels. As with the process cooling setup, the availability of free cooling proved to be an efficient measure for improving the performance of the energy supply system in terms of energy cost, energy demand, and CO_2 emissions (Factor Level 2).

However, due to the lower overall demand for space cooling compared to process cooling, the average savings potential is lower. The use of free cooling is also limited in the summer months due to the small temperature differences between the flow and outdoor temperature. However, this is the period of the year with the highest space cooling demand. A positive effect of free cooling on energy flexibility could not be quantified in this assessment.

H - Cold reservoir for space cooling

With regard to energy costs, energy demand, CO_2 emissions, and renewables share, the storage size in the space cooling setup (Factor H) performed best at Factor Level 2 for medium size and medium charging and discharging capacity. Not surprisingly, the energy flexibility within the system setup increases with increasing storage sizes.

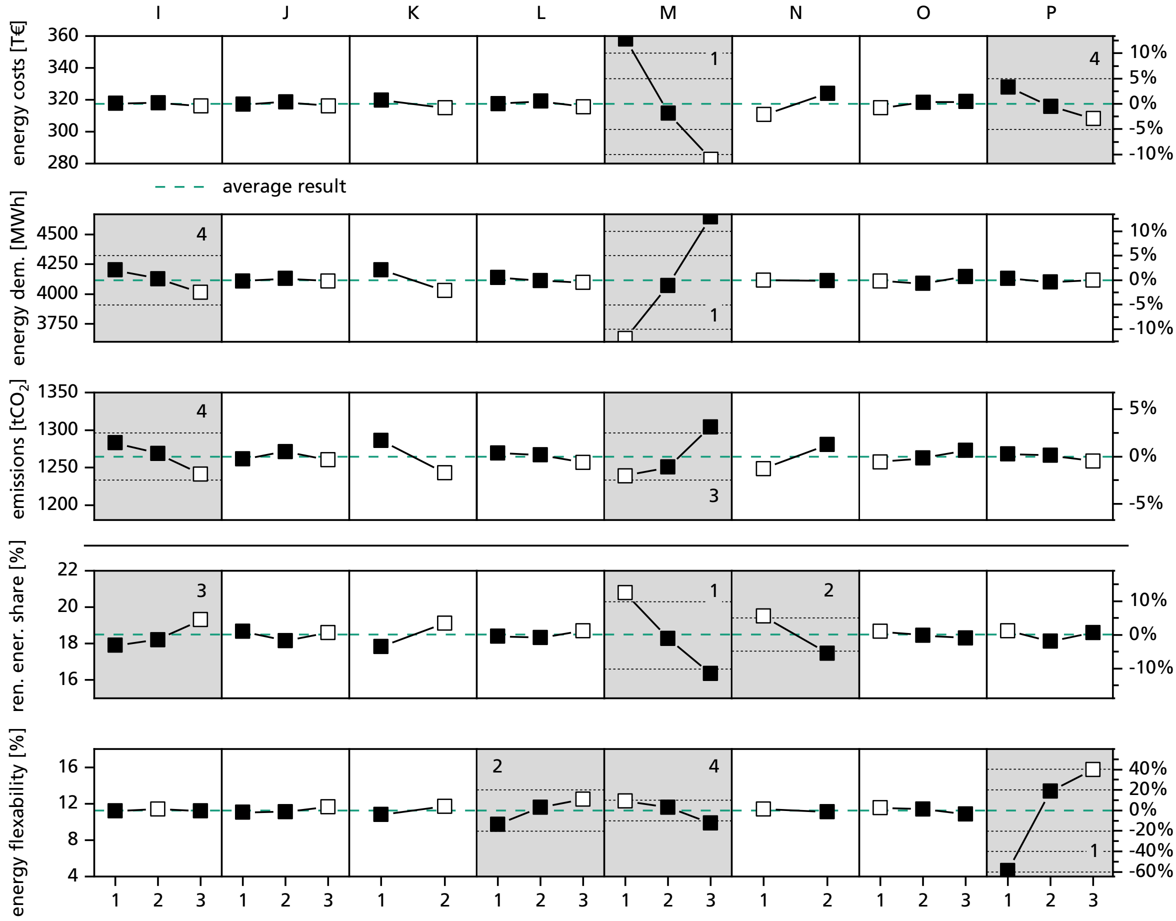


Figure 6-23 Main effects plot (factor I – P) on energy cost, energy demand, CO2 emissions, renewable energy share, and energy flexibility (the strongest effects are highlighted by gray boxes, and the numbers indicate the order of significance)

I – Space heating setup

The system setup for space heating (Factor I) showed superior performance at Factor Level 3, indicating the use of an electric heat pump in combination with a gas-fired boiler. Based on the peak heating demand, a 75% / 25% split between the installed capacity of the heat pump and the boiler showed the best results. Again, no significant impact on energy flexibility performance could be quantified.

J – Heating source for heat pump

Factor J evaluated the use of different heat sources for the heat pump. Sourcing heat from geothermal probes (Factor Level 3) was rated best in terms of its potential to reduce energy costs, energy demand, and CO_2 emissions. However, due to the low space heating demand, the main effects plot indicates generally low impacts on the different performance metrics.

K – Heat recovery

Heat recovery from the process cooling and compressed air system (Factor K) was evaluated to having a positive impact on the overall performance of the energy supply system. The assessment showed that heat pump technology can reuse waste heat in the space heating system, reducing energy demand, costs, and CO_2 emissions. Effects on the renewable energy share and the system's ability to provide energy flexibility are also positiv.

L – Heat reservoir for space heating

Looking at the dimensioning of the thermal storage in the space heating setup, larger tank sizes together with maximum charging and discharging capacities (Factor Level 3) show uniformly positive effects on all performance criteria of the system. A major positive effect was demonstrated for the performance metrics energy flexibility.

M – Cogeneration system

The use of a combined heat and power (CHP) plant (Factor M) reduced the energy costs within the given energy supply system. As shown in the main effects plot, as system size increases, the cost advantage increases proportionally. The average saving potential is highest at Factor Level 3. The cost advantage is due to the low cost of natural gas, the guaranteed subsidies for in-house consumption of electricity generated by a CHP plant ("CHP Bonus") as well as guaranteed feed-in tariffs.

The additional demand for natural gas to operate the CHP plant, while economically beneficial, increases the total energy demand and associated CO_2 emissions. As space heating is the only heat sink where cogenerated heat can be reused, the CHP plant is mainly operated for electricity generation. Meanwhile, most of the cogenerated heat is dissipated in an emergency cooler. This reduces the overall efficiency of a CHP plant operation. The performance of the system in terms of energy flexibility decreases with larger CHP plant sizes due to the increasing energy demand for the CHP plant operation. Energy flexibility peaks at Factor Level 1.

Finally, the impact of the use of on-site renewable energy and the modification of the corresponding design parameters was evaluated. The influence of a photovoltaic system on the energy supply system setup was evaluated by varying two different factors, namely the orientation and the tilt angle.

N – Photovoltaic system – Orientation

Factor N was employed to test the effect of changing the orientation of the photovoltaic system. Based on the simulation results, north-south orientation (Factor Level 1) showed the highest cost and emission reduction potential. It also has a major impact on the renewable energy share used in the system setup. The orientation of the photovoltaic system showed no significant influence on the overall energy demand and the energy flexibility potential.

O – Photovoltaic system – Tilt angle

Taking into account the specific location of the building and its roof orientation, the photovoltaic system showed its best reduction potential in terms of energy costs when installed with a tilt angle of 10 degrees (Factor Level 1).

P – Electrical energy storage system

The use of an electrical energy storage system with varying charging and discharging power has been shown to contribute best to the overall performance of the energy supply system at Factor Level 3. In addition to the energy costs, the CO_2 emissions are also lowest at Factor Level 3. This is mainly due to the fact that the higher storage capacity can increase the share of self-consumption from renewable energy sources (e.g., photovoltaic system). This results in lower energy surpluses that have to be fed to the grid when the electricity demand of the factory is low. Besides, higher charging and discharging rates of the electrical energy storage system can also improve the ability of the energy supply system setup to absorb peak electricity demands of the factory, further reducing the need to source electricity from the grid.

In summary, the individual performance metrics were most influenced by the following four factors and their subsequent order. For energy costs, the most influential factors were M, D, B, and P. For energy demand, the order was M, D, B, and I, for CO_2 emissions D, B, M, and I, for the renewable energy share M, N, I, and D, and for energy flexibility P, L, H, M. Conflicting effects between the performance metrics energy cost, energy demand, CO_2 emissions, and energy flexibility could be identified for the factors C, D and H and between energy cost, energy demand, and CO_2 emissions for the factor M. In both cases the improvement of one performance metrics (e.g., energy flexibility or energy costs) leads to deterioration in the other performance metrics (e.g., energy demand or CO_2 emissions.

Figure 6-24 A and B show the simulation runs that performed best in terms of each performance metric, s23 for energy costs, s19 for energy demand and energy flexibility, s24 for CO_2 emissions, and s34 for the renewables share.

Identical to the process for evaluating the measures at the building and technical building systems levels, additional simulation runs were carried out with the combination of best factor levels with respect to individual performance metrics. Then, the project team selected the levels for all factors individually based on the analysis of the main effects plots. The result was the ultimate simulation, which was called “select” or “S”. In making their decision, they prioritized factor levels that help reduce energy costs, followed by factor levels that reduce energy demand and CO_2 emissions. Renewables share and energy flexibility has been considered whenever it is complementary to the other performance metrics or when significant improvements warrant minor trade-offs with the other performance metrics. The selection favored A-L3, B-L3, C-L3, D-L2, E-L3, F-L2, G-L2, H-L3, I-L3, J-L3, K-L2, L-L3, M-L2, N-L1, O-L1, P-L3).

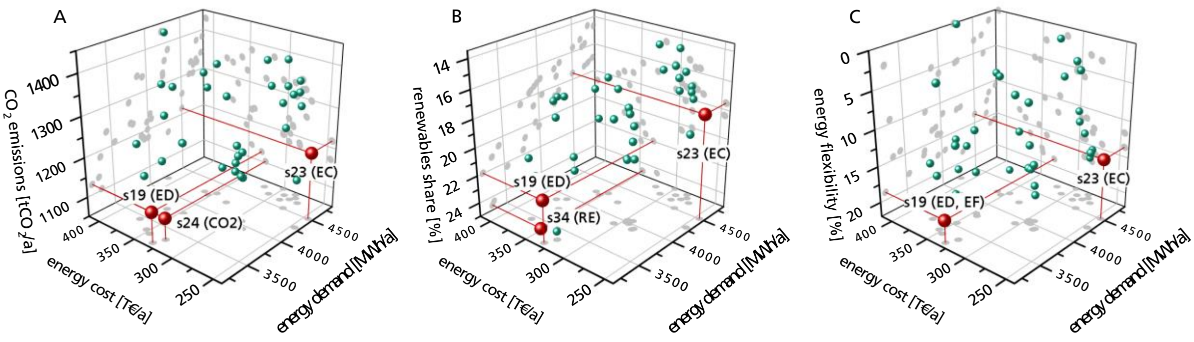


Figure 6-24 3D visualization of the simulation results for (A) – energy cost, energy demand, and CO_2 emissions, (B) – energy cost, energy demand, and renewables share, and (C) – energy cost, energy demand, and energy flexibility

Figure 6-25 shows the results of all simulation runs for various performance metrics. The shaded and dashed bars indicate the results of the simulation runs combining the best performing factor level in terms of lowest energy costs ("EC"), lowest energy demand ("ED"), lowest CO_2 emissions ("CO_2"), highest renewable energy share ("RE"), and highest energy flexibility ("EF"). The black bar shows the simulation result for the combination of factor levels chosen by the project team.

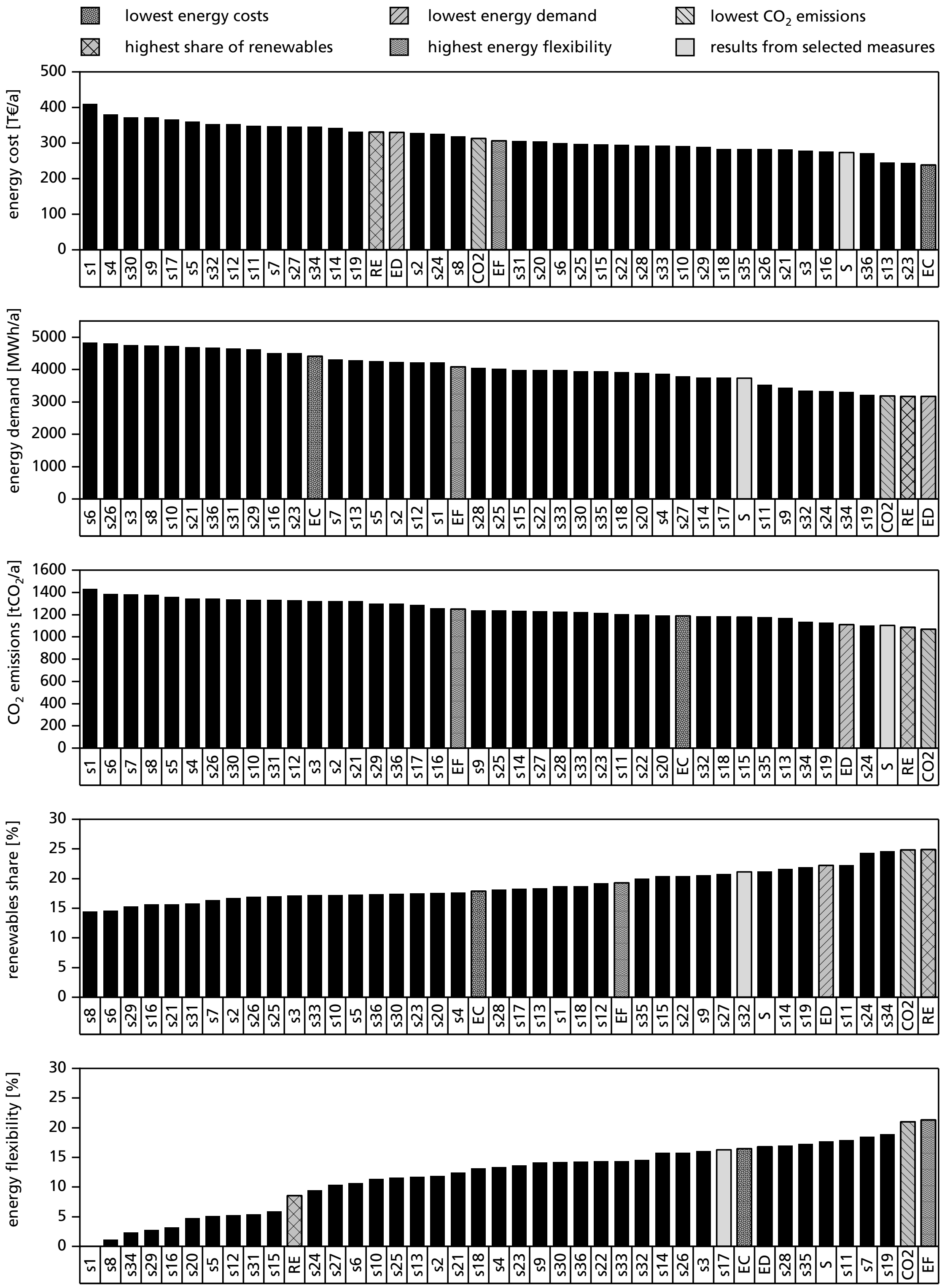


Figure 6-25 Ranking of simulation results for the different performance metrics

Figure 6-26 further specifies the relative improvements for each performance metric considering the worst (w), median (m), best (b), and selected (s) results from the simulation runs. In the case where the factor levels are chosen to improve individual performance metrics, the pie charts in the top row of Figure 6-26 show (from left to right) the relative change in performance for all performance metrics compared to median results. The cost-optimized factor level combination can reduce energy costs by a maximum of 22%. The energy demand optimized factor level combination can reduce energy demand by 21% compared to median results. The emission-optimized factor level combination has a maximum reduction potential of 13%. If the sole aim is to improve the renewables share or energy flexibility, the maximum relative improvements are 36% or 58%, respectively. For the combination of factor levels chosen by the project team, the pie chart in the bottom row illustrates the relative improvements for all performance metrics. Compared to the median results of all performance metrics, the annual energy costs could be reduced by 10% (~ -31,700 €), the annual energy demand by 7% (~ -285.5 MWh/a), CO_2 emissions by 11% (~ -134.9 tCO_2/a), the renewables share could be increased by 16% to 21% (≙ +52.3 MWh/a) and energy flexibility by 31% to 18% (≙ +43.0 MWh/a).

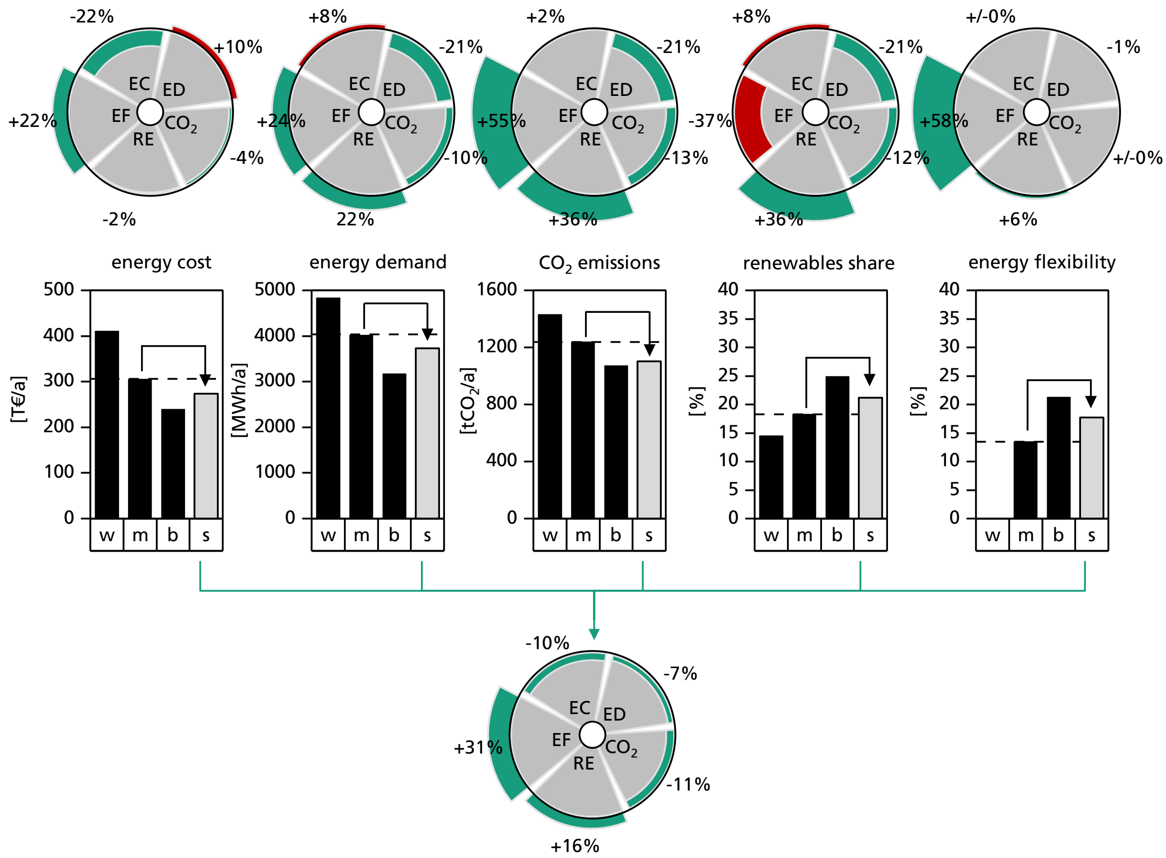


Figure 6-26 Top: pie-chart showing the relative improvement per performance metric compared to median simulation results (EC – energy cost, ED – energy demand, CO2 – CO2 emissions, RE – renewables share, EF – energy flexibility). Middle: worst (w), median (m), best (b), and selected (s) simulation results per performance metric. Bottom: pie-chart showing relative improvement per performance metric for selected factor levels

Figure 6-27 summarizes the results from both simulation experiments with a particular focus on energy demand and supply. In Figure 6-27 A, the total energy demand of the manufacturing system is differentiated into the demands for operation of the process chain, building, and technical building systems. Considering different factor level combinations, the worst, median, and best results are presented. Assuming that trial-and-error approaches cannot realize superior performance improvements, the structured evaluation using design of simulation experiments was able to achieve a 34% reduction in energy demand compared to the median results of all simulation runs. Taking into account the factor levels selected, the reduction is still 26%.

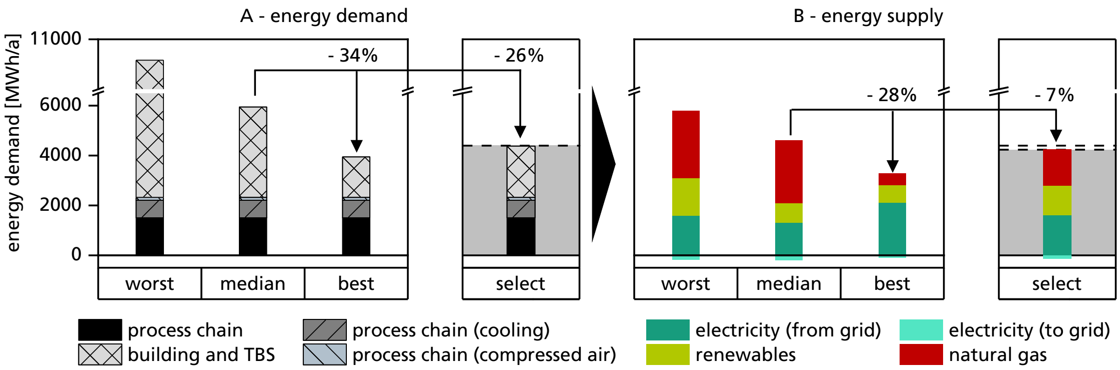


Figure 6-27 Summary of results from Simulation Experiment One (A) and Two (B) - (A – focus on energy demand reduction, B – focus on energy supply system efficiency)

Figure 6-27 B illustrates the composition of the energy sources that can be used to supply the requirements of the manufacturing system for the case “select”. The sources are differentiated into electricity that is retrieved and fed to the grid, gas retrieved from the grid, and electricity that is provided on-site from renewable energies. Again, the worst, median, and best results for different factor level combinations are outlined and contrasted with the selected setup (“select”). Again, the structured evaluation using simulation experiments was able to reduce energy demand by 28% when the setup is optimized for the lowest energy demand only. For the factor level combination selected by the project team, it was still possible to achieve 7% compared to the median result from all simulation runs.

Considering the energy efficiency metrics introduced in Section 5.2, the factory system achieves an energy efficiency performance of 106% for the combination of selected factor levels. This result is obtained by dividing the useful energy demand required for the operation of the process chain, auxiliary equipment, and the technical building systems (ref. Figure 6-27 A – “select”) by the final energy demand used to supply these demands (ref. Figure 6-27 B – “select”). Efficiencies of more than 100% can be explained by the heat pumps and chillers used to meet the heating and cooling demands. These technologies can make use of “environmental energy” and have performance factors greater than one.

6.6 Summary

The developed methodology was applied to a case study in a factory manufacturing composite parts for the aerospace industry. First, the manufacturing system was modeled by coupling different software tools. Tecnomatix Plant Simulation 14 was used to model machines and their interaction within a process chain. Buildings and technical building systems were implemented in the EQUA IDA ICE 4.8 software. Finally, both the auxiliary equipment and the energy supply system were modeled in the TOP-Energy 2.10 software environment. Various submodels were verified using measurement data obtained during visits to the factory site. Together with a group of company and third party experts, several improvement measures were preselected and adapted to individual matrix experiments. The step-by-step approach of the developed methodology made it possible to evaluate several improvement measures simultaneously in terms of different performance metrics. A total of two simulation experiments were conducted. The first experiment focused on improving the operation of the building and the technical building systems. The evaluation included measures to reduce energy demand and improve non-energy benefits in terms of occupational safety and product quality. In the present case study, no improvement measures at the process chain level were considered. Based on the results of the first simulation experiment, the second experiment focused on improving the design of the energy supply system with respect to the selected performance metrics – energy costs, energy demand, CO_2 emissions, and energy flexibility. Main effects plots were used to illustrate the effect of various design parameters (factors) on several performance metrics and to determine the best settings (levels) for each design parameter. The implementation of the selected measures at the building and technical building system level was assessed as having the potential to reduce the energy demand of the factory system by 26%, compared with the median from all simulation runs. This is the case if median results are considered to be the best results that can be obtained in a non-systematic trial-and-error procedure.

Following the procedure proposed by the methodology, it was possible to select and combine improvement measures that could reduce the energy demand of the building and technical building systems by 38% and the PPM value by 17%, and increase the stability of temperature and humidity levels by 40% and 58% compared to the median results.

Based on the improvement of the energy demand side, the supply system setup that best meets the remaining energy demands was designed. Using matrix experiments, it was possible to improve trial-and-error approaches and outperform median scenarios by 10 % (~ -31,700 €) in energy costs, 7% (~ -285.5 MWh/a) in energy demand, and 11% (~ -134.9 tCO_2/a) in CO_2 emissions. In addition, the share of renewable energies on the final energy demand of the factory was increased by 16% to 21% (≙ +52.3 MWh/a) and the energy flexibility was increased by 31% to 18% (≙ +43.0 MWh/a).

7 Evaluation of the Methodology

Chapter 7 evaluates the developed methodology and compares its performance with respect to the requirements identified in Chapter 4 (ref. Section 7.1). Section 7.2 evaluates the research contribution and outlines the limitations of the methodology developed before Section 7.3 summarizes the evaluation and generalizes the findings related to the development and application of the methodology in this thesis.

7.1 Evaluation of the Requirements

In this section, the requirements identified in Chapter 4 are evaluated with a view to their application in the case study in Chapter 6. First, the requirements for the factory simulation model are evaluated.

Due to the achieved level of detail of the individual submodels, as well as the extensive consideration of multiple factory peripheries within the simulation model (ref. Section 5.4), full compliance with Requirements 1 and 8 can be confirmed. The offline exchange of simulation data enables the flexible use and coupling of different domain-specific simulation tools. Thus, Requirement 5 (flexible model coupling) can also be evaluated as completely fulfilled.

To enable the adaptation of the factory model to individual use cases and the extension of the model in the future, Requirement 2 (modular and expandable model architecture) was introduced. Since the submodels of the factory simulation model can all be individualized and extended as needed, Requirement 2 is also rated as completely fulfilled. In addition to customization, the predefined factory model setup enables the rapid implementation of the first version of a factory model. Full compliance with Requirement 3 is only limited by the transparency regarding the numerous model parameters. As a result, the user has to pay considerable attention when parameterizing the model.

Depending on the simulation duration, the temporal resolution and the number of submodels, the execution time for the individual simulation runs varies considerably. To overcome this limitation and ensure fast model execution (Requirement 4), the temporal resolution of the factory model was customized. While the resolution of seconds or minutes can provide valuable insights at the level of processes or machines, this benefit is significantly reduced at the energy supply system level. The use of data compression in handling data between the different levels of the simulation model was identified as an effective way to reduce execution times. In this work, the execution time of each simulation model varied between 1-15 min. for the process chain model, 15-60 min. for the building and technical building system models, and 15-60 min. for the energy supply system model. These figures refer to one simulation run and take into account a simulation period of one year.

The evaluations of simulation models for complex technical systems (e.g., factories) require considerable effort. In this work, the model accuracy of the factory model was ensured by evaluating the individual submodels. However, it is expected that future metering systems will bring the representation of the real world and the model even closer together. This confirms partial compliance with Requirement 6.

The main application of the factory simulation model is the evaluation of improvement measures regarding the use of the resource energy as well as the evaluation of individual energy supply system setups. For this purpose, the model accuracy (Requirement 7) and resolution proved to be sufficient. Again, using domain-specific simulation tools with a considerable history of evaluated submodels ensures the accuracy of the factory representation in the simulation model. However, the heterogeneity of existing factory environments, together with the limited access to measurement data, still poses a challenge to model accuracy. Thus, Requirement 7 is also only partially fulfilled. The evaluating of the requirements for the assessment procedure is presented next.

The assessment procedure developed in this work complements the existing performance metrics (Requirement 1) with additional categories related to non-energy benefits, renewables share and energy flexibility. Following the methodology presented in this work, the user is able to select improvement measures, taking into account their performance trade-offs. Future developments will certainly add further performance categories to which a factory system must respond. Furthermore, the non-energy benefits introduced in this work require additional specification in terms of quantifiability. Hence, Requirement 1 is assessed as only partly fulfilled.

Requirements 2 and 3 address the need to develop efficient and statistically sound ways to experiment with complex simulation models. In this respect, existing trial-and-error approaches changing one factor at a time are considered insufficient and efficient. By introducing design of simulation experiments, it is possible to analyze factory systems with a minimum of individual simulation runs. The simulation results obtained hereby allow prioritization of the measures according to their influence on the overall system performance. Requirements 2 and 3 are therefore assessed as fulfilled. In terms of efficiency, the fulfillment of the requirement is only limited by the time-consuming transfer of the parameter levels in the individual models. This currently limits efficiency gains but is expected to be resolved by future improvements of the methodology.

Within the scope of this work, measured data were used wherever possible to evaluate the simulation model. However, existing factory environments with fragmented and heterogeneous energy metering infrastructures still significantly limit these efforts, leaving white spaces of unverifiable submodels within complex factory simulation models. Hence, Requirement 4 is only confirmed as partially fulfilled.

Innumerable parameters characterize complex simulation models. However, only a few parameters have the appropriate level of detail that can be used and influenced by decision-makers in the early stages of a factory planning process. In this work, the practical relevance of the selected parameters (Requirement 5) was ensured by experimental design. The matrix experiments used predominately involve yes or no decisions for the use of individual technologies, capacity, and the number of units for equipment installations. This information is considered to be available in early design phases while providing a sufficient level of detail to be used proactively by decision-makers during the development of conceptual designs. Again, the fulfillment is attributed to Requirement 5.

Finally, Requirement 6 is also assessed as fulfilled by the use of several graphical representations to visualize intermediate and final simulation results. For example, main effects plots are used to show the average effect of individual factor levels in relation to different performance categories. Pie charts are used to illustrate performance improvements across all performance categories. Table 7-1 summarizes the evaluation of the requirements. Their individual levels of fulfillment are represented with Harvey balls.

Table 7-1 Evaluation of the requirements for the factory simulation model and assessment procedure (degree of fulfillment: not ○, partial ◔◑◕, complete ●)

		Factory simulation model			Assessment procedure
●	1.	Comprehensive representation of energy consumption characteristics	◕	1.	Extended performance metrics
●	2.	Modular and extensible model architecture	◕	2.	Efficient way of experimenting with simulation models
◕	3.	Fast model implementation and adaptation	●	3.	Statistically sound way of experimenting with simulation models
◑	4.	Fast model execution	◑	4.	Improved use of measurement data
●	5.	Flexible model coupling	●	5.	Practical relevance of the selected parameters
◑	6.	Good verifiability of the model	●	6.	Graphical support of the decision-making process and presentation of results
◕	7.	High model accuracy			
●	8.	Extended energy supply system model			

7.2 Research Contribution and Limitations

The main contribution of the developed methodology is to promote the use and evaluation capabilities of factory simulation models during the planning of a factory modernization (e.g., during redesign, revitalization, expansion, renovation, or restructuring) with regard to their energy use. In this case, measurements can provide the relevant information to parameterize and verify the factory simulation model.

Embedded in a consistent assessment procedure, the combination of a multi-peripheral factory simulation model together with an evaluation process using design of simulation experiments, allows to first, reduce the energy demand of the factory system and second to design demand-oriented energy supply systems. Hence, the assessment procedure supports the synthesis of energy improvement measures and energy supply system designs for factories. It assists in both the selection and combination of appropriate improvement measures, energy supply technologies, and associated operational strategies. Therefore, it is a beneficial approach that helps identify the components and parameters within a factory system that most affect its energy-related performance. The developed evaluation process is a further development of trial-and-error approaches, which are still predominant in the optimization of energy demand in factories and the design of their energy supply infrastructure. It has been shown that the use of matrix experiments reduces the number of simulation runs and thus the computational cost of analyzing the available design space. The design of simulation experiments also allows the identification of interdependencies between parameters and their positive (reinforcing) and negative (mitigating) effects with respect to various energy-related performance metrics. In summary, the methodology developed represents a good compromise between modeling effort, the number of simulation runs required, and model accuracy. Therefore, it allows screening for the most effective combination of measures given customer preferences and design space constraints. The derived results enable prioritization of further design and engineering efforts focused on the detailed design of energy-related equipment installations and their operational strategies.

The support provided by the proposed methodology is limited when it comes to detailing conceptual designs, technical specifications, and control strategies. The approach to design of simulation experiments presented in this thesis primarily aims to screen the design space for parameters that have a dominant effect on the energy-related performance metrics of a factory. This also includes identifying significant interactions between parameters, both reinforcing and mitigating. Another limitation is that simulation studies based on matrix experiments offer limited flexibility when it comes to changing the number of parameters (factors) and parameter (factor) levels analyzed. Moreover, matrix experiments based on orthogonal arrays are highly fractional factorial designs. This limits the analysis to main effects. Omitting higher-order factor interactions can lead to misinterpretation of simulation results and requires a lot of experience from the user. Although various visualization approaches are implemented in the presented approach, considerable expert knowledge is still required to interpret the simulation results. Another limitation of this work is the lack of an optimization approach that can weigh off different performance metrics against each other and automatically select the best combination of measures in search of a global optimum. In this work, optimization is limited to the selection of best-performing factor levels from the main effects plots.

In the spirit of generalization, the methodology developed in this thesis introduces new strategies for using complex simulation models in consulting practice. The adaptation of the decision parameters to a user-specific level of detail and the effective handling of heterogeneous, multiparametric factory simulation models using desing of simulation experiments represents another valuable contribution of this work. The extension of the peripheral factory model further generalizes the structure of a factory and presents a framework that helps to locate energy-consuming equipment and categorize improvement measures. This also provides a valuable link between the research fields of manufacturing engineering and architecture. If sufficiently verified information on the energy demand characteristics of the underlying manufacturing process is available from measurements in existing, currently operating factories, the presented methodology can also support during the planning of new factories in a greenfield approach.

7.3 Summary

With reference to the requirements specified in Chapter 4, Chapter 7 (ref. Section 7.1) evaluated the fulfillment based on the application of the developed methodology in the case study in Chapter 6. The evaluation is presented both for the requirements on the development of the factory simulation model and on the improvement of existing assessment procedures. For the factory simulation model, major fulfillment can be attributed to Requirements 1, 2, 5, and 8. This is because in this work, existing multi-peripheral factory models have been extended towards the energy supply system. Also, the presented model allows flexible coupling, extension, and adoption to different use cases. For the assessment procedure, major fulfillment has been evaluated for Requirements 3, 5, and 6. This is because in this work, existing performance metrics have been extended towards non-energy benefits. Besides, design of simulation experiments has been introduced as a new approach to support experimenting with factory simulation models in an efficient and statistically sound way. Section 7.2 evaluates the general research contribution of the developed methodology and outlines its limitations.

Supporting modernization planning with a special focus on energy use and improving the planning results by promoting the evaluation capabilities of factory simulation models was found to be one major contribution of this work. A limitation of this work is its primary focus on conceptional designs and the missing link to support detailed planning of technical systems and control strategies for example by using more advanced optimization methods.

8 Summary and Outlook

Chapter 8 summarizes the content of this work. The chapter also includes a brief outlook on research fields related to the findings and shortcomings of this work that demand further research.

Summary

Chapter 1 motivates this research by providing a general background on environmental protection measures that directly or indirectly affect factory design and operation requirements. The research question is derived from the shortcomings of simulation-based methodologies available for the assessment of energy use in factories. The lack of these approaches to shed light on the complex interactions of different improvement measures in relation to multiple energy-related performance metrics is translated into the central aim of this work. Chapter 1 concludes with an outline of the research design and structure of this thesis. Chapter 2 presents the basic principles and theoretical foundations relevant to this work. This includes terms and definitions for factory systems, energy use, modeling and simulation, and the design of simulation experiments. Chapter 3 provides an overview of the state of science relevant to the research question in Chapter 1. Existing simulation-based methodologies used to assess energy use in factory systems are evaluated with respect to the four evaluation criteria (suitability, completeness, inclusiveness, comprehensiveness) and their additional sub-criteria (transferability, generalizability, precision, usefulness, and integrability). Chapter 3 concludes by refining the research question. With reference to the criteria introduced in Chapter 3, Chapter 4 outlines the objectives and requirements relevant to the development of a new multi-peripheral factory simulation model and its role in the assessment of energy use in factories. Chapter 5 presents the methodology developed. The methodology consists of two parts, first, the development of a procedure model for a step-by-step assessment of energy use in factories using extended energy-related performance metrics, and second, the development and implementation of the factory simulation model with several peripheries. Chapter 6 applies the developed methodology to a case study in the aerospace composites industry. By following the steps of the assessment procedure, it is possible to make a joint evaluation of various improvement measures from the energy efficiency, energy flexibility, and renewable energy category. The evaluations are done in a composite manner using the multi-peripheral factory simulation model along with the design of simulation experiments. The focus of the evaluation process is twofold. In the first experiment, the focus is on reducing the final energy demand of the factory. In the second experiment, the focus is on improving the design of the energy supply system with respect to the selected performance metrics – energy costs, energy demand, CO_2 emissions, energy flexibility, and renewable energy share. Chapter 7 evaluates the developed methodology against the objectives and requirements presented in Chapter 4. It also provides a critical overview of the contributions and limitations of this research.

Outlook and recommendations for future work

This study offers several starting points for further research. This section aims to provide a brief outlook on the urgent need for further research.

In order for decision-makers to focus their efforts and companies to prioritize their financial resources, it is important to further explore the topic of holistic performance metrics for manufacturing systems. This also includes the development of methods that allow various performance metrics to be flexibly adjusted, weighted, and balanced. Model-based assessments require functions to evaluate the impact of a change in priorities and preferences within complex performance metrics. In general, performance metrics need to be extended to include other dimensions, including the resilience of the manufacturing system and its individual elements (e.g., the energy supply system design). The quantifiability of non-energy benefits also needs further elaboration, including consideration of the associated model requirements. Moreover, for the use of the performance metric "energy efficiency" and its use at the level of an entire manufacturing system (ref. Section 6.5), a further specification is required. This includes, for example, a distinction between the individual energy carriers and their ability to perform work (exergy).

Expanding the scope of the multi-peripheral factory model is a desirable goal for future developments. This includes improving the level of detail within individual peripheries of the presented factory model. Here, the implementation of further energy carriers (e.g., hydrogen and other synthetic fuels) together with the corresponding system components (e.g., electrolyzer, fuel cells) is a requirement for the future. In addition to improving the level of detail, adding new peripheries to the factory model is another necessity. At the lower end of the peripheral scale, consideration of a product level can specify the influence of product design on the energy requirements during manufacturing. At the upper end, expansion toward industrial parks and coupling with other sectors (households, transportation) offers the possibility to design energy networks in a way that optimally matches demand and supply. Grid infrastructures and energy markets can represent further model extensions.

In order to improve the applicability of the presented methodology, it is necessary to standardize the presented workflow in terms of software. This is motivated partly to encourage the use of the tool by practitioners who do not yet have experience with modeling and simulation and partly to reduce error-proneness. The focus is on the development of a uniform input mask for all design parameters selected for evaluation in the factory simulation model. This includes a workflow that supports model coupling and data handling between the different submodels with a graphical user interface.

Necessary future developments consider the implementation of an automated workflow that can select the appropriate design of simulation experiments based on the number of design parameters (factors) and parameter levels (factor levels). This workflow also includes the automated generation and execution of model variants. The use of optimization algorithms within complex, multi-peripheral factory models represents another possible field of action for future research activities. This can extend the screening for near-optimal factor settings presented in this work to include demand-based selection, stepwise execution, and coupling of optimization algorithms with the simulation model.

To improve model accuracy and flexibility, the multi-peripheral factory model needs to be extended with data-driven modeling approaches. To overcome the limitations of current energy metering systems and establish consistent data sources, the author suggests investigating the development and implementation of value stream-oriented measurement concepts for energy data collection. These measurement concepts aim to allocate the total energy demand from all the peripheries of a factory to specific value-added processes and individually manufactured products. The alignment of the model with data interfaces also allows for better adjustment of design parameters and verification of submodels. Subsequently, the multi-peripheral factory model can be expanded to include additional levels of detail, for example, around the characteristics of partial-load operation for machines, auxiliary equipment, and technical building systems.

To advance the use of factory simulation models in the context of the digital factory, the link between the model and the real world must be extended. This includes linking the various submodels of complex factory simulation models with data streams from machine sensors and value stream-oriented energy metering systems. Based on these data streams, the model can be continuously updated and always represent the latest information and status of the physical assets represented. The research focus is to strengthen the concept of digital twins (the virtual representation of physical assets) to always present an up-to-date digital representation of the factory using a data-driven factory simulation model (ref. Figure 8-1).

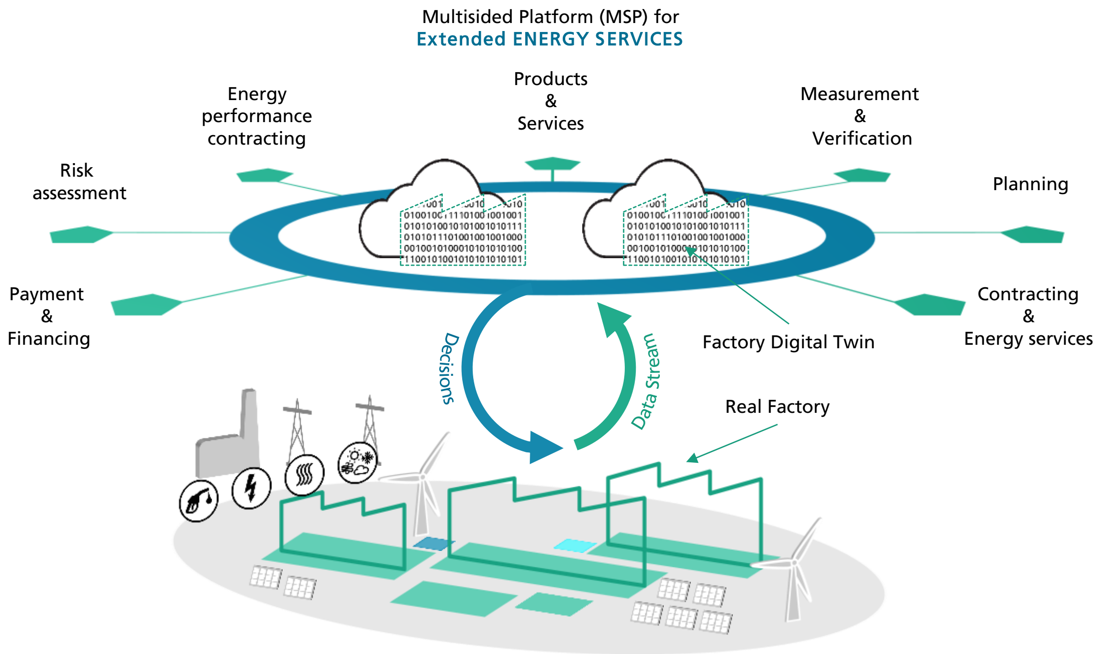


Figure 8-1 Connecting of factory simulation models to platform-driven services

Within this virtual representation, it is possible to compare the effects of different improvement measures (e.g., control strategies, retrofits, and equipment installations) before applying the results and insights to the real world. This also expands the current focus from optimized planning to the optimized and robust operation of factories, taking into account different production scenarios and changing environmental conditions. Improved data usage, model performance, and accuracy can further extend its use in platform-based services environments. Based on the current virtual representation of the factory, an expanded service portfolio can support companies in their efforts to achieve environmentally friendly, resource-saving, and low-emission manufacturing practices.

Table 8-1 summarizes the demand for future research and provides an assessment of its priority based on the author's experience during the research presented in this work.

Table 8-1 Summary of future research needs (priority: ∗∗∗ high, ∗∗ medium, ∗ low-priority)

	Factory simulation model		Assessment procedure
∗∗∗	Expanding the scope of the multi-peripheral factory model	∗∗∗	Extending existing manufacturing performance metrics
∗∗∗	Implementing data-driven modeling approaches	∗∗∗	Use of optimization algorithms
∗∗∗	Extension of multi-peripheral factory models toward digital twins	∗∗	Automated selection and execution of appropriate design of simulation experiments
∗∗	Detail and verify individual submodels	∗∗	Development and implementation of value stream-oriented energy metering systems
∗	Development of digital platforms and platform services	∗	Improve the usability when using complex multi-peripheral simulation models

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Abele et al. 2012 — Abele, Eberhard, Eisele, Christian & Schrems, Sebastian. Simulation of the Energy Consumption of Machine Tools for a Specific Production Task. *In:* Dornfeld, David A. & Linke, Barbara S., (eds.) 19th CIRP International Conference on Life Cycle Engineering - Leveraging Technology for a Sustainable World, 2012 Berkeley, California, USA. Springer, pp. 233-237. DOI: 10.1007/978-3-642-29069-5_40

ADEME 2017 — ADEME. 2017. Odyssee-Mure Project - Energy efficiency index ODEX by industry branch EU. Grenoble: Agency for Ecological Transition (ADEME). URL: http://www.odyssee-mure.eu/publications/efficiency-by-sector/industry/european-efficiency-trends.html [Accessed 11.05.2022].

AGEB 2018 — AGEB. 2018. Energieverbrauch in Deutschland im Jahr 2017. Berlin: Arbeitsgemeinschaft Energiebilanzen e. V. (AGEB). URL: https://ag-energiebilanzen.de/wp-content/uploads/2021/02/ageb_jahresbericht2017_20180315-02_dt.pdf. [Accessed 05.05.2022].

AGEE-Stat 2021 — AGEE-Stat. 2021. Zeitreihen zur Entwicklung der erneuerbaren Energien in Deutschland unter Verwendung von Daten der Arbeitsgruppe Erneuerbare Energien-Statistik (AGEE-Stat) (Stand: Februar 2021). Dessau-Roßlau: Umweltbundesamt (UBA) - Arbeitsgruppe Erneuerbare Energien-Statistik (AGEE-Stat). URL: https://www.erneuerbare-energien.de/EE/Navigation/DE/Service/Erneuerbare_Energien_in_Zahlen/Zeitreihen/zeitreihen.html [Accessed 05.05.2022].

Amara et al. 2015 — Amara, Fatima, Agbossou, Kodjo, Cardenas, Alben, Dub, Yves & Kelouwani, Sousso 2015. Comparison and Simulation of Building Thermal Models for Effective Energy Management. *Smart Grid and Renewable Energy*, **6** (4), pp. 95-112. DOI: 10.4236/sgre.2015.64009

Apostolos et al. 2013 — Apostolos, Fysikopoulos, Alexios, Papacharalampopoulos, Georgios, Pastras, Panagiotis, Stavropoulos & George, Chryssolouris 2013. Energy Efficiency of Manufacturing Processes: A Critical Review. *Procedia CIRP*, **7**, pp. 628-633. DOI: 10.1016/j.procir.2013.06.044

ASHRAE 2020 — ASHRAE. 2020. *ASHRAE IWEC2 Weather Files for International Locations* [Online]. URL: http://ashrae.whiteboxtechnologies.com/home [Accessed 17.08.2020].

Augenstein et al. 2005 — Augenstein, Eckardt, Herbergs, Stefan, Kuperjans, Isabel & Lucas, Klaus. Simulation of industrial energy supply systems with integrated cost optimization. *In:* Kjelstrup, Signe, (ed.) 18th International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, 2005 Trondheim, Norway. Tapir Academic Press, pp. 627-634.

Augenstein et al. 2004 — Augenstein, Eckardt, Wrobel, Gregor, Kuperjans, Isabel & Plessow, Matthias. Top-energy: computational support for energy system engineering processes. 1st International Conference from Scientific Computing to Computational Engineering (IC-SCCE), 2004 Athens, Greece.

BAFA 2019 — BAFA. 2019. *KWK-Anlagen* [Online]. URL: https://www.bafa.de/DE/Energie/Energieeffizienz/Kraft_Waerme_Kopplung/Stromverguetung/Stromverguetung_50_KW_bis_2_MW/stromverguetung_50_kw_bis_2_mw_node.html [Accessed 10.01.2020].

Bakshi et al. 2011 — Bakshi, Bhavik R., Gutowski, Timothy G. & Sekulić, Dušan P. 2011. Introduction. *In:* Bakshi, Bhavik R., Sekulić, Dušan P. & Gutowski, Timothy G. (eds.) *Thermodynamics and the Destruction of Resources.* Cambridge: Cambridge University Press, pp. 1-12. ISBN: 978-0-52188-455-6

Balci 1998a — Balci, Osman. Verification, validation, and accreditation. 1998 Winter Simulation Conference (WSC), 1998a Washington, DC, USA. IEEE, pp. 41-48. DOI: 10.1109/WSC.1998.744897

Balci 1998b — Balci, Osman 1998b. Verification, validation, and testing. *In:* Banks, Jerry (ed.) *Handbook of Simulation - Principles, Methodology, Advances, Application, and Practice.* 1st ed. Hoboken, New York: John Wiley & Sons, Inc., pp. 335-393. ISBN: 0-471-13403-1

Banks 2012 — Banks, Caterine M. 2012. Research and Analysis for Real-World Applications. *In:* Sokolowski, John A. & Banks, Catherine M. (eds.) *Handbook of Real-World Applications in Modeling and Simulation.* 1st ed. Hoboken, New York: John Wiley & Sons, Inc., pp. 8-25. ISBN: 978-1-11811-777-4

Banks 1998a — Banks, Jerry 1998a. *Handbook of Simulation - Principles, Methodology, Advances, Application, and Practice*. Hoboken, New York: John Wiley & Sons, Inc. ISBN: 0-471-13403-1

Banks 1998b — Banks, Jerry 1998b. Principles of Simulation. *In:* Banks, Jerry (ed.) *Handbook of Simulation - Principles, Methodology, Advances, Application, and Practice.* 1st ed. Hoboken, New York: John Wiley & Sons, Inc., pp. 3-30. ISBN: 0-471-13403-1

Banks et al. 2010 — Banks, Jerry, Carson, John S., Nelson, Barry L. & Nicol, David M. 2010. *Discrete-Event System Simulation*. Upper Saddle River, New Jersey: Pearson Education, Inc. ISBN: 978-0-13606-212-7

Barton 2013 — Barton, Russell R. Designing simulation experiments. 2013 Winter Simulations Conference (WSC), 2013 Washington, DC, USA. IEEE, pp. 342-353. DOI: 10.1109/WSC.2013.6721432

BAuA 2010 — Bundesanstalt für Arbeitsschutz und Arbeitsmedizin (BAuA), 2010. Technische Regeln für Arbeitsstätten - ASR A3.5 - Raumtemperatur.

BAuA 2012 — Bundesanstalt für Arbeitsschutz und Arbeitsmedizin (BAuA), 2012. Technische Regeln für Arbeitsstätten - ASR A3.6 - Lüftung.

BBSR 2011 — BBSR. 2011. Sustainable Buildings - Strategies, Methods, Practices. Bonn: Federal Insitute for Research on Building, Urban Affairs and Spatial Development. ISBN 978-3-87994-614-3. URL: https://www.bnb-nachhaltigesbauen.de/fileadmin/pdf/veroeffentlichungen/DL_8_2011.pdf [Accessed 09.05.2022].

BCG and Prognos 2018 — BCG & Prognos. 2018. Klimapfade für Deutschland. Gerbert, Philipp, Herhold, Patrick, Burchardt, Jens, Schönberger, Stefan, Rechenmacher, Florian, Kirchner, Almut, Kemmler, Andreas & Wünsch, Marco. München: Boston Consulting Group, Prognos. URL: https://www.prognos.com/de/projekt/klimapfade-fuer-deutschland [Accessed 09.05.2022].

Beck et al. 2018 — Beck, Hylke E., Zimmermann, Niklaus E., McVicar, Tim R., Vergopolan, Noemi, Berg, Alexis & Wood, Eric F. 2018. Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data*, **5**, pp. 1-12. DOI: 10.1038/sdata.2018.214

Beier 2017 — Beier, Jan. 2017. *Simulation Approach Towards Energy Flexible Manufacturing Systems.* Institut für Werkzeugmaschinen und Fertigungstechnik, Technische Universität Braunschweig. *In:* Sustainable Production, Life Cycle Engineering and Management. Springer International Publishing, Berlin, Heidelberg, Diss. DOI: 10.1007/978-3-319-46639-2.

Beier et al. 2016 — Beier, Jan, Neef, Benjamin, Thiede, Sebastian & Herrmann, Christoph 2016. Integrating on-site Renewable Electricity Generation into a Manufacturing System with Intermittent Battery Storage from Electric Vehicles. *Procedia CIRP*, **48**, pp. 483-488. DOI: 10.1016/j.procir.2016.04.057

Beier et al. 2015 — Beier, Jan, Thiede, Sebastian & Herrmann, Christoph 2015. Increasing Energy Flexibility of Manufacturing Systems through Flexible Compressed Air Generation. *Procedia CIRP*, **37**, pp. 18-23. DOI: 10.1016/j.procir.2015.08.063

Beier et al. 2017 — Beier, Jan, Thiede, Sebastian & Herrmann, Christoph 2017. Energy flexibility of manufacturing systems for variable renewable energy supply integration: Real-time control method and simulation. *Journal of Cleaner Production*, **141**, pp. 648-661. DOI: 10.1016/j.jclepro.2016.09.040

Biles 1984 — Biles, William E. Design of simulation experiments. *In:* Sheppard, Sallie, Pooch, Udo W. & Pegden, C. Dennis, (eds.) 1984 Winter Simulation Conference (WSC), 1984 Dallas, Texas, USA. IEEE, pp. 99-104.

Black 2000 — Black, J. T. 2000. Manufacturing Systems. *In:* Swamidass, P. M. (ed.) *Encyclopedia of Production and Manufacturing Management.* Boston, MA: Springer US, pp. 423-431. ISBN: 978-1-4020-0612-8

Bleicher et al. 2014 — Bleicher, Friedrich, Duer, Fabian, Leobner, Ines, Kovacic, Iva, Heinzl, Bernhard & Kastner, Wolfgang 2014. Co-simulation environment for optimizing energy efficiency in production systems. *CIRP Annals*, **63** (1), pp. 441-444. DOI: 10.1016/j.cirp.2014.03.122

Bloomberg 2017	Bloomberg 2017. The cost of carbon - where polluters pay. URL: https://www.bloomberg.com/quicktake/carbon-markets-2-0 [Accessed 06.07.2018].
BMWi 2016	BMWi. 2016. Die Energie der Zukunft - Fünfter Monitoring-Bericht zur Energiewende. Berlin: Bundesministerium für Wirtschaft und Energie (BMWi). URL: https://www.bmwk.de/Redaktion/DE/Publikationen/Energie/fuenfter-monitoring-bericht-energie-der-zukunft.html [Accessed 09.05.2022].
BMWi 2019	BMWi. 2019. Energiedaten: Gesamtausgabe. Berlin: Bundesministerium für Wirtschaft und Energie (BMWi). URL: https://www.bmwi.de/Redaktion/DE/Artikel/Energie/energiedaten-gesamtausgabe.html [Accessed 01.07.2021].
BMWi 2021a	BMWi. 2021a. Die Energie der Zukunft - Achter Monitoring-Bericht zur Energiewende. Berlin: Bundesministerium für Wirtschaft und Energie (BMWi). URL: https://www.bmwk.de/Redaktion/DE/Publikationen/Energie/achter-monitoring-bericht-energie-der-zukunft.html [Accessed 09.05.2022].
BMWi 2021b	BMWi. 2021b. *How does CO2 pricing actually work?* [Online]. URL: https://www.bmwi-energiewende.de/EWD/Redaktion/EN/Newsletter/2019/09/Meldung/direkt-account.html [Accessed 03.03.2021].
Bogner and Menz 2009	Bogner, Alexander & Menz, Wolfgang 2009. The Theory-Generating Expert Interview: Epistemological Interest, Forms of Knowledge, Interaction. *In:* Bogner, Alexander, Littig, Beate & Menz, Wolfgang (eds.) *Interviewing Experts.* London: Palgrave Macmillan, pp. 43-80. ISBN: 978-0-230-24427-6
Böhner 2013	Böhner, Johannes. 2013. *Ein Beitrag zur Energieeffizienzsteigerung in der Stückgutproduktion.* Lehrstuhl für Umweltgerechte Produktionstechnik, Universität Bayreuth. *In:* Fortschritte in Konstruktion und Produktion Forschungsbericht Band 26. Shaker Verlag, Aachen, Diss. ISBN: 978-3-8440-2189-9.
Boiral 2006	Boiral, Olivier 2006. Global Warming: Should Companies Adopt a Proactive Strategy? *Long Range Planning*, **39** (3), pp. 315-330. DOI: 10.1016/j.lrp.2006.07.002
Bonfig et al. 2014	Bonfig, Karl-Walter, Drahm, Wolfgang, Mágori, Valentin, Höcker, Rainer, Konzelmann, Uwe & Rieder, Alfred 2014. Sensorik zur Durchflussmessung. *In:* Tränkler, Hans-Rolf & Reindl, Leo (eds.) *Sensortechnik: Handbuch für Praxis und Wissenschaft.* Berlin, Heidelberg: Springer, pp. 793-901. ISBN: 978-3-642-29942-1
Boot-Handford et al. 2014	Boot-Handford, Matthew E, Abanades, Juan C, Anthony, Edward J, Blunt, Martin J, Brandani, Stefano, Mac Dowell, Niall, Fernández, José R, Ferrari, Maria-Chiara, Gross, Robert & Hallett, Jason P 2014. Carbon capture and storage update. *Energy & Environmental Science*, **7** (1), pp. 130-189. DOI: 10.1039/c3ee42350f
Borshchev and Filippov 2004	Borshchev, Andrei & Filippov, Alexei. From system dynamics and discrete event to practical agent based modeling: reasons, techniques, tools. 22nd International Conference of the System Dynamics Society, 25-29 July 2004, 2004 Oxford, England.

BP 2020	BP. 2020. BP Statistical Review of World Energy 69th Eidition. London: BP p.l.c. URL: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html [Accessed 09.05.2022].
Brade 2004	Brade, Dirk. 2004. *A generalized process for the verification and validation of models and simulation results.* Fakultät für Informatik, Universität der Bundeswehr München. Open Access, Neubiberg, Diss.
Bradke et al. 2002	Bradke, Harald, Eichhammer, Wolfgang, Schlomann, Barbara & Radgen, Peter 2002. Effiziente Energieanwendung. *In:* Rebhan, Eckhard (ed.) *Energiehandbuch: Gewinnung, Wandlung und Nutzung von Energie.* Berlin, Heidelberg: Springer, pp. 713-896. ISBN: 978-3-642-55451-3
Brecher et al. 2012	Brecher, Christian, Bäumler, Stephan, Jasper, David & Triebs, Johannes. Energy Efficient Cooling Systems for Machine Tools. *In:* Dornfeld, David A. & Linke, Barbara S., (eds.) 19th CIRP International Conference on Life Cycle Engineering - Leveraging Technology for a Sustainable World, 2012 Berkely, California, USA. Springer, pp. 239-244. DOI: 10.1007/978-3-642-29069-5_41
Brundage et al. 2014	Brundage, Michael P., Chang, Qing, Li, Yang, Xiao, Guoxian & Arinez, Jorge 2014. Energy Efficiency Management of an Integrated Serial Production Line and HVAC System. *IEEE Transactions on Automation Science and Engineering*, **11** (3), pp. 789-797. DOI: 10.1109/TASE.2013.2284915
Brunke 2017	Brunke, Jean Christian Ulf. 2017. *Energieeinsparpotenziale von energieintensiven Produktionsprozessen in Deutschland: eine Analyse mit Hilfe von Energieeinsparkostenkurven.* Institut für Energiewirtschaft und Rationale Energieanwendungen, Universität Stuttgart. Forschungsbericht Band 134. Open Access, Stuttgart, Diss. DOI: 10.18419/opus-9242. ISSN: 0938-1228.
Buchholz and Styczynski 2020	Buchholz, Bernd M. & Styczynski, Zbigniew A. 2020. Vision and Strategy for the Electricity Networks of the Future. *In:* Buchholz, Bernd M. & Styczynski, Zbigniew A. (eds.) *Smart Grids: Fundamentals and Technologies in Electric Power Systems of the future.* Berlin, Heidelberg: Springer, pp. 1-17. ISBN: 978-3-662-60930-9
Bundesnetzagentur 2019	Bundesnetzagentur. 2019. Monitoringbericht 2019. Bonn: Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen - Referat 603; Bundeskartellamt - Arbeitsgruppe Energie-Monitoring. URL: https://www.bundesnetzagentur.de/SharedDocs/Pressemitteilungen/DE/2019/20191127_Monitoringbericht.html [Accessed 09.05.2022].
Bundesnetzagentur 2020a	Bundesnetzagentur. 2020a. *EEG-Registerdaten und -Fördersätze* [Online]. URL: https://www.bundesnetzagentur.de/DE/Sachgebiete/ElektrizitaetundGas/Unternehmen_Institutionen/ErneuerbareEnergien/ZahlenDatenInformationen/EEG_Registerdaten/EEG_Registerdaten_node.html [Accessed 10.01.2020].

Bundesnetzagentur 2020b	Bundesnetzagentur. 2020b. *EEG-Umlage* [Online]. URL: https://www.bundesnetzagentur.de/SharedDocs/FAQs/DE/Sachgebiete/Energie/Verbraucher/Energielexikon/EEGUmlage.html [Accessed 10.01.2020].
Bunse et al. 2011	Bunse, Katharina, Vodicka, Matthias, Schönsleben, Paul, Brülhart, Marc & Ernst, Frank O. 2011. Integrating energy efficiency performance in production management – gap analysis between industrial needs and scientific literature. *Journal of Cleaner Production*, **19** (6–7), pp. 667–679. DOI: 10.1016/j.jclepro.2010.11.011
Cagno and Trianni 2013	Cagno, Enrico & Trianni, Andrea 2013. Exploring drivers for energy efficiency within small- and medium-sized enterprises: First evidences from Italian manufacturing enterprises. *Applied Energy*, **104**, pp. 276-285. DOI: 10.1016/j.apenergy.2012.10.053
Carbon Neutrality Coalition 2021	Carbon Neutrality Coalition. 2021. *The Declaration of the Carbon Neutrality Coalition* [Online]. URL: https://carbon-neutrality.global/ [Accessed 02.03.2021].
Cavazzuti 2013	Cavazzuti, Marco 2013. Design of Experiments. *Optimization Methods: From Theory to Design Scientific and Technological Aspects in Mechanics.* Berlin, Heidelberg: Springer, pp. 13-42. ISBN: 978-3-642-31187-1
Chalmers 2001	Chalmers, Alan F. 2001. Der Falsifikationismus. *In:* Bergemann, Niels & Altstötter-Gleich, Christine (eds.) *Wege der Wissenschaft: Einführung in die Wissenschaftstheorie.* Berlin, Heidelberg: Springer, pp. 51-62. ISBN: 978-3-662-10879-6
Chen et al. 2006	Chen, Victoria C. P., Tsui, Kwok-Leung, Barton, Russell R. & Meckesheimer, Martin 2006. A review on design, modeling and applications of computer experiments. *IIE Transactions*, **38** (4), pp. 273-291. DOI: 10.1080/07408170500232495
Chung 2004	Chung, Christopher A. 2004. *Simulation modeling handbook: a practical approach,* 1st ed. Boca Raton: CRC press. ISBN: 0-8493-1241-8
Coakley et al. 2014	Coakley, Daniel, Raftery, Paul & Keane, Marcus 2014. A review of methods to match building energy simulation models to measured data. *Renewable and Sustainable Energy Reviews*, **37**, pp. 123-141. DOI: 10.1016/j.rser.2014.05.007
Cosgrove et al. 2017	Cosgrove, John, Littlewood, John & Wilgeroth, Paul 2017. Development of a Holistic Method to Analyse the Consumption of Energy and Technical Services in Manufacturing Facilities. *In:* Littlewood, John, Spataru, Catalina, Howlett, Robert J. & Jain, Lakhmi C. (eds.) *Smart Energy Control Systems for Sustainable Buildings.* Cham: Springer International Publishing, pp. 199-224. ISBN: 978-3-319-52076-6
Crawley et al. 2008	Crawley, Drury B., Hand, Jon W., Kummert, Michaël & Griffith, Brent T. 2008. Contrasting the capabilities of building energy performance simulation programs. *Building and Environment*, **43** (4), pp. 661-673. DOI: 10.1016/j.buildenv.2006.10.027
Creswell 2017	Creswell, John W. 2017. *Research design: Qualitative, Quantitative, and Mixed Methods Approaches,* 5th ed. Los Angeles: SAGE Publications, Inc. ISBN: 978-1-4522-2609-5

Davé et al. 2015	Davé, Aanand, Ball, Peter, Salonitis, Konstantinos & Astfalck, Craig. Factory Eco-Efficiency Modelling: Framework Development and Testing. 2nd International Conference on Sustainable Design and Manufacturing (SDM 2015), 12-14 April 2015, 2015 Seville, Spain.
Davé et al. 2016	Davé, Aanand, Salonitis, Konstantinos, Ball, Peter, Adams, Mark & Morgan, David 2016. Factory Eco-Efficiency Modelling: Framework Application and Analysis. *Procedia CIRP*, **40**, pp. 214-219. DOI: 10.1016/j.procir.2016.01.105
Davis et al. 2018	Davis, Steven J., Lewis, Nathan S., Shaner, Matthew, Aggarwal, Sonia, Arent, Doug, Azevedo, Inês L., Benson, Sally M., Bradley, Thomas, Brouwer, Jack, Chiang, Yet-Ming, Clack, Christopher T. M., Cohen, Armond, Doig, Stephen, Edmonds, Jae, Fennell, Paul, Field, Christopher B., Hannegan, Bryan, Hodge, Bri-Mathias, Hoffert, Martin I., Ingersoll, Eric, Jaramillo, Paulina, Lackner, Klaus S., Mach, Katharine J., Mastrandrea, Michael, Ogden, Joan, Peterson, Per F., Sanchez, Daniel L., Sperling, Daniel, Stagner, Joseph, Trancik, Jessika E., Yang, Chi-Jen & Caldeira, Ken 2018. Net-zero emissions energy systems. *Science*, **360** (6396), pp. 1-9. DOI: 10.1126/science.aas9793
de Bruyn et al. 2020	de Bruyn, Sander, Jongsma, Chris, Kampman, Bettina, Görlach, Benjamin & Thie, Jan-Erik. 2020. Energy-intensive industries - Challenges and opportunities in energy transition. Luxembourg: Committee on Industry, Research and Energy (ITRE), Policy Department for Economic, Scientific and Quality of Life Policies, European Parliament. URL: https://cedelft.eu/publications/energy-intensive-industries-challenges-and-opportunities-in-the-energy-transition/ [Accessed 08.05.2022].
Deckel Maho Seebach GmbH 2014	Deckel Maho Seebach GmbH 2014. Kap. 17 - Technik Allgemein - Elektr. Verlustleistung Maschine - Wärmeabgabe. Seebach: Deckel Maho Seebach GmbH.
Dekkers 2015	Dekkers, Rob. Design and Evaluation of Research Methods. 23rd International Conference on Production Research (ICPR), 31 July 2015, 2015 Manila, Philippines. Adam Smith Business School/Scottish Research Group for Industrial Management, p. 53.
Dentel and Dietrich 2013	Dentel, Arno & Dietrich, Udo 2013. Thermische Behaglichkeit – Komfort in Gebäuden. *Dokumentation Primero – Komfort. Hamburg, HafenCity Universität, Institut für Energie und Gebäude.* URL: https://rom-umwelt-stiftung.de/wp-content/uploads/2006/02/Dokumentation_Thermische_Behaglichkeit.pdf [Accessed 08.05.2022].
Despeisse et al. 2013	Despeisse, Mélanie, Oates, Michael R. & Ball, Peter D. 2013. Sustainable manufacturing tactics and cross-functional factory modelling. *Journal of Cleaner Production*, **42**, pp. 31-41. DOI: 10.1016/j.jclepro.2012.11.008
DGUV 2010	Deutsche Gesetzliche Unfallversicherung e.V. (DGUV), 2010. BGI/GUV-I 7003 - Beurteilung des Raumklimas.

Diaz et al. 2012	Diaz, Rafael , Behr, Joshua G. & Tulpule, Mandar 2012. Business Process Modeling. *In:* Sokolowski, John A. & Banks, Catherine M. (eds.) *Handbook of Real-World Applications in Modeling and Simulation.* 1st ed. Hoboken, New York: John Wiley & Sons, Inc., pp. 207-260.
Dietmair and Verl 2009	Dietmair, Anton & Verl, Alexander 2009. A generic energy consumption model for decision making and energy efficiency optimisation in manufacturing. *International Journal of Sustainable Engineering*, **2** (2), pp. 123-133. DOI: 10.1080/19397030902947041
Dietrich et al. 2020	Dietrich, Bastian, Walther, Jessica, Weigold, Matthias & Abele, Eberhard 2020. Machine learning based very short term load forecasting of machine tools. *Applied Energy*, **276** (115440), pp. 1-11. DOI: 10.1016/j.apenergy.2020.115440
DIN EN 16247-1	DIN EN 16247-1:2012-10. Energy audits - Part 1: General requirements.
DIN EN 16798-3	DIN EN 16798-3:2017-11. Energy performance of buildings – Ventilation for buildings - Part 3: For non-residential buildings - Performance requirements for ventilation and room-conditioning systems.
DIN EN IEC 60904-3 2020	Deutsches Institut für Normung e.V., 2020. Photovoltaic devices - Part 3: Measurement principles for terrestrial photovoltaic (PV) solar devices with reference spectral irradiance data (IEC 60904-3:2019).
DIN EN ISO 7730	DIN EN ISO 7730:2006-05. Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria.
DIN EN ISO 50001	DIN EN ISO 50001:2018-12. Energy management systems – Requirements with guidance for use.
DIN EN ISO 164842	DIN EN ISO 164842:2004-10. Building automation and control systems (BACS) - Part 2: Hardware.
DIN V 18599-10	DIN V 18599-10:2018-09. Energy efficiency of buildings – Calculation of the net, final and primary energy demand for heating, cooling, ventilation, domestic hot water and lighting – Part 10: Boundary conditions of use, climatic data.
Dombrowski and Ernst 2014	Dombrowski, Uwe & Ernst, Stefan 2014. Effects of Climate Change on Factory Life Cycle. *Procedia CIRP*, **15**, pp. 337-342. DOI: 10.1016/j.procir.2014.06.012
Duflou et al. 2012	Duflou, Joost R., Sutherland, John W., Dornfeld, David, Herrmann, Christoph, Jeswiet, Jack, Kara, Sami, Hauschild, Michael & Kellens, Karel 2012. Towards energy and resource efficient manufacturing: A processes and systems approach. *CIRP Annals - Manufacturing Technology*, **61** (2), pp. 587–609. DOI: 10.1016/j.cirp.2012.05.002

Dunkelberg et al. 2018 — Dunkelberg, Heiko, Wagner, Johannes, Hannen, Conrad, Schlüter, B. Alexander, Phan, Long, Hesselbach, Jens & Lin, Cheng-Xian 2018. Optimization of the energy supply in the plastics industry to reduce the primary energy demand. *Journal of Cleaner Production*, **192**, pp. 790-800. DOI: 10.1016/j.jclepro.2018.04.254

DWD 2020 — DWD. 2020. *Climate Data Center* [Online]. URL: https://www.dwd.de/EN/ourservices/cdc_portal/cdc_portal.html [Accessed 17.08.2020].

Dyckhoff and Spengler 2010 — Dyckhoff, Harald & Spengler, Thomas Stefan 2010. *Produktionswirtschaft: Eine Einführung,* 3rd ed. Berlin, Heidelberg: Springer. ISBN: 978-3-642-13684-9

Dyllick and Tomczak 2009 — Dyllick, Thomas & Tomczak, Torsten 2009. Erkenntnistheoretische Basis der Marketingwissenschaft. *In:* Buber, Renate & Holzmüller, Hartmut H. (eds.) *Qualitative Marktforschung: Konzepte – Methoden – Analysen.* Wiesbaden: Gabler, pp. 65-79. ISBN: 978-3-8349-9441-7

E et al. 2018 — E, Jiaqiang, Han, Dandan, Qiu, An, Zhu, Hao, Deng, Yuanwang, Chen, Jingwei, Zhao, Xiaohuan, Zuo, Wei, Wang, Hongcai, Chen, Jianmei & Peng, Qingguo 2018. Orthogonal experimental design of liquid-cooling structure on the cooling effect of a liquid-cooled battery thermal management system. *Applied Thermal Engineering*, **132**, pp. 508-520. DOI: 10.1016/j.applthermaleng.2017.12.115

EEP 2017 — EEP. 2017. The Energy Efficiency Index (EEI) of the German Industry - 2017 Survey. Stuttgart: Institut für Energy Efficiency in Production (EEP), University of Stuttgart. URL: https://www.eep.uni-stuttgart.de/eei/archiv-aeltere-erhebungen/ [Accessed 11.05.2022].

EIA 2016 — EIA. 2016. International Energy Outlook 2016 With Projections to 2040. Conti, John, Holtberg, Paul, Diefenderfer, Jim, LaRose, Angelina, Turnure, James T & Westfall, Lynn. USDOE Energy Information Administration (EIA), Washington, DC (United States). Office of Energy Analysis. 10.2172/1296780. URL: https://www.osti.gov/biblio/1296780 [Accessed 11.05.2022].

EIA 2019 — EIA. 2019. International Energy Outlook 2019. Washington: U.S. Energy Information Administration, Office of Energy Analysis, U.S. Department of Energy. URL: https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf [Accessed 11.05.2022].

Eisenhauer et al. 2018 — Eisenhauer, Stefan, Reichart, Markus, Sauer, Alexander, Weckmann, Sebastian & Zimmernann, Fabian. 2018. Energieflexibilität in der Industrie: Eine Metastudie. Stuttgart, Germany: Institut für Energieeffizienz in der Produktion, Universität Stuttgart. URL: https://synergie-projekt.de/aus-synergie/downloads [Accessed 12.05.2022].

El-Emam and Özcan 2019 — El-Emam, Rami S. & Özcan, Hasan 2019. Comprehensive review on the techno-economics of sustainable large-scale clean hydrogen production. *Journal of Cleaner Production*, **220**, pp. 593-609. DOI: 10.1016/j.jclepro.2019.01.309

Emec et al. 2013a — Emec, Soner, Kuschke, Maren, Chemnitz, Moritz & Strunz, Kai. Potential for demand side management in automotive manufacturing. 4th IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), 2013a Copenhagen, Denmark. IEEE, pp. 1-5. DOI: 10.1109/ISGTEurope.2013.6695303

Emec et al. 2013b — Emec, Soner, Kuschke, Maren, Huber, FW., Stephan, R., Strunz, Kai & Seliger, Günther. Stochastic optimization method to schedule production steps according to volatile energy price. *In:* Seliger, Günther, (ed.) 11th Global Conference on Sustainable Manufacturing - Innovative Solutions, 23-25 September 2013, 2013b Berlin, Germany. Universitätsverlag der TU Berlin.

Engelmann 2009 — Engelmann, Jörg. 2009. *Methoden und Werkzeuge zur Planung und Gestaltung energieeffizienter Fabriken.* Institut für Betriebswirtschaft und Fabriksysteme, Technische Universität Chemnitz. Forschungsbericht Heft 71. Open Access, Chemnitz, Diss. ISSN 0947-2495.

ENOPA 2011 — ENOPA. 2011. ENOPA Energieeffizienz durch optimierte Abstimmung von Produktion und TGA: Abschlussbericht zum BMWi Förderprojekt. Martin, Lars, Hesselbach, Jens, Thiede, Sebastian & Herrmann, Christoph. Kassel: Universität Kassel. URL: not available [Accessed 13.08.2018].

EQUA 2020 — EQUA. 2020. *EQUE IDA ICE 4.8 - New developments* [Online]. URL: https://www.equa.se/en/ida-ice/what-is-new/highlights-in-4-8 [Accessed 18.08.2000].

Erlach 2009 — Erlach, Klaus 2009. *Energiewertstrom: der Weg zur energieeffizienten Fabrik*. Fraunhofer Verlag. ISBN: 978-3-8396-0010-8

Erlach 2013 — Erlach, Klaus 2013. *Value Stream Analysis*. Berlin, Heidelberg: Springer. ISBN: 978-3-642-12568-3

Erlach and Sheehan 2014 — Erlach, Klaus & Sheehan, Erin 2014. Die CO2-Wertstrom-Methode zur Steigerung von Energie-und Materialeffizienz in der Produktion. *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, **109** (9), pp. 655-658.

EU 2012 — European Parliament, 2012. Energy Efficiency Directive (2012/27/EU).

EU 2018a — European Parliament, 2018a. Energy Efficiency Directive (2018/2002/EU).

EU 2018b — European Parliament, 2018b. Renewable Energy Directive (2018/2001/EU).

EU 2019 — EU. 2019. Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions - The European Green Deal. Brussels: European Commission,. URL: https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1588580774040&uri=CELEX%3A52019DC0640 [Accessed 08.05.2022].

European Comission 2021 — European Comission. 2021. *EU Emissions Trading System (EU ETS)* [Online]. URL: https://ec.europa.eu/clima/policies/ets_en#tab-0-0 [Accessed 04.03.2021].

Fang et al. 2006 — Fang, Kai-Tai, Li, Runze & Sudjianto, Agus 2006. *Design and modeling for computer experiments*. CRC press. ISBN: 1-58488-546-7

Fang et al. 2011 — Fang, Kan, Uhan, Nelson, Zhao, Fu & Sutherland, John W. 2011. A new approach to scheduling in manufacturing for power consumption and carbon footprint reduction. *Journal of Manufacturing Systems*, **30** (4), pp. 234-240. DOI: 10.1016/j.jmsy.2011.08.004

Faulkner and Badurdeen 2014 — Faulkner, William & Badurdeen, Fazleena 2014. Sustainable Value Stream Mapping (Sus-VSM): methodology to visualize and assess manufacturing sustainability performance. *Journal of Cleaner Production*, **85**, pp. 8-18. DOI: 10.1016/j.jclepro.2014.05.042

Feder et al. 2015 — Feder, Florian, Erlach, Klaus, Hosak, Florian & Lepple, Helmut 2015. Der energieflexible und effiziente Energiewertstrom. *wt Werkstatttechnik online*, **105** (5-2015), pp. 313-318.

Feng et al. 2016 — Feng, Lujia, Mears, Laine, Beaufort, Cleveland & Schulte, Joerg 2016. Energy, economy, and environment analysis and optimization on manufacturing plant energy supply system. *Energy Conversion and Management*, **117**, pp. 454-465. DOI: 10.1016/j.enconman.2016.03.031

Feyerabend 1975 — Feyerabend, Paul 1975. *Against method: Outline of an anarchistic theory of knowledge*. London: Verso. ISBN: 0-86091-481-X

Fischer et al. 2015 — Fischer, Jan, Weinert, Nils & Herrmann, Christoph 2015. Method for Selecting Improvement Measures for Discrete Production Environments Using an Extended Energy Value Stream Model. *Procedia CIRP*, **26**, pp. 133-138. DOI: 10.1016/j.procir.2014.07.100

Flatau 2019 — Flatau, Roman. 2019. *Integrierte Bewertung interdependenter Energieeffizienzmaßnahmen: eine modellgestützte Analyse am Beispiel von Querschnittstechnologien.* Institut für Energiewirtschaft und Rationale Energieanwendungen, Universität Stuttgart. Forschungsbericht Band 141. Open Access, Stuttgart, Diss. DOI: 10.18419/opus-10707. ISSN: 0938-1228.

Fleiter et al. 2012 — Fleiter, Tobias, Hirzel, Simon & Worrell, Ernst 2012. The characteristics of energy-efficiency measures – a neglected dimension. *Energy Policy*, **51**, pp. 502-513. DOI: 10.1016/j.enpol.2012.08.054

Forbes 2019 — Forbes. 2019. 101 Companies Committed To Reducing Their Carbon Footprint. *Morgan, Blake*, 26.08.2019, Available: https://www.forbes.com/sites/blakemorgan/2019/08/26/101-companies-committed-to-reducing-their-carbon-footprint/ [Accessed 02.03.2021].

Fox 2008 — Fox, J. Nick 2008. Postpositivism. *In:* Given, Lisa M. (ed.) *The Sage encyclopedia of qualitative research methods.* Los Angeles: SAGE Publications, Inc., pp. 659-664. ISBN: 978-1-4129-4163-1

Fraunhofer ISI 2003 — Fraunhofer ISI. 2003. Druckluft effizient. Karlsruhe: Fraunhofer-Institut für Systemtechnik und Innovationsforschung. URL: http://druckluft-effizient.de/wp-content/uploads/2020/09/fakten-00-09.pdf [Accessed 08.05.2022].

Friedrichs 2000 — Friedrichs, Kay 2000. Integrale Gebäudeplanung. *In:* Schulte, Karl-Werner & Pierschke, Barbara (eds.) *Facilities Management.* Köln: Immobilien Informationsverlag Rudolf Müller, pp. 55-79. ISBN: 978-3-93268-729-7

Fuss and Beißert 2014 — Fuss, Emanuel & Beißert, Ulrike. Beitrag zur Energie- und Materialflusssimulation in Produktion und Logistik. 19. Magdeburger Logistiktage "Sichere und nachhaltige Logistik" 2014: Tagungsband im Rahmen der IFF-Wissenschaftstage, 25-26 Juni 2014, 2014 Magdeburg. Fraunhofer IFF, pp. 39-48.

Garwood et al. 2017 — Garwood, Tom Lloyd, Hughes, Ben Richard, Oates, Michael R, O'Connor, Dominic & Hughes, Ruby 2017. A review of energy simulation tools for the manufacturing sector. *Renewable and Sustainable Energy Reviews*, **81**, pp. 895-911.

Garwood et al. 2018 — Garwood, Tom Lloyd, Hughes, Ben Richard, Oates, Michael R., O'Connor, Dominic & Hughes, Ruby 2018. A review of energy simulation tools for the manufacturing sector. *Renewable and Sustainable Energy Reviews*, **81**, pp. 895-911. DOI: 10.1016/j.rser.2017.08.063

Gellings 2009 — Gellings, Clark W. 2009. *Efficient Use and Conservation of Energy - Volume I*. Oxford, United Kingdom: EOLSS Publishers Co. Ltd. ISBN: 978-1-84826-931-6

Giunta et al. 2003 — Giunta, Anthony, Wojtkiewicz, Steven & Eldred, Michael. Overview of modern design of experiments methods for computational simulations. 41st Aerospace Sciences Meeting and Exhibit, 6-9 January 2003, 2003 Reno, Nevada, USA. p. 649.

Gößling-Reisemann 2011 — Gößling-Reisemann, Stefan 2011. Entropy Production and Resource Consumption in Life-Cycle Assessments. *In:* Bakshi, Bhavik R., Sekulić, Dušan P. & Gutowski, Timothy G. (eds.) *Thermodynamics and the Destruction of Resources.* Cambridge: Cambridge University Press, pp. 265-291. ISBN: 978-0-52188-455-6

Gourlis and Kovacic 2016 — Gourlis, Georgios & Kovacic, Iva 2016. A study on building performance analysis for energy retrofit of existing industrial facilities. *Applied Energy*, **184**, pp. 1389-1399. DOI: 10.1016/j.apenergy.2016.03.104

Gourlis and Kovacic 2017 — Gourlis, Georgios & Kovacic, Iva 2017. Passive measures for preventing summer overheating in industrial buildings under consideration of varying manufacturing process loads. *Energy*, **137**, pp. 1175-1185. DOI: 10.1016/j.energy.2017.05.134

Gourlis and Kovacic 2020 — Gourlis, Georgios & Kovacic, Iva 2020. Energy efficient operation of industrial facilities: the role of the building in simulation-based optimization. *IOP Conference Series: Earth and Environmental Science*, **410** (012019), pp. 1-9. DOI: 10.1088/1755-1315/410/1/012019

Graßl 2015 — Graßl, Markus. 2015. *Bewertung der Energieflexibilität in der Produktion.* Lehrstuhl für Betriebswissenschaften und Montagetechnik am Institut für Werkzeugmaschinen und Betriebswissenschaften, Technische Universität München. Forschungsberichte IWB Band 300. Herbert Utz Verlag, München, Diss. ISBN: 978-3-8316-4476-6.

Graßl and Reinhart 2014	Graßl, Markus & Reinhart, Gunther 2014. Evaluating Measures for Adapting the Energy Demand of a Production System to Volatile Energy Prices. *Procedia CIRP*, **15**, pp. 129-134. DOI: 10.1016/j.procir.2014.06.081
Graßl et al. 2014	Graßl, Markus, Vikdahl, Erik & Reinhart, Gunther. A Petri-net Based Approach for Evaluating Energy Flexibility of Production Machines. *In:* Zaeh, F. Michael, (ed.) 5th International Conference on Changeable, Agile, Reconfigurable and Virtual Production (CARV 2013), 6-9 Oktober 2013, 2014 Munich, Germany. Springer International Publishing, pp. 303-308. DOI: 10.1007/978-3-319-02054-9_51
Gregor et al. 2008	Gregor, Milan, Hromada, Juraj & Matuszek, Jozef 2008. Digital Factory supported by simulation and metamodelling. *Applied Computer Science*, **4**, pp. 63-74.
Greinacher 2017	Greinacher, Sebastian. 2017. *Simulationsgestützte Mehrzieloptimierung schlanker und ressourceneffizienter Produktionssysteme.* Institut für Produktionstechnik, Fakultät für Maschinenbau, Karlsruher Institut für Technologie. Shaker Verlag, Aachen, Diss. ISBN: 978-3-8440-5316-6.
Greinacher et al. 2020	Greinacher, Sebastian, Overbeck, Leonard, Kuhnle, Andreas, Krahe, Carmen & Lanza, Gisela 2020. Multi-objective optimization of lean and resource efficient manufacturing systems. *Production Engineering*, **14** (2), pp. 165-176. DOI: 10.1007/s11740-019-00945-9
Gutowski et al. 2006	Gutowski, Timothy, Dahmus, Jeffrey & Thiriez, Alex. Electrical energy requirements for manufacturing processes. 13th CIRP International Conference on Life Cycle Engineering, 2006 Lueven, Belgium. pp. 623-638.
Gutowski et al. 2005	Gutowski, Timothy, Murphy, Cynthia, Allen, David, Bauer, Diana, Bras, Bert, Piwonka, Thomas, Sheng, Paul, Sutherland, John, Thurston, Deborah & Wolff, Egon 2005. Environmentally benign manufacturing: Observations from Japan, Europe and the United States. *Journal of Cleaner Production*, **13** (1), pp. 1-17. DOI: 10.1016/j.jclepro.2003.10.004
Haag 2013	Haag, Holger. 2013. *Eine Methodik zur modellbasierten Planung und Bewertung der Energieeffizienz in der Produktion.* Institut für Industrielle Fertigung und Fabrikbetrieb, Universität Stuttgart. *In:* Stuttgarter Beiträge zur Produktionsforschung Band 11. Fraunhofer Verlag, Stuttgart, Diss. ISBN: 978-3-8396-0547-9.
Hall and Roth 2003	Hall, Nick P. & Roth, Johna A. Non-energy benefits from commercial and industrial energy efficiency programs: Energy efficiency may not be the best story. Proceedings of the 2003 International Energy Program Evaluation Conference, 2003. pp. 689-702.
Hao et al. 2011	Hao, Liu, Qianchuan, Zhao, Weihua, Cao, Ningjian, Huang & Xiang, Zhao. Simulation based evaluation and optimization for energy consumption of a typical welding shop. 2011 International Conference on Automation Science and Engineering, 2011 Trieste, Italy. IEEE, pp. 660-665. DOI: 10.1109/CASE.2011.6042482

He et al. 2012 — He, Yan, Liu, Bo, Zhang, Xiaodong, Gao, Huai & Liu, Xuehui 2012. A modeling method of task-oriented energy consumption for machining manufacturing system. *Journal of Cleaner Production*, **23** (1), pp. 167-174. DOI: 10.1016/j.jclepro.2011.10.033

Heffron et al. 2020 — Heffron, Raphael, Körner, Marc-Fabian, Wagner, Jonathan, Weibelzahl, Martin & Fridgen, Gilbert 2020. Industrial demand-side flexibility: A key element of a just energy transition and industrial development. *Applied Energy*, **269** (115026), pp. 1-13. DOI: 10.1016/j.apenergy.2020.115026

Heilala et al. 2013 — Heilala, Juhani, Paju, Marja, Montonen, Jari, Ruusu, Reino, Sorli, Mikel, Armijo, Alberto, Bermell-Garcia, Pablo, Astwood, Simon & Quintana, Santiago. Discrete Part Manufacturing Energy Efficiency Improvements with Modelling and Simulation. *In:* Technology, IFIP Advances in Information and Communication, (ed.) IFIP WG 5.7 International Conference, APMS 24-26 September 2012, 2013 Rhodes, Greece. Springer Berlin Heidelberg, pp. 142-150. DOI: 10.1007/978-3-642-40352-1_19

Heilala et al. 2008 — Heilala, Juhani, Vatanen, Saija, Tonteri, Hannele, Montonen, Jari , Lind, Salla, Johansson, Björn & Stahre, Johan. Simulation-based sustainable manufacturing system design. 2008 Winter Simulation Conference (WSC), 2008 Miami, Florida, USA. IEEE, pp. 1922-1930. DOI: 10.1109/WSC.2008.4736284

Heinen et al. 2008 — Heinen, Tobias, Rimpau, Christoph & Wörn, Arno 2008. Wandlungsfähigkeit als Ziel der Produktionssystemgestaltung. *In:* Nyhuis, Peter, Reinhart, Gunther & Abele, Eberhard (eds.) *Wandlungsfähige Produktionssysteme - Heute die Industrie von morgen gestalten.* Garbsen: PZH Produktionstechnisches Zentrum GmbH, pp. 13-18. ISBN: 978-3-939026-96-9

Heinzl et al. 2018 — Heinzl, Bernhard, Raich, Philipp, Preyser, Franz & Kastner, Wolfgang 2018. Simulation-based Assessment of Energy Efficiency in Industry: Comparison of Hybrid Simulation Approaches. *IFAC-PapersOnLine*, **51** (2), pp. 689-694. DOI: 10.1016/j.ifacol.2018.03.117

Heinzl et al. 2013 — Heinzl, Bernhard, Rößler, Matthias, Popper, Niki, Leobner, Ines, Ponweiser, Karl, Kastner, Wolfgang, Dür, Fabian, Bleicher, Friedrich & Breitenecker, Felix. Interdisciplinary Strategies for Simulation-Based Optimization of Energy Efficiency in Production Facilities. 15th International Conference on Computer Modelling and Simulation (UKSim), 10-12 April 2013, 2013 Cambridge, UK. pp. 304-309. DOI: 10.1109/UKSim.2013.115

Henjes 2014 — Henjes, Jan 2014. Process Chain Design. *In:* Laperrière, Luc & Reinhart, Gunther (eds.) *CIRP Encyclopedia of Production Engineering.* Berlin, Heidelberg: Springer, pp. 975-978. ISBN: 978-3-642-20617-7

Hering et al. 2016 — Hering, Ekbert, Martin, Rolf & Stohrer, Martin 2016. Thermodynamik. *In:* Hering, Ekbert, Martin, Rolf, Stohrer, Martin & Käß, Hanno (eds.) *Physik für Ingenieure.* 12th ed. Berlin, Heidelberg: Springer, pp. 153-236. ISBN: 978-3-662-49355-7

Herrmann et al. 2014 — Herrmann, Christoph, Schmidt, Christopher, Kurle, Denis, Blume, Stefan & Thiede, Sebastian 2014. Sustainability in manufacturing and factories of the future. *International Journal of Precision Engineering and Manufacturing-Green Technology*, **1** (4), pp. 283-292. DOI: 10.1007/s40684-014-0034-z

Herrmann and Thiede 2009 — Herrmann, Christoph & Thiede, Sebastian 2009. Process chain simulation to foster energy efficiency in manufacturing. *CIRP Journal of Manufacturing Science and Technology*, **1** (4), pp. 221-229. DOI: 10.1016/j.cirpj.2009.06.005

Herrmann et al. 2011 — Herrmann, Christoph, Thiede, Sebastian, Kara, Sami & Hesselbach, Jens 2011. Energy oriented simulation of manufacturing systems – Concept and application. *CIRP Annals - Manufacturing Technology*, **60** (1), pp. 45–48. DOI: 10.1016/j.cirp.2011.03.127

Hesselbach 2012 — Hesselbach, Jens 2012. *Energie- und klimaeffiziente Produktion*. Wiesbaden: Vieweg+Teubner Verlag. ISBN: 978-3-8348-0448-8

Hesselbach et al. 2008 — Hesselbach, Jens, Herrmann, Christoph, Detzer, Rüdiger, Martin, Lars, Thiede, Sebastian & Lüdemann, Bruno. Energy Efficiency through optimized coordination of production and technical building services. 15th CIRP International Conference on Life Cycle Engineering, 2008 Sydney, Australia. pp. 624-628.

Hesselbach et al. 2009 — Hesselbach, Jens, Junge, Mark, Lang, Bastian, Mirciov, Sabine, Mostert, Clemens, Schlüter, Alexander & Weishaar, Georg-Hans. 2009. Praxisleitfaden - Energieeffizienz in der Produktion. HA Hessen Agentur GmbH. Wiesbaden: Hessisches Ministerium für Wirtschaft, Verkehr und Landesentwicklung. URL: http://upp-kassel.de/wp-content/uploads/2013/09/Praxisleitfaden-Energieeffizienz-in-der-Produktion.pdf [Accessed 09.05.2022].

Hileman et al. 2008 — Hileman, James, Katz, Jeremy B, Mantilla, José G & Fleming, Gregg. Payload fuel energy efficiency as a metric for aviation environmental performance. 26th International Congress of Aeronautical Sciences, 14-19 September 2008, 2008 Anchorage, Alaska, USA.

Hilliaho et al. 2015 — Hilliaho, Kimmo, Lahdensivu, Jukka & Vinha, Juha 2015. Glazed space thermal simulation with IDA-ICE 4.61 software—Suitability analysis with case study. *Energy and Buildings*, **89**, pp. 132-141. DOI: 10.1016/j.enbuild.2014.12.041

Hinker et al. 2018 — Hinker, Jonas, Wohlfahrt, Thomas, Drewing, Emily, Contreras Paredes, Sergio, Mayorga González, Daniel & Myrzik, Johanna 2018. Adaptable Energy Systems Integration by Modular, Standardized and Scalable System Architectures: Necessities and Prospects of Any Time Transition. *Energies*, **11** (3), p. 581. DOI: 10.3390/en11030581

Ho et al. 1993 — Ho, Nai Choon, Lee, Stephen Guan, Loh, Y. L. & Nee, Andrew Y.C. 1993. A Two-Stage Approach for Optimizing Simulation Experiments. *CIRP Annals*, **42** (1), pp. 501-504. DOI: 10.1016/S0007-8506(07)62495-0

Hopf 2016 — Hopf, Hendrik. 2016. *Methodik zur Fabriksystemmodellierung im Kontext von Energie- und Ressourceneffizienz.* Institut für Betriebswissenschaften und Fabriksysteme, Technischen Universität Chemnitz. Springer Fachmedien, Wiesbaden, Diss. DOI: 10.1007/978-3-658-11599-9. ISBN: 978-3-658-11599-9.

Huynh 2011 — Huynh, Thomas V. 2011. Orthogonal array experiment in systems engineering and architecting. *Systems Engineering*, **14** (2), pp. 208-222. DOI: 10.1002/sys.20172

IEA 2017 — IEA. 2017. World Energy Outlook 2017. Paris: International Energy Agency. ISBN: 978-92-64-28230-8. URL: https://www.iea.org/reports/world-energy-outlook-2017 [Accessed 11.05.2022].

INFO 2013a — INFO. 2013a. INFO - Interdisziplinäre Forschung zur Energieoptimierung in Fertigungsbetrieben. Dür, Fabian, Flatz, Thomas, Kovacic, Iva, Waltenberger, Linus , Wiegand, Diemar , Emrich, Stefan , Leobner, Ines , Bednar, Thomas , Eder, Katharina , Kastner, Wolfgang , Heinzl, Bernhard & Kiesel, Kristina. Wien: Technische Universität Wien. URL: http://www.projekt-info.org/endbericht/2013-09-30%20publizierbarer_endbericht_final.pdf [Accessed 23.02.2015].

INFO 2013b — INFO. 2013b. Roadmap - Energieeffiziente Fertigungsbetriebe. Bednar, Thomas, Bleicher, Friedrich , Dür, Fabian , Eder, Katharina , Emrich, Stefan , Flatz, Thomas, Heinzl, Bernhard , Kastner, Wolfgang , Kiesel, Kristina , Kovacic, Iva , Leobner, Ines , Orehounig, Kristina , Ponweiser, Karl , Waltenberger, Linus & Wiegand, Dietmar. Wien: Technische Universität Wien. URL: http://www.projekt-info.org/endbericht/2013-09-30%20publizierbarer_endbericht_final.pdf [Accessed 23.02.2015].

IPCC 2014 — IPCC. 2014. Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change. Pachauri, Rajendra K, Allen, Myles R, Barros, Vicente R, Broome, John, Cramer, Wolfgang, Christ, Renate, Church, John A, Clarke, Leon, Dahe, Qin & Dasgupta, Purnamita. Geneve: Intergovernmental Panel on Climate Change (IPCC). ISBN: 978-92-9169-143-2. URL: https://www.ipcc.ch/report/ar5/syr/ [Accessed 11.05.2022].

IRENA 2019 — IRENA. 2019. Time-of-use tariffs - Innovation landscape brief. Abu Dhabi: International Renewable Energy Agency. ISBN: 978-92-9260-115-7. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2019/Feb/IRENA_Innovation_ToU_tariffs_2019.pdf?la=en&hash=36658ADA8AA98677888DB2C184D1EE6A048C7470 [Accessed 11.05.2022].

ISO 1217 — ISO 1217:2009-07. Displacement compressors - Acceptance tests.

ISO 1217 AMD 1 — ISO 1217 AMD 1:2016-04. Displacement compressors - Acceptance tests - Amendment 1: Calculation of isentropic efficiency and relationship with specific energy.

Jarić et al. 2013 — Jarić, Marko, Budimir, Nikola, Pejanović, Milica & Svetel, Igor. A review of energy analysis simulation tools. TQM 2013, Proceedings of 7-th International Working Conference of Total Quality Management-Advanced and Intelligent approaches, 4-7 June 2013, 2013 Belgrade, Serbia. Mechanical Engineering Faculty, pp. 103-110.

Junge 2007 — Junge, Mark. 2007. *Simulationsgestützte Entwicklung und Optimierung einer energieeffizienten Produktionssteuerung.* Institut für Produktionstechnik und Logistik Universität Kassel. *In:* Produktion & Energie Band 1. kassel university press, Kassel, Diss. ISBN: 978-3-89958-301-9.

Kasikci 2018 — Kasikci, Ismail 2018. Spannungsänderung und Blindleistung. *In:* Kasikci, Ismail (ed.) *Planung von Elektroanlagen: Theorie, Vorschriften, Praxis.* 3rd ed. Berlin, Heidelberg: Springer, pp. 229-238. ISBN: 978-3-662-56427-1

Katunsky et al. 2013 — Katunsky, Dusan, Korjenic, Azra, Katunska, Jana, Lopusniak, Martin, Korjenic, Sinan & Doroudiani, Saeed 2013. Analysis of thermal energy demand and saving in industrial buildings: A case study in Slovakia. *Building and Environment*, **67**, pp. 138-146. DOI: 10.1016/j.buildenv.2013.05.014

Kellens 2013 — Kellens, Karel. 2013. *Energy and resource efficient manufacturing—unit process analysis and optimisation.* Faculty of Engineering Science - Department of Mechanical Engineering - Centre for Industrial Management, Traffic and Infrastructure, KU Leuven. Leuven, Diss. ISBN: 978-94-6018-765-0.

Kellens et al. 2013 — Kellens, Karel, Dewulf, Wim, Lauwers, Bert, Kruth, Jean-Pierre & Duflou, Joost R. 2013. Environmental Impact Reduction in Discrete Manufacturing: Examples for Non-Conventional Processes. *Procedia CIRP*, **6**, pp. 27-34. DOI: 10.1016/j.procir.2013.03.003

Keller 2018 — Keller, Fabian Karl. 2018. *Methodik zur energiebezugsorientierten Auftragsplanung.* Lehrstuhl für Betriebswissenschaften und Montagetechnik am Institut für Werkzeugmaschinen und Betriebswissenschaften, Technische Universität München. Forschungsberichte IWB Band 341. Herbert Utz Verlag, München, Diss. ISBN: 978-3-8316-4761-3.

Keller et al. 2016 — Keller, Fabian, Schultz, Cedric, Braunreuther, Stefan & Reinhart, Gunther 2016. Enabling Energy-Flexibility of Manufacturing Systems through New Approaches within Production Planning and Control. *Procedia CIRP*, **57**, pp. 752-757. DOI: 10.1016/j.procir.2016.11.130

Khattak 2016 — Khattak, Sanober Hassan. 2016. *An exergy based method for resource accounting in factories.* Institute of Energy and Sustainable Development, De Montfort University. Leicester, Diss.

Khattak et al. 2016 — Khattak, Sanober Hassan, Greenough, Richard, Korolija, Ivan & Brown, Neil 2016. An exergy based approach to resource accounting for factories. *Journal of Cleaner Production*, **121**, pp. 99-108. DOI: 10.1016/j.jclepro.2015.12.029

Khattak et al. 2018	Khattak, Sanober Hassan, Oates, Michael & Greenough, Rick 2018. Towards improved energy and resource management in manufacturing. *Energies*, **11** (4), pp. 1-15. DOI: 10.3390/en11041006
Khripko et al. 2018	Khripko, Diana, Dunkelberg, Heiko, Summerbell, Daniel L. & Hesselbach, Jens 2018. Energy Efficiency and demand side management: A case study of a holistic energy concept in polymer processing. *Procedia Manufacturing*, **21**, pp. 702-709. DOI: 10.1016/j.promfg.2018.02.174
Kirschbaum et al. 2008	Kirschbaum, Stefan, Jung, Johannes & Wrobel, Gregor. Multi-objective Approach to Analysis of Industrial Energy Systems. 21st International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems, 2008 Krakau-Gliwice, Polen. pp. 957-964.
Kleijnen et al. 2005	Kleijnen, Jack P. C., Sanchez, Sudsan M., Lucas, Thomas W. & Cioppa, Thomas M. 2005. A user's guide to the brave new world of designing simulation experiments. *INFORMS Journal on Computing*, **17** (No. 3), pp. 263–289. DOI: 10.1287/ijoc.1050.0136
Klein 2014	Klein, Bernd 2014. *Versuchsplanung-DoE: Einführung in die Taguchi/Shainin-Methodik,* 3rd ed.: Walter de Gruyter GmbH & Co KG. ISBN: 978-3-486-70684-0
Kleppmann 2016	Kleppmann, Wilhelm 2016. *Versuchsplanung: Produkte und Prozesse optimieren,* 9th ed.: Carl Hanser Verlag GmbH Co KG. ISBN: 978-3-446-44716-5
Koch et al. 2014	Koch, Nicolas, Fuss, Sabine, Grosjean, Godefroy & Edenhofer, Ottmar 2014. Causes of the EU ETS price drop: Recession, CDM, renewable policies or a bit of everything?—New evidence. *Energy Policy*, **73**, pp. 676-685. DOI: 10.1016/j.enpol.2014.06.024
Kordonowy 2002	Kordonowy, David N. 2002. *A Power Assessment of Machining Tools.* Mechanical Engineering, Massachusetts Institute of Technology. Cambridge, Bachelor Thesis.
Kories and Schmidt-Walter 2003	Kories, Ralf & Schmidt-Walter, Heinz 2003. Current, Voltage and Power Measurement. *In:* Kories, Ralf & Schmidt-Walter, Heinz (eds.) *Electrical Engineering: A Pocket Reference.* Berlin, Heidelberg: Springer, pp. 169-191. ISBN: 978-3-642-55629-6
Kossel et al. 2006	Kossel, Roland, Tegethoff, Wilhelm, Bodmann, Michael & Lemke, Nicholas. Simulation of complex systems using Modelica and tool coupling. 5th Modelica Conference, 2006 Vienna, Austria. pp. 485-490.
Kothari 2004	Kothari, Chakravanti Rajagopalachari 2004. *Research methodology: Methods and techniques,* 2nd ed.: New Age International. ISBN: 978-81-224-2488-1
Kramer et al. 2017	Kramer, Rick P., van Schijndel, A. W. M. & Schellen, Henk L. 2017. The importance of integrally simulating the building, HVAC and control systems, and occupants' impact for energy predictions of buildings including temperature and humidity control: validated case study museum Hermitage Amsterdam. *Journal of Building Performance Simulation*, **10** (3), pp. 272-293. DOI: 10.1080/19401493.2016.1221996

Kropf and Zweifel 2001 — Kropf, Sven & Zweifel, Gerhard 2001. Validation of the Building Simulation Program IDA-ICE According to CEN 13791 „Thermal Performance of Buildings-Calculation of Internal Temperatures of a Room in Summer Without Mechanical Cooling-General Criteria and Validation Procedures ". *Hochschule Technik+ Architektur Luzern. HLK Engineering*.

Kubicek 1977 — Kubicek, Herbert 1977. Heuristische Bezugsrahmen und heuristisch angelegte Forschungsdesign als Elemente einer Konstruktionsstrategie empirischer Forschung. *In:* Köhler, Richard (ed.) *Empirische und handlungstheoretische Forschungskonzeptionen in der Betriebswirtschaftslehre: Bericht über d. Tagung in Aachen, März 1976 / Komm. Wissenschaftstheorie im Verb. d. Hochschullehrer für Betriebswirtschaft.* Stuttgart: J. B. Metzlersche Verlagsbuchhandlung und Carl Ernst Poeschel Verlag GmbH, pp. 3-36. ISBN: 3-7910-0214-7

Kuhlmann 2020 — Kuhlmann, Timm. 2020. *Methode zur Gestaltung der energetischen Wandlungsfähigkeit in Fabriken.* Institut für Energieeffizienz in der Produktion, Universität Stuttgart. *In:* Stuttgarter Beiträge zur Produktionsforschung Band 102. Fraunhofer Verlag, Stuttgart, Diss. DOI: 10.18419/opus-10871. ISBN: 978-3-8396-1596-6.

Kuhn 1970 — Kuhn, Thomas 1970. *The structure of scientific revolutions,* 2nd ed. Chicago and London: University of Chicago Press. ISBN: 0-226-45803-2

Kujawski 2014 — Kujawski, Edouard 2014. Interaction Effects in the Design of Computer Simulation Experiments for Architecting Systems-of-Systems. *Systems Engineering*, **17** (4), pp. 426-441. DOI: 10.1111/sys.21280

Lam and Hui 1996 — Lam, Joseph C. & Hui, Sam C. M. 1996. Sensitivity analysis of energy performance of office buildings. *Building and Environment*, **31** (1), pp. 27-39. DOI: 10.1016/0360-1323(95)00031-3

Langeheinecke et al. 2017 — Langeheinecke, Klaus, Kaufmann, André, Langeheinecke, Kay & Thieleke, Gerd 2017. *Thermodynamik für Ingenieure: Ein Lehr- und Arbeitsbuch für das Studium,* 10th ed. Wiesbaden: Springer Fachmedien Wiesbaden. ISBN: 978-3-658-14300-8

Law 2015 — Law, Averill M. 2015. *Simulation modeling and analysis,* 5th ed. New York: McGraw-Hill Education. ISBN: 978-0-07-340132-4

Lehmann et al. 2016 — Lehmann, Christian, Weeber, Max, Böhner, Johannes & Steinhilper, Rolf 2016. Techno-economical Analysis of Photovoltaic-battery Storage Systems for Peak-shaving Applications and Self-consumption Optimization in Existing Production Plants. *Procedia CIRP*, **48**, pp. 313-318. DOI: 10.1016/j.procir.2016.03.017

Leobner et al. 2011 — Leobner, Ines, Ponweiser, Karl, Neugschwandtner, Georg & Kastner, Wolfgang. Energy efficient production - a holistic modeling approach. 2011 World Congress on Sustainable Technologies (WCST), 7-10 November 2011, 2011 London, UK. pp. 62-67.

Lerch 2007	Lerch, Reinhard 2007. Messung der elektrischen Leistung. *In:* Lerch, Reinhard (ed.) *Elektrische Messtechnik: Analoge, digitale und computergestützte Verfahren.* 4th ed. Berlin, Heidelberg: Springer, pp. 203-218. ISBN: 978-3-540-75727-6
Leutgöb et al. 2019	Leutgöb, Klemens, Amann, Christof, Tzovaras, Dimitrios & Ioannidis, Dimosthenis. New business models enabling higher flexibility on energy markets. *In:* (ECEEE), European Council for an Energy Efficient Economy, (ed.) ECEEE 2019 Summer Study, 3-8 Jun 2019, 2019 Belambra Presqu'île de Giens, France. DOI: 10.5281/zenodo.3706509
Liu et al. 2013	Liu, Hao, Zhao, Qianchuan, Huang, Ningjian & Zhao, Xiang 2013. A Simulation-Based Tool for Energy Efficient Building Design for a Class of Manufacturing Plants. *IEEE Transactions on Automation Science and Engineering*, **10** (1), pp. 117-123. DOI: 10.1109/TASE.2012.2203595
Löschel et al. 2015	Löschel, Andreas, Kaltenegger, Oliver & Baikowski, Martin 2015. Die Rolle der indirekten Energiekosten im deutschen Produzierenden Gewerbe. *Wirtschaftsdienst*, **95** (12), pp. 837-844.
Machalek and Powell 2019	Machalek, Derek & Powell, Kody 2019. Automated electrical demand peak leveling in a manufacturing facility with short term energy storage for smart grid participation. *Journal of Manufacturing Systems*, **52**, pp. 100-109. DOI: 10.1016/j.jmsy.2019.06.001
Malico et al. 2019	Malico, Isabel, Nepomuceno Pereira, Ricardo, Gonçalves, Ana Cristina & Sousa, Adélia M. O. 2019. Current status and future perspectives for energy production from solid biomass in the European industry. *Renewable and Sustainable Energy Reviews*, **112**, pp. 960-977. DOI: 10.1016/j.rser.2019.06.022
Maria 1997	Maria, Anu. Introduction to modeling and simulation. *In:* Andradóttir, Sigrún, Healy, Kevin J., Withers, David H. & Nelson, Barry L., (eds.) 1997 Winter Simulation Conference (WSC), 1997 Atlanta, Georgia, USA. IEEE Computer Society, pp. 7-13. DOI: 10.1145/268437.268440
Martin et al. 2012	Martin, Lars , Schäfer, Mirko , Schlüter, Alexander & Weisharr, Natalja 2012. Energieströme simulieren: Vom Prozess bis zur Fabrik. *In:* Hesselbach, Jens (ed.) *Energie- und klimaeffiziente Produktion.* Wiesbaden: Vieweg+Teubner Verlag, pp. 103-136. ISBN: 978-3-8348-0448-8
Martin et al. 2008	Martin, Lars, Hesselbach, Jens, Thiede, Sebastian, Herrmann, Christoph, Lüdemann, Bruno & Detzer, Rüdiger. Energieeffizienz durch optimierte Abstimmung zwischen Produktion und technischer Gebäudeausrüstung. *In:* Rabe, Markus, (ed.) 13th ASIM Conference on Simulation in Production and Logistics - Advances in Simulation for Production and Logistics Applications, 1-2 October 2008, 2008 Berlin, Germany. Fraunhofer IRB Verlag, pp. 121–129.
Mawson and Hughes 2019	Mawson, Victoria Jayne & Hughes, Ben Richard 2019. The development of modelling tools to improve energy efficiency in manufacturing processes and systems. *Journal of Manufacturing Systems*, **51**, pp. 95-105. DOI: 10.1016/j.jmsy.2019.04.008

May et al. 2016 — May, Gökan, Stahl, Bojan & Taisch, Marco 2016. Energy management in manufacturing: Toward eco-factories of the future – A focus group study. *Applied Energy*, **164**, pp. 628-638. DOI: 10.1016/j.apenergy.2015.11.044

Meteotest AG 2020 — Meteotest AG. 2020. *Meteonorm 7.3.4* [Online]. URL: https://meteonorm.com/download [Accessed 17.08.2020].

Meyer 1978 — Meyer 1978. *Meyers Enzyklopädisches Lexikon*. Mannheim: Bibliographisches Institut.

Michaloski et al. 2011 — Michaloski, John L., Shao, Guodong, Arinez, Jorge, Lyons, Kevin, Leong, Swee & Riddick, Frank. Analysis of sustainable manufacturing using simulation for integration of production and building service. Symposium on Simulation for Architecture and Urban Design (SimAUD '11), 2011 Boston, Massachusetts, USA. Society for Computer Simulation International, pp. 93-101. DOI: 10.5555/2048536.2048548

Mill 1843 — Mill, John Stuart 1843. *A system of logic, ratiocinative and inductive: Being a connected view of the principles of evidence and the methods of scientific investigation*. London, UK: John W. Parker.

Mitsubishi 2020 — Mitsubishi. 2020. *Partial load chiller efficiency* [Online]. URL: https://innovations.mitsubishi-les.com/en/chiller/e-series [Accessed 06.04.2020].

Montgomery 2001 — Montgomery, Douglas C 2001. *Design and analysis of experiments,* 5th ed. New York: John Wiley & Sons. ISBN: 0-471-31649-0

Mose and Weinert 2015 — Mose, Christian & Weinert, Nils 2015. Process chain evaluation for an overall optimization of energy efficiency in manufacturing—The welding case. *Robotics and Computer-Integrated Manufacturing*, **34**, pp. 44–51. DOI: 10.1016/j.rcim.2014.12.011

Mourtzis et al. 2014 — Mourtzis, Dimitris, Doukas, Michael & Bernidaki, Dimitra 2014. Simulation in Manufacturing: Review and Challenges. *Procedia CIRP*, **25**, pp. 213-229. DOI: 10.1016/j.procir.2014.10.032

Mousavi et al. 2016 — Mousavi, Smaeil, Thiede, Sebastian, Li, Wen, Kara, Sami & Herrmann, Christoph 2016. An integrated approach for improving energy efficiency of manufacturing process chains. *International Journal of Sustainable Engineering*, **9** (1), pp. 11-24. DOI: 10.1080/19397038.2014.1001470

Moynihan and Triantafillu 2012 — Moynihan, Gary P. & Triantafillu, Dimos 2012. Energy Savings for a Manufacturing Facility Using Building Simulation Modeling: A Case Study. *Engineering Management Journal*, **24** (4), pp. 73-84. DOI: 10.1080/10429247.2012.11431957

Müller et al. 2009 — Müller, Egon, Engelmann, Jörg, Löffler, Thomas & Strauch, Jörg 2009. *Energieeffiziente Fabriken planen und betreiben*. Heidelberg: Springer. ISBN: 978-3-540-89643-2

Nageler et al. 2018 — Nageler, Peter, Schweiger, Gerald, Pichler, Martin, Brandl, Daniel, Mach, Tomasz, Heimrath, Richard, Schranzhofer, Hermann & Hochenauer, Christoph 2018. Validation of dynamic building energy simulation tools based on a real test-box with thermally activated building systems (TABS). *Energy and Buildings*, **168**, pp. 42-55. DOI: 10.1016/j.enbuild.2018.03.025

National Research Council 2005 — National Research Council 2005. APPENDIX D Definitions of Basic, Applied, and Fundamental Research. *In:* National Research Council (ed.) *Assessment of Department of Defense Basic Research.* Washington, DC: The National Academies Press, p. 70. ISBN: 978-0-309-09443-6

Nehler 2018 — Nehler, Therese 2018. A Systematic Literature Review of Methods for Improved Utilisation of the Non-Energy Benefits of Industrial Energy Efficiency. *Energies*, **11** (12), p. 3241. DOI: 10.3390/en11123241

Nehler and Rasmussen 2016 — Nehler, Therese & Rasmussen, Josefine 2016. How do firms consider non-energy benefits? Empirical findings on energy-efficiency investments in Swedish industry. *Journal of Cleaner Production*, **113**, pp. 472-482. DOI: 10.1016/j.jclepro.2015.11.070

O'Driscoll and O'Donnell 2013 — O'Driscoll, Eoin & O'Donnell, Garret E. 2013. Industrial power and energy metering – a state-of-the-art review. *Journal of Cleaner Production*, **41**, pp. 53–64. DOI: 10.1016/j.jclepro.2012.09.046

Oates 2013 — Oates, Michael. 2013. *A new approach to modelling process and building energy flows in manufacturing industry.* Institute of Energy and Sustainable Development, De Montfort University. Open Access, Leicester, Diss.

Oates et al. 2011 — Oates, Michael R., Wright, Andrew, Greenough, Richard & Shao, Li. A new modelling approach which combines energy flows in manufacturing with those in a factory building. Proceedings of Building Simulation 2011: 12th Conference of International Building Performance Simulation Association, 2011 Sydney, Australia. pp. 223-230.

Obara and Morel 2017 — Obara, Shin'ya & Morel, Jorge 2017. *Clean energy microgrids*. Stevenage, United Kingdom: Institution of Engineering & Technology. ISBN: 978-1-78561-097-4

OECD 2015 — OECD 2015. *Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development, The Measurement of Scientific, Technological and Innovation Activities*. Paris: OECD Publishing. ISBN: 978-926423901-2

Ohno 1988 — Ohno, Taiichi 1988. *Toyota production system: beyond large-scale production,* 1st ed. New York: Productivity Press. ISBN: 978-0-91529-914-0

Ohno 1993 — Ohno, Taiichi 1993. *Das Toyota-Produktionssystem,* 1st ed. Frankfurt a. M.: Campus. ISBN: 978-3-59334-946-6

Oldewurtel et al. 2012 — Oldewurtel, Frauke, Parisio, Alessandra, Jones, Colin N., Gyalistras, Dimitrios, Gwerder, Markus, Stauch, Vanessa, Lehmann, Beat & Morari, Manfred 2012. Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, **45**, pp. 15-27. DOI: 10.1016/j.enbuild.2011.09.022

Park et al. 2020 — Park, Yoon Soo, Konge, Lars & Artino, Anthony R. 2020. The positivism paradigm of research. *Academic Medicine*, **95** (5), pp. 690-694. DOI: 10.1097/ACM.0000000000003093

Patterson 1996 — Patterson, Murray G. 1996. What is energy efficiency?: Concepts, indicators and methodological issues. *Energy Policy*, **24** (5), pp. 377-390. DOI: 10.1016/0301-4215(96)00017-1

Pehnt 2010 — Pehnt, Martin 2010. *Energieeffizienz,* 1st ed. Heidelbarg: Springer. ISBN: 978-3-642-14250-5

Phylipsen et al. 1997 — Phylipsen, Gerardina Josephina Maria, Blok, Kornelis & Worrell, Ernst 1997. International comparisons of energy efficiency-Methodologies for the manufacturing industry. *Energy Policy*, **25** (7), pp. 715-725. DOI: 10.1016/S0301-4215(97)00063-3

Plaßmann and Schulz 2009 — Plaßmann, Wilfried & Schulz, Detlef 2009. Grundlagen der Elektrotechnik. *In:* Plaßmann, Wilfried & Schulz, Detlef (eds.) *Handbuch Elektrotechnik: Grundlagen und Anwendungen für Elektrotechniker.* Wiesbaden: Vieweg+Teubner Verlag, pp. 253-317. ISBN: 978-3-8348-9245-4

Pohl et al. 2012 — Pohl, Christoph, Schevalje, Christoph & Hesselbach, Jens 2012. Grüne Druckluft durch Wärmerückgewinnung. *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, **107** (10), pp. 736-740.

Pohl et al. 2013 — Pohl, Christoph, Schevalje, Christoph & Hesselbach, Jens 2013. Energetische Simulation - Ein effektives Werkzeug zur Identifikation von Optimierungspotenzialen in Druckluftnetzen. *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, **108** (3), pp. 137-142.

Popp et al. 2017 — Popp, Richard S. H., Liebl, Corinna & Zäh, Michael F. 2017. Evaluation of the Energy Flexible Operation of Machine Tool Components. *Procedia CIRP*, **63**, pp. 76-81. DOI: 10.1016/j.procir.2017.02.037

Popper 1935 — Popper, Karl 1935. *Logik der Forschung*. Wien: Springer-Verlag Wien GmbH. ISBN: 978-3-7091-2021-7

Popper 1969 — Popper, Karl R. 1969. Die Logik der Sozialwissenschaften. *Kölner Zeitschrift für Soziologie und Sozialpsychologie*, **14** (2), pp. 233-248.

Posselt et al. 2014 — Posselt, Gerrit, Fischer, Jan, Heinemann, Tim, Thiede, Sebastian, Alvandi, Samira, Weinert, Nils, Kara, Sami & Herrmann, Christoph 2014. Extending Energy Value Stream Models by the TBS Dimension – Applied on a Multi Product Process Chain in the Railway Industry. *Procedia CIRP*, **15**, pp. 80-85. DOI: 10.1016/j.procir.2014.06.067

Pritsker 1998 — Pritsker, A. Alan B. 1998. Principles of Simulation Modeling. *In:* Banks, Jerry (ed.) *Handbook of Simulation - Principles, Methodology, Advances, Application, and Practice.* First Edition ed. Hoboken, New York: John Wiley & Sons, Inc., pp. 31-51. ISBN: 0-471-13403-1

Probst and Schnell 1993 — Probst, Stefan & Schnell, Gerhard 1993. Durchflußmessung. *In:* Schnell, Gerhard (ed.) *Sensoren in der Automatisierungstechnik.* Wiesbaden: Vieweg+Teubner Verlag, pp. 193-208. ISBN: 978-3-528-13370-2

Puls et al. 2019 — Puls, Philipp, Lange, Christopher & Öchsner, Richard 2019. Hybrid Cooling Towers in a Free-Cooling Application: Modeling and Field Measurement Verification. *Chemical Engineering & Technology*, **42** (9), pp. 1871-1878. DOI: 10.1002/ceat.201800712

Puls et al. 2015 — Puls, Philipp, Linhardt, Simon & Öchsner, Richard. Entwicklung von Betriebsstrategien zur Verbesserung der Effizienz von Kälteversorgungssystemen mit thermischen Speichern. *In:* Schulz, Detlef, (ed.) Nachhaltige Energieversorgung und Integration von Energiespeichern (NEIS) 2015, 2015 Hamburg. Springer Fachmedien Wiesbaden, pp. 166-171. DOI: 10.1007/978-3-658-10958-5_26

Pye and McKane 2000 — Pye, Miriam & McKane, Aimee 2000. Making a stronger case for industrial energy efficiency by quantifying non-energy benefits. *Resources, Conservation and Recycling*, **28** (3), pp. 171-183. DOI: 10.1016/S0921-3449(99)00042-7

Quaschning and Hanitsch 1998 — Quaschning, Volker & Hanitsch, Rolf. Höhere Flächenausbeute durch Optimierung bei aufgeständerten Modulen. Proceedings of the Symposium Photovoltaische Solarenergie, Staffelstein, Germany, 11-13 March 1998, 1998 Staffelstein, Germany. pp. 11-13.

Race to Zero 2021 — Race to Zero. 2021. *The new normal: 1,000 companies aligned with science* [Online]. URL: https://racetozero.unfccc.int/the-new-normal-1000-companies-are-now-setting-science-based-climate-targets/ [Accessed 02.03.2021].

Rahäuser 2015 — Rahäuser, Raphael. 2015. *Energieeffizienter Betrieb von Kühlschmierstoff-Reinigungsanlagen mit Anschwemmfiltern.* Institut für Steuerungstechnik der Werkzeugmaschinen und Fertigungseinrichtungen, Universität Stuttgart. *In:* Stuttgarter Beiträge zur Produktionsforschung Band 52. Fraunhofer Verlag, Stuttgart, Diss. DOI: 10.18419/opus-8809. ISBN: 978-3-8396-1016-9.

Raich et al. 2016 — Raich, Philipp, Heinzl, Bernhard, Preyser, Franz & Kastner, Wolfgang. Modeling techniques for integrated simulation of industrial systems based on hybrid PDEVS. 2016 Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES), 11 April 2016, 2016 Vienna, Austria. pp. 1-6. DOI: 10.1109/MSCPES.2016.7480221

Rambhujun et al. 2020 — Rambhujun, Nigel, Salman, Muhammad Saad, Wang, Ting, Pratthana, Chulaluck, Sapkota, Prabal, Costalin, Mehdi, Lai, Qiwen & Aguey-Zinsou, Kondo-Francois 2020. Renewable hydrogen for the chemical industry. *MRS Energy & Sustainability*, **7**, pp. 1-16. DOI: 10.1557/mre.2020.33

Rasmussen 2014 — Rasmussen, Josefine. Energy-efficiency investments and the concepts of non-energy benefits and investment behaviour. ECEEE 2014, Industrial Summer Study: Retool for a competitive and sustainable industry, June 2-5, 2014, , 2-5 June 2014, 2014 Arnhem, Netherlands. European Council for an Energy Efficient Economy (ECEEE), pp. 733-744.

Reinhart 2000 — Reinhart, Gunther 2000. Simulation — ein Experiment am digitalen Modell. *In:* Feldmann, Klaus & Reinhart, Gunther (eds.) *Simulationsbasierte Planungssysteme für Organisation und Produktion: Modellaufbau, Simulationsexperimente, Einsatzbeispiele.* Berlin, Heidelberg: Springer, pp. 13-30. ISBN: 978-3-662-42587-9

Reinhart et al. 2011	Reinhart, Gunther, Karl, Florian, Krebs, Pascal, Maier, Tobias, Niehues, Klemens, Niehues, Michael & Reinhardt, Saskia 2011. Energiewertstromdesign: Ein wichtiger Bestandteil zum Erhöhen der Energieproduktivität. *wt Werkstattstechnik online, 101, 253*, **260**, pp. 253-260.
Reinhart et al. 2010	Reinhart, Gunther, Karl, Florian, Krebs, Pascal & Reinhardt, Saskia 2010. Energiewertstrom - Eine Methode zur ganzheitlichen Erhöhung der Energieproduktivität. *ZWF: Zeitschrift für Wirtschaftlichen Fabrikbetrieb*, **105** (10), pp. 870-875.
Rieberer et al. 2015	Rieberer, René, Zotter, Gerald, Hannl, David, Moser, Harald, Kotenko, Oleksander, Zottel, Andreas, Fleckl, Thomas & Malenkovic, Ivan. 2015. IEA Heat Pump Programme Annex 35: Anwendungsmöglichkeiten für industrielle Wärmepumpen. Wien: Bundesministerium für Verkehr,, Innovation und Technologie. URL: https://nachhaltigwirtschaften.at/de/iea/publikationen/iea-hpp-annex-35-application-of-industrial-heat-pumps.php [Accessed 11.05.2022].
Robson and McCartan 2016	Robson, Colin & McCartan, Kieran 2016. *Real world research: a resource for users of social research methods in applied settings,* 4th ed. Chichester, United Kingdom: John Wiley & Sons. ISBN: 9781119144854
Rubel and Kottek 2010	Rubel, Franz & Kottek, Markus 2010. Observed and projected climate shifts 1901-2100 depicted by world maps of the Köppen-Geiger climate classification. *Meteorologische Zeitschrift*, **19** (2), pp. 135-141. DOI: 10.1127/0941-2948/2010/0430
Saaty 2008	Saaty, Thomas L. 2008. Decision making with the analytic hierarchy process. *International Journal of Services Sciences*, **1** (1), pp. 83-98. DOI: 10.1504/IJSSCI.2008.017590
Sacks et al. 1989	Sacks, Jerome, Welch, William J., Mitchell, Toby J. & Wynn, Henry P. 1989. Design and analysis of computer experiments. *Statistical Science*, **4** (4), pp. 409-423.
Sahlin et al. 2004	Sahlin, Per, Eriksson, Lars, Grozman, Pavel, Johnsson, Hans, Shapovalov, Alexander & Vuolle, Mika 2004. Whole-building simulation with symbolic DAE equations and general purpose solvers. *Building and Environment*, **39** (8), pp. 949-958. DOI: 10.1016/j.buildenv.2004.01.019
Saidur et al. 2010	Saidur, R., Rahim, N. A. & Hasanuzzaman, M. 2010. A review on compressed-air energy use and energy savings. *Renewable and Sustainable Energy Reviews*, **14** (4), pp. 1135–1153. DOI: 10.1016/j.rser.2009.11.013
Saltelli et al. 2008	Saltelli, Andrea, Ratto, Marco, Andres, Terry, Campolongo, Francesca, Cariboni, Jessica, Gatelli, Debora, Saisana, Michaela & Tarantola, Stefano 2008. *Global sensitivity analysis: the primer*. Chichester, UK: John Wiley & Sons. ISBN: 978-0-470-05997-5
Sanchez 2005	Sanchez, Susan M. Work smarter, not harder: guidelines for designing simulation experiments. 2005 Winter Simulation Conference (WSC), 2005 Monterey, California, USA. IEEE, pp. 69-82. DOI: 10.1109/WSC.2005.1574241

Santner et al. 2018	Santner, Thomas J., Williams, Brian J. & Notz, William I. 2018. *The Design and Analysis of Computer Experiments,* 2nd ed. New York: Springer. ISBN: 978-1-4757-3799-8
Sauer and Bauernhansl 2016	Sauer, Alexander & Bauernhansl, Thomas 2016. *Energieeffizienz in Deutschland - eine Metastudie: Analyse und Empfehlungen,* 2nd ed. Berlin: Springer. ISBN: 978-3-662-48882-9
Sauer et al. 2019	Sauer, Alexander, Reichart, Markus, Zimmermann, Fabian, Weckmann, Sebastian, Eisenhauer, Stefan, Tristan, Alejandro, Krings, Bettina-Johanna & Nierling, Linda 2019. Das Energieflexibilitätspotential der deutschen Industrie. *In:* Sauer, Alexander, Abele, Eberhard & Buhl, Hans Ulrich (eds.) *Energieflexibilität in der deutschen Industrie: Ergebnisse aus dem Kopernikus-Projekt-Synchronisierte und energieadaptive Produktionstechnik zur flexiblen Ausrichtung von Industrieprozessen auf eine fluktuierende Energieversorgung (SynErgie).* Stuttgart: Fraunhofer Verlag. ISBN: 978-3-8396-1479-2
Schäfer et al. 2012	Schäfer, Mirko, Wagner, Johannes, Schlüter, Alexander & Hesselbach, Jens 2012. Energy flows in industrial buildings and machines using the example of a node model. *SNE Simulation News Europe, SNE*, **22** (1), p. 2012.
Schemme et al. 2020	Schemme, Steffen, Breuer, Janos Lucian, Köller, Maximilian, Meschede, Sven, Walman, Fiona, Samsun, Remzi Can, Peters, Ralf & Stolten, Detlef 2020. H2-based synthetic fuels: A techno-economic comparison of alcohol, ether and hydrocarbon production. *International Journal of Hydrogen Energy*, **45** (8), pp. 5395-5414. DOI: 10.1016/j.ijhydene.2019.05.028
Schenk et al. 2014	Schenk, Michael, Müller, Egon & Wirth, Siegfried 2014. *Fabrikplanung und Fabrikbetrieb: Methoden für die wandlungsfähige, vernetzte und ressourceneffiziente Fabrik,* 2nd ed. Berlin, Heidelberg: Springer. ISBN: 978-3-642-05458-7
Schenk and Wirth 2004	Schenk, Michael & Wirth, Siegfried 2004. *Fabrikplanung und Fabrikbetrieb: Methoden für die wandlungsfähige und vernetzte Fabrik*. Berlin, Heidelberg: Springer. ISBN: 978-3-540-35046-0
Schlüter et al. 2011	Schlüter, Alexander, Schäfer, Mirko, Wagner, Johannes, Schrodt, Alexander & Hesselbach, Jens 2011. Simulation von Maschinen und Anlagen als thermische Lasten in der Produktion. *ZWF Zeitschrift für wirtschaftlichen Fabrikbetrieb*, **106** (5), pp. 346-351.
Schönemann 2017	Schönemann, Malte. 2017. *Multiscale Simulation Approach for Battery Production Systems.* Institut für Werkzeugmaschinen und Fertigungstechnik, Technische Universität Braunschweig. *In:* Sustainable Production, Life Cycle Engineering and Management. Springer International Publishing, Berlin, Heidelberg, Diss. DOI: 10.1007/978-3-319-49367-1. ISBN: 978-3-319-49367-1.
Schönemann et al. 2019	Schönemann, Malte, Bockholt, Henrike, Thiede, Sebastian, Kwade, Arno & Herrmann, Christoph 2019. Multiscale simulation approach for production systems. *The International Journal of Advanced Manufacturing Technology*, **102**, pp. 1373–1390. DOI: 10.1007/s00170-018-3054-y

Schramek and Recknagel 2011	Schramek, Ernst-Rudolf & Recknagel, Hermann 2011. *Taschenbuch für Heizung+ Klimatechnik 2011/2012,* 75th ed. München: Oldenbourg Industrieverlag. ISBN: 978-3-8356-3200-4
Schülein and Reitze 2021	Schülein, Johann August & Reitze, Simon 2021. *Wissenschaftstheorie für Einsteiger,* 5th ed. Stuttgart: UTB. ISBN: 978-3-8252-5675-3
Schultz 2002	Schultz, Axel. 2002. *Methode zur integrierten ökologischen und ökonomischen Bewertung von Produktionsprozessen und-technologien.* Fakultät Maschinenbau, Otto-von-Buericke-Universität Magdeburg. Open Access, Magdeburg, Diss. DOI: 10.25673/4978.
Seidl 2017	Seidl, Hannes 2017. Energieeffiziente Querschnittstechnologien. *In:* Matzen, Frank J. & Tesch, Ralf (eds.) *Industrielle Energiestrategie: Praxishandbuch für Entscheider des produzierenden Gewerbes.* Wiesbaden: Springer Fachmedien, pp. 275-300. ISBN: 978-3-658-07606-1
Shang et al. 2004	Shang, Jen S., Li, Shanling & Tadikamalla, Pandu 2004. Operational design of a supply chain system using the Taguchi method, response surface methodology, simulation, and optimization. *International Journal of Production Research*, **42** (18), pp. 3823-3849. DOI: 10.1080/00207540410001704050
Shin and Haberl 2019	Shin, Minjae & Haberl, Jeff S. 2019. Thermal zoning for building HVAC design and energy simulation: A literature review. *Energy and Buildings*, **203**, pp. 1-14. DOI: 10.1016/j.enbuild.2019.109429
Siebertz et al. 2017	Siebertz, Karl, Bebber, David van & Hochkirchen, Thomas 2017. *Statistische Versuchsplanung: Design of Experiments (DoE),* 2nd ed. Berlin: Springer. ISBN: 978-3-662-55742-6
Siemens 1999	Siemens Building Technologies AG - Landis & Staefa Division, 1999. Grafische Symbole der Anlagenelemente für Lüftung und Klima.
Sihn et al. 2018	Sihn, Wilfried, Sobottka, Thomas, Heinzl, Bernhard & Kamhuber, Felix 2018. Interdisciplinary multi-criteria optimization using hybrid simulation to pursue energy efficiency through production planning. *CIRP Annals*, **67** (1), pp. 447-450. DOI: 10.1016/j.cirp.2018.04.059
Simpson et al. 1997	Simpson, Timothy W., Peplinski, Jesse D., Koch, Patrick N. & Allen, Janet K. On the use of statistics in design and the implications for deterministic computer experiments. ASME Design Engineering Technical Conferences (DETC), 14-17 September 1997 1997 Sacramento, California, USA. pp. 14-17. DOI: 10.1115/DETC97/DTM-3881
Simpson et al. 2001	Simpson, Timothy W., Poplinski, Jesse D., Koch, Patrick N. & Allen, Janet K. 2001. Metamodels for computer-based engineering design: survey and recommendations. *Engineering with Computers*, **17** (2), pp. 129-150. DOI: 10.1007/PL00007198

Smolek et al. 2018	Smolek, Peter, Leobner, Ines, Gourlis, Georgios, Mörzinger, Benjamin, Heinzl, Bernhard & Ponweiser, Karl 2018. Hybrid Building Performance Simulation Models for Industrial Energy Efficiency Applications. *Journal of Sustainable Development of Energy, Water and Environment Systems*, **6** (2), pp. 381-393. DOI: 10.13044/j.sdewes.d6.0194
Sobottka et al. 2018	Sobottka, Thomas, Kamhuber, Felix, Rössler, Matthias & Sihn, Wilfried 2018. Hybrid simulation-based optimization of discrete parts manufacturing to increase energy efficiency and productivity. *Procedia Manufacturing*, **21**, pp. 413-420. DOI: 10.1016/j.promfg.2018.02.139
Song 2016	Song, Tian 2016. An Impossible Ideal: The Use and Misuse of Zero Waste. *In:* Mauch, Christof (ed.) *A future without waste? Zero Waste in Theory and Practice.* Munich: RCC Perspectives - Transformations in Environment and Society, pp. 15-25.
Stahl et al. 2013	Stahl, Bojan, Taisch, Marco, Cannata, Alessandro, Müller, Florian, Thiede, Sebastian, Herrmann, Christoph, Cataldo, Andrea & Antonio, Franco Cavadini. Combined Energy, Material and Building Simulation for Green Factory Planning. *In:* Nee, Andrew Y. C., Song, Bin & Ong, Soh-Khim, (eds.) 20th CIRP International Conference on Life Cycle Engineering, 17-19 April 2013, 2013 Singapore. Springer, pp. 493-498. DOI: 10.1007/978-981-4451-48-2_80
Steffen and Bausch 2007	Steffen, Horst & Bausch, Hansjürgen 2007. *Elektrotechnik: Grundlagen,* 6th ed. Wiesbaden: Teubner. ISBN: 978-3-8351-9095-5
Steffen et al. 2015	Steffen, Will, Broadgate, Wendy, Deutsch, Lisa, Gaffney, Owen & Ludwig, Cornelia 2015. The trajectory of the Anthropocene: The Great Acceleration. *The Anthropocene Review*, **2** (1), pp. 81-98. DOI: 10.1177/2053019614564785
Steinhilper et al. 2017	Steinhilper, Rolf, Weeber, Max, Lehmann, Christian, Christian, Bay, Küfner, Thomas, Thorenz, Benjamin & Böhner, Johannes. 2017. Die Energieeffiziente Fabrik - Wechselwirkungen von Produktkion und Technischer Gebäudeausrüstung. bayme - Bayerischer Unternehmensverband Metall und Elektro e. V. & vbm - Verband der Bayerischen Metall- und Elektro-Industrie e. V. München: Universität Bayreuth - Lehrstuhl für Umweltgerechte Produktionstechnik, Fraunhofer Projektgruppe Regenerative Produktion. URL: https://eref.uni-bayreuth.de/id/eprint/67628 [Accessed 11.05.2022].
Stoldt et al. 2015	Stoldt, Johannes, Franz, Enrico, Schlegel, Andreas & Putz, Matthias 2015. Resource Networks: Decentralised Factory Operation Utilising Renewable Energy Sources. *Procedia CIRP*, **26**, pp. 486-491. DOI: 10.1016/j.procir.2014.07.154
Su 2016	Su, Chao-Ton 2016. *Quality engineering: off-line methods and applications*. Boca Raton: CRC press. ISBN: 978-1-46656-948-5
Sun et al. 2015	Sun, Zeyi, Li, Lin, Bego, Andres & Dababneh, Fadwa 2015. Customer-side electricity load management for sustainable manufacturing systems utilizing combined heat and power generation system. *International Journal of Production Economics*, **165**, pp. 112-119. DOI: 10.1016/j.ijpe.2015.04.002

Sun et al. 2016 | Sun, Zeyi, Li, Lin & Dababneh, Fadwa 2016. Plant-level electricity demand response for combined manufacturing system and heating, venting, and air-conditioning (HVAC) system. *Journal of Cleaner Production*, **135**, pp. 1650-1657. DOI: 10.1016/j.jclepro.2015.12.098

Taguchi 1987 | Taguchi, Genichi 1987. *System of experimental design; engineering methods to optimize quality and minimize costs,* 1st ed. New York UNIPUB/Kraus International Publications. ISBN: 978-0-52791-621-3

The World Bank 2021 | The World Bank. 2021. *Carbon Pricing Dashboard* [Online]. URL: https://carbonpricingdashboard.worldbank.org/ [Accessed 02.03.2021].

The World Bank and Ecofys 2017 | The World Bank & Ecofys. 2017. Carbon Pricing Watch 2017. Washington: World Bank. ISBN: 978-1-4648-1129-6. URL: http://hdl.handle.net/10986/26565 [Accessed 11.05.2022].

Thiede 2012 | Thiede, Sebastian. 2012. *Energy efficiency in manufacturing systems.* Institut für Werkzeugmaschinen und Fertigungstechnik, Technische Universität Braunschweig. *In:* Sustainable Production, Life Cycle Engineering and Management. Springer International Publishing, Berlin, Heidelberg, Diss. DOI: 10.1007/978-3-642-25914-2. ISBN: 978-3-642-25913-5.

Thiede et al. 2012 | Thiede, Sebastian, Bogdanski, Gerrit & Herrmann, Christoph 2012. A Systematic Method for Increasing the Energy and Resource Efficiency in Manufacturing Companies. *Procedia CIRP*, **2**, pp. 28-33. DOI: 10.1016/j.procir.2012.05.034

Thiede et al. 2016 | Thiede, Sebastian, Schönemann, Malte, Kurle, Denis & Herrmann, Christoph 2016. Multi-level simulation in manufacturing companies: The water-energy nexus case. *Journal of Cleaner Production*, **139**, pp. 1118-1127. DOI: 10.1016/j.jclepro.2016.08.144

Trianni et al. 2014 | Trianni, Andrea, Cagno, Enrico & De Donatis, Alessio 2014. A framework to characterize energy efficiency measures. *Applied Energy*, **118**, pp. 207-220. DOI: 10.1016/j.apenergy.2013.12.042

UBA 2015 | UBA. 2015. Emissionshandel in Zahlen. Berlin: Deutsche Emissionshandelsstelle (DEHSt). URL: https://www.dehst.de/SharedDocs/downloads/DE/publikationen/Broschuere_EH-in-Zahlen.pdf?__blob=publicationFile&v=1 [Accessed 11.05.2022].

UBA 2020 | UBA. 2020. Endenergieproduktivität. Dessau-Roßlau: Umweltbundesamt (UBA). URL: https://www.umweltbundesamt.de/daten/umweltindikatoren/indikator-endenergieproduktivitaet#die-wichtigsten-fakten [Accessed 11.05.2022].

Ulrich 2001 | Ulrich, Hans 2001. *Systemorientiertes Management: das Werk von Hans Ulrich*. St. Gallen, Schweiz: Haupt. ISBN: 978-3-25806-359-1

UN 2015 | UN. 2015. Paris Agreement. Paris: United Nations. URL: https://unfccc.int/process/conferences/pastconferences/paris-climate-change-conference-november-2015/paris-agreement [Accessed 11.05.2022].

UN 2017	UN. 2017. World Population Prospects: The 2017 revision - Key findings & advances tables 2017. New York: United Nations, Department of Economic and Social Affairs - Population Division. URL: https://population.un.org/wpp/Publications/Files/WPP2017_KeyFindings.pdf [Accessed 11.05.2022].
UNEP 2011	UNEP. 2011. Decoupling natural resource use and environmental impacts from economic growth. A Report of the Working Group on Decoupling to the International Resource Panel. Fischer-Kowalski, Marina;, Swilling, Mark;, von Weizsäcker, Ernst Ulrich;, Ren, Yong;, Moriguchi, Yuichi;, Crane, Wendy;, Krausmann, Fridolin;, Eisenmenger, Nina;, Giljum, Stefan;, Hennicke, Peter;, Romero Lankao, Paty;, Siriban Manalang, Anna Bella; & Sewerin, Sebastian;. Paris: United Nations Environment Programme. International Resource Panel. ISBN: 978-92-807-3167-5. URL: https://www.resourcepanel.org/reports/decoupling-natural-resource-use-and-environmental-impacts-economic-growth [Accessed 11.05.2022].
Upadhya et al. 2011	Upadhya, A. R., Dayananda, G. N., Kamalakannan, G. M., Ramaswamy Setty, J. & Christopher Daniel, J. 2011. Autoclaves for Aerospace Applications: Issues and Challenges. *International Journal of Aerospace Engineering*, **2011**, pp. 1-11. DOI: 10.1155/2011/985871
VDI 2067	VDI 2067:2013-06. Economic efficiency of building installations - Fundamentals and economic calculation.
VDI 2221	VDI 2221:1993-05. Systematic approach to the development and design of technical systems and products.
VDI 3633	VDI 3633 Part 1:2014-12. Simulation of systems in materials handling, logistics and production - Fundamentals.
VDI 3802	VDI 3802 Part 1 u. 2: 2014-09. Air conditioning systems for factories.
VDI 3922	VDI 3922:1998-06. Energy Consulting for Industry and Business.
VDI 4465	VDI 4465 Part 1:2016-05. Modelling and simulation - Building the model.
VDI 4608	VDI 4608 Part 1:2005-03. Energy systems - Combined heat and power, Terms, defintions, examples.
VDI 5200	VDI 5200 Part 1:2011-02. Factory planning - Planning procedures.
Voll et al. 2015	Voll, Philip, Jennings, Mark, Hennen, Maike, Shah, Nilay & Bardow, André 2015. The optimum is not enough: A near-optimal solution paradigm for energy systems synthesis. *Energy*, **82**, pp. 446-456. DOI: 10.1016/j.energy.2015.01.055
Wagner 2015	Wagner, Andreas 2015. Energieversorgung mit PV-Anlagen. *In:* Wagner, Andreas (ed.) *Photovoltaik Engineering: Handbuch für Planung, Entwicklung und Anwendung.* 4th ed. Berlin, Heidelberg: Springer, pp. 177-196. ISBN: 978-3-662-48640-5

Wang et al. 2009 Wang, Jiang-Jiang, Jing, You-Yin, Zhang, Chun-Fa & Zhao, Jun-Hong 2009. Review on multi-criteria decision analysis aid in sustainable energy decision-making. *Renewable and Sustainable Energy Reviews*, **13** (9), pp. 2263-2278. DOI: 10.1016/j.rser.2009.06.021

Weeber et al. 2018 Weeber, Max, Ghisi, Enedir & Sauer, Alexander 2018. Applying Energy Building Simulation in the Assessment of Energy Efficiency Measures in Factories. *Procedia CIRP*, **69**, pp. 336-341. DOI: 10.1016/j.procir.2017.11.148

Weeber et al. 2017 Weeber, Max, Lehmann, Christian, Böhner, Johannes & Steinhilper, Rolf 2017. Augmenting Energy Flexibility in the Factory Environment. *Procedia CIRP*, **61**, pp. 434-439. DOI: 10.1016/j.procir.2016.12.004

Weeber and Sauer 2018 Weeber, Max & Sauer, Alexander 2018. Total Energy Planning – A Working Paper. *Procedia CIRP*, **72**, pp. 820-825. DOI: 10.1016/j.procir.2018.03.286

Weinert 2010 Weinert, Nils. 2010. *Vorgehensweise für Planung und Betrieb energieeffizienter Produktionssysteme.* Institut für Werkzeugmaschinen und Fabrikbetrieb, Technische Universität Berlin. *In:* Berichte aus dem Produktionstechnischen Zentrum. Fraunhofer Verlag, Berlin, Diss. ISBN: 978-3-83960-173-0.

Weinert et al. 2011 Weinert, Nils, Chiotellis, Stylianos & Seliger, Günther 2011. Methodology for planning and operating energy-efficient production systems. *CIRP Annals - Manufacturing Technology*, **60** (1), pp. 41–44. DOI: 10.1016/j.cirp.2011.03.015

Weissenberger-Eibl et al. 2014 Weissenberger-Eibl, Marion A., Bradke, Harald, Walz, Rainer, Schröter, Marcus & Ziegaus, Sebastian 2014. Energie- und Rohstoffpolitik. *In:* Neugebauer, Reimund (ed.) *Handbuch Ressourcenorientierte Produktion.* München: Hanser, pp. 3-25. ISBN: 978-3-446-43008-2

Westkämper and Hummel 2009 Westkämper, Engelbert & Hummel, Vera 2009. Grundlagen des Stuttgarter Unternehmensmodells. *In:* Westkämper, Engelbert & Zahn, Erich (eds.) *Wandlungsfähige Produktionsunternehmen: Das Stuttgarter Unternehmensmodell.* Berlin, Heidelberg: Springer, pp. 47-66. ISBN: 978-3-540-68890-7

Wetter 2005 Wetter, Michael 2005. BuildOpt—a new building energy simulation program that is built on smooth models. *Building and Environment*, **40** (8), pp. 1085-1092. DOI: 10.1016/j.buildenv.2004.10.003

Wetter 2009 Wetter, Michael 2009. Modelica-based modelling and simulation to support research and development in building energy and control systems. *Journal of Building Performance Simulation*, **2** (2), pp. 143-161. DOI: 10.1080/19401490902818259

Wetter 2011 Wetter, Michael 2011. Co-simulation of building energy and control systems with the Building Controls Virtual Test Bed. *Journal of Building Performance Simulation*, **4** (3), pp. 185-203. DOI: 10.1080/19401493.2010.518631

Wiendahl 1999	Wiendahl, Hans-Peter 1999. Fabrikplanung - Grundlagen der Fabrikplanung. *In:* Eversheim, Walter & Schuh, Günther (eds.) *Produktion und Management 3: Gestaltung von Produktionssystemen.* Berlin, Heidelberg: Springer, pp. 1-31. ISBN: 978-3-642-58399-5
Wiendahl et al. 2007	Wiendahl, Hans-Peter, ElMaraghy, Hoda A., Nyhuis, Peter, Zäh, Michael F., Wiendahl, Hans Hermann, Duffie, Neil A. & Brieke, Michael 2007. Changeable Manufacturing - Classification, Design and Operation. *CIRP Annals*, **56** (2), pp. 783-809. DOI: 10.1016/j.cirp.2007.10.003
Wiendahl et al. 2015	Wiendahl, Hans-Peter, Reichardt, Jürgen & Nyhuis, Peter 2015. *Handbook Factory Planning and Design*. Berlin: Springer. ISBN: 978-3-662-46391-8
Wilberforce et al. 2021	Wilberforce, Tabbi, Olabi, A. G., Sayed, Enas Taha, Elsaid, Khaled & Abdelkareem, Mohammad Ali 2021. Progress in carbon capture technologies. *Science of The Total Environment*, **761** (143203), pp. 1-11. DOI: 10.1016/j.scitotenv.2020.143203
Wirth et al. 2000	Wirth, S., Günther, U. & David, T. 2000. Durchgängiges Planungskonzept mit ganzheitlicher simulationsbasierter Layoutplanung. *Vortragsband "Vernetzt planen und produzieren", TU Chemnitz.*
Wirth 1990	Wirth, Siegfried 1990. *Flexible Fertigungssysteme: Gestaltung und Anwendung in der Teilefertigung*. Berlin, Heidelberg: VEB Verlag Technik, Hütig Buch Verlag. ISBN: 3-7785-1850-X
WMO and GAW 2017	WMO & GAW. 2017. WMO Greenhouse Gas Bulletin -The State of Greenhouse Gases in the Atmosphere Based on Global Observations through 2016 - No. 16. Geneve, Tokyo: World Meteorological Organization, Global Atmosphere Watch. ISSN 2078-0796. URL: https://library.wmo.int/index.php?lvl=notice_display&id=20041 [Accessed 11.05.2022].
Worrell 2010	Worrell, Ernst 2010. The Next Frontier in Industrial Energy Efficiency. pp. 1-15.
Worrell et al. 2003	Worrell, Ernst, Laitner, John A., Ruth, Michael & Finman, Hodayah 2003. Productivity benefits of industrial energy efficiency measures. *Energy*, **28** (11), pp. 1081–1098. DOI: 10.1016/S0360-5442(03)00091-4
Wright et al. 2013	Wright, Andrew John, Oates, Michael R. & Greenough, Richard 2013. Concepts for dynamic modelling of energy-related flows in manufacturing. *Applied Energy*, **112**, pp. 1342-1348. DOI: 10.1016/j.apenergy.2013.01.056
Yingjie 2014	Yingjie, Zhang 2014. Energy efficiency techniques in machining process: a review. *The International Journal of Advanced Manufacturing Technology*, **71** (5-8), pp. 1123-1132. DOI: 10.1007/s00170-013-5551-3
Yu and Chan 2007	Yu, Fu-Wing & Chan, Kwoktai 2007. Part load performance of air-cooled centrifugal chillers with variable speed condenser fan control. *Building and Environment*, **42** (11), pp. 3816-3829. DOI: 10.1016/j.buildenv.2006.11.029

Zein 2012

Zein, André. 2012. *Transition towards energy efficient machine tools.* Institut für Werkzeugmaschinen und Fertigungstechnik, Technische Universität Braunschweig. *In:* Sustainable Production, Life Cycle Engineering and Management. Springer International Publishing, Berlin, Heidelberg, Diss.
DOI: 10.1007/978-3-642-32247-1. ISBN: 978-3-642-32246-4.

Appendix

A1 Detailed simulation results

Table 8-2 L_{18} orthogonal array

		factors							
	L_{18}	A	B	C	D	E	F	G	H
simulation runs	s1	1	1	1	1	1	1	1	1
	s2	1	1	2	2	2	2	2	2
	s3	1	1	3	3	3	3	3	3
	s4	1	2	1	1	2	2	3	3
	s5	1	2	2	2	3	3	1	1
	s6	1	2	3	3	1	1	2	2
	s7	1	3	1	2	1	3	2	3
	s8	1	3	2	3	2	1	3	1
	s9	1	3	3	1	3	2	1	2
	s10	2	1	1	3	3	2	2	1
	s11	2	1	2	1	1	3	3	2
	s12	2	1	3	2	2	1	1	3
	s13	2	2	1	2	3	1	3	2
	s14	2	2	2	3	1	2	1	3
	s15	2	2	3	1	2	3	2	1
	s16	2	3	1	3	2	3	1	2
	s17	2	3	2	1	3	1	2	3
	s18	2	3	3	2	1	2	3	1

Table 8-3 L_{18} orthogonal array – results

	results		energy demand	PPM	humidity outside range	temperature outside range
	L_{18}		MWh	%	%	%
simulation runs	s1	f_{s1}	4702,08	35,57	20,64	1,42
	s2	f_{s2}	7584,81	32,17	39,90	14,93
	s3	f_{s3}	2066,60	34,73	21,37	0,73
	s4	f_{s4}	3036,14	34,08	49,34	0,37
	s5	f_{s5}	2594,43	31,73	49,54	0,11
	s6	f_{s6}	3825,77	39,80	46,52	21,08
	s7	f_{s7}	4145,40	31,42	3,07	0,23
	s8	f_{s8}	2146,75	27,47	12,40	0,90
	s9	f_{s9}	8110,59	51,54	14,58	12,26
	s10	f_{s10}	2209,17	28,94	73,00	3,22
	s11	f_{s11}	7943,01	35,15	40,34	14,98
	s12	f_{s12}	3893,13	59,13	95,86	0,61
	s13	f_{s13}	6919,91	32,48	49,25	14,69
	s14	f_{s14}	2332,54	29,73	76,30	12,20
	s15	f_{s15}	2906,59	59,47	49,39	0,14
	s16	f_{s16}	7021,16	27,01	47,11	15,62
	s17	f_{s17}	4929,77	33,63	2,36	0,05
	s18	f_{s18}	3635,33	57,73	36,37	0,35
	final		1889,85	36,90	34,34	12,51
	select		2328,00	28,01	24,14	3,21

Table 8-4 L_{36} orthogonal array

		parameters															
	L_{36}	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
simulation runs	s1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
	s2	2	2	2	1	2	2	2	2	2	2	1	2	1	1	2	2
	s3	3	3	3	1	3	3	3	3	3	3	1	3	1	1	3	3
	s4	2	3	3	1	1	1	1	1	2	2	1	2	2	2	3	3
	s5	3	1	1	1	2	2	2	2	3	3	1	3	2	2	1	1
	s6	1	2	2	1	3	3	3	3	1	1	1	1	2	2	2	2
	s7	3	1	2	1	1	1	2	3	1	2	2	3	1	2	2	3
	s8	1	2	3	1	2	2	3	1	2	3	2	1	1	2	3	1
	s9	2	3	1	1	3	3	1	2	3	1	2	2	1	2	1	2
	s10	2	2	1	1	1	1	3	2	1	3	2	3	2	1	3	2
	s11	3	3	2	1	2	2	1	3	2	1	2	1	2	1	1	3
	s12	1	1	3	1	3	3	2	1	3	2	2	2	2	1	2	1
	s13	1	3	2	2	1	2	3	1	3	2	1	3	1	1	1	2
	s14	2	1	3	2	2	3	1	2	1	3	1	1	1	1	2	3
	s15	3	2	1	2	3	1	2	3	2	1	1	2	1	1	3	1
	s16	3	3	3	2	1	2	3	2	1	1	1	2	2	2	2	1
	s17	1	1	1	2	2	3	1	3	2	2	1	3	2	2	3	2
	s18	2	2	2	2	3	1	2	1	3	3	1	1	2	2	1	3
	s19	1	2	1	2	1	2	1	3	3	3	2	2	1	2	2	3
	s20	2	3	2	2	2	3	2	1	1	1	2	3	1	2	3	1
	s21	3	1	3	2	3	1	3	2	2	2	2	1	1	2	1	2
	s22	2	1	3	2	1	2	2	3	3	1	2	1	2	1	3	2
	s23	3	2	1	2	2	3	3	1	1	2	2	2	2	1	1	3
	s24	1	3	2	2	3	1	1	2	2	3	2	3	2	1	2	1
	s25	3	3	1	3	1	3	2	1	2	3	1	1	1	1	2	2
	s26	1	1	2	3	2	1	3	2	3	1	1	2	1	1	3	3
	s27	2	2	3	3	3	2	1	3	1	2	1	3	1	1	1	1
	s28	1	2	3	3	1	3	2	2	2	1	1	3	2	2	1	3
	s29	2	3	1	3	2	1	3	3	3	2	1	1	2	2	2	1
	s30	3	1	2	3	3	2	1	1	1	3	1	2	2	2	3	2
	s31	2	1	2	3	1	3	3	3	2	3	2	2	1	2	1	1
	s32	3	2	3	3	2	1	1	1	3	1	2	3	1	2	2	2
	s33	1	3	1	3	3	2	2	2	1	2	2	1	1	2	3	3
	s34	3	2	2	3	1	3	1	2	3	2	2	1	2	1	3	1
	s35	1	3	3	3	2	1	2	3	1	3	2	2	2	1	1	2
	s36	2	1	1	3	3	2	3	1	2	1	2	3	2	1	2	3

Table 8-5 L_{36} orthogonal array – results

	results		energy cost	energy demand	CO_2-emissions	renewables share	energy flexibility
	L_{18}		T€/a	MWh/a	tCO_2/a	%	%
simulation runs	s1	f_{s1}	410,69	4225,32	1430,37	18,7%	0,0%
	s2	f_{s2}	328,23	4231,25	1320,79	16,7%	11,9%
	s3	f_{s3}	278,74	4749,71	1322,40	17,2%	16,1%
	s4	f_{s4}	380,97	3875,47	1343,99	17,7%	13,3%
	s5	f_{s5}	360,50	4258,54	1357,12	17,3%	5,1%
	s6	f_{s6}	300,13	4831,87	1383,96	14,6%	10,7%
	s7	f_{s7}	347,77	4309,31	1381,44	16,4%	18,5%
	s8	f_{s8}	318,78	4739,61	1378,71	14,5%	1,1%
	s9	f_{s9}	372,40	3441,44	1239,70	20,5%	14,2%
	s10	f_{s10}	291,58	4728,13	1331,29	17,2%	11,4%
	s11	f_{s11}	348,84	3539,08	1206,41	22,3%	17,9%
	s12	f_{s12}	353,09	4228,56	1327,75	19,2%	5,3%
	s13	f_{s13}	245,83	4287,77	1169,71	18,4%	11,8%
	s14	f_{s14}	342,73	3759,87	1235,31	21,6%	15,8%
	s15	f_{s15}	296,66	3994,81	1179,03	20,4%	5,9%
	s16	f_{s16}	276,72	4510,42	1255,29	15,7%	3,2%
	s17	f_{s17}	365,58	3749,94	1287,56	18,3%	16,3%
	s18	f_{s18}	283,77	3924,92	1183,99	18,8%	13,1%
	s19	f_{s19}	331,89	3218,75	1126,52	22,0%	18,9%
	s20	f_{s20}	304,59	3898,21	1191,61	17,6%	4,8%
	s21	f_{s21}	282,24	4691,77	1319,20	15,7%	12,5%
	s22	f_{s22}	295,83	3989,24	1200,99	20,4%	14,4%
	s23	f_{s23}	245,03	4500,87	1216,95	17,5%	13,7%
	s24	f_{s24}	326,34	3334,39	1104,09	24,4%	9,4%
	s25	f_{s25}	297,99	4030,82	1237,85	17,0%	11,6%
	s26	f_{s26}	282,94	4808,96	1343,48	17,0%	15,8%
	s27	f_{s27}	346,62	3792,06	1230,57	20,8%	10,4%
	s28	f_{s28}	292,78	4048,95	1223,97	18,2%	17,0%
	s29	f_{s29}	289,49	4623,70	1299,21	15,3%	2,8%
	s30	f_{s30}	372,77	3944,63	1337,59	17,4%	14,2%
	s31	f_{s31}	305,95	4647,89	1329,43	15,9%	5,4%
	s32	f_{s32}	353,28	3345,77	1184,95	21,1%	14,6%
	s33	f_{s33}	292,52	3984,55	1220,72	17,2%	14,4%
	s34	f_{s34}	345,62	3311,42	1136,27	24,6%	2,4%
	s35	f_{s35}	283,21	3944,04	1179,00	20,0%	17,3%
	s36	f_{s36}	271,60	4682,63	1298,25	17,4%	14,3%
	final		238,78	3186,35	1069,91	24,9%	21,3%
	select		273,57	3727,30	1101,65	21,2%	17,7%

A2 Publications by the author

The following list outlines the scientific peer-reviewed publications relevant to the topic domain addressed in this thesis and published by or published with a major contribution of the author. The author wants to thank all his fellow colleagues from research, the great teamwork, and their excellent contributions.

Weeber et al. 2020	Weeber, Max, Wanner, Johannes, Schlegel, Philipp, Birke, Kai Peter & Sauer, Alexander 2020. Methodology for the Simulation based Energy Efficiency Assessment of Battery Cell Manufacturing Systems. *Procedia Manufacturing*, **43**, pp. 32-39. DOI: 10.1016/j.promfg.2020.02.179
Sauer et al. 2019	Sauer, Alexander, Emde, Alexander, Bogdanov, Ivan, Gamnitzer, Martin, Hofmann, Philipp, Schneider, Amelie, Tristan, Alejandro, Weeber, Max & Zimmermann, Fabian 2019. Energieflexibilität im Fahrzeugbau. *In:* Sauer, Alexander, Abele, Eberhard & Buhl, Hans Ulrich (eds.) *Energieflexibilität in der deutschen Industrie: Ergebnisse aus dem Kopernikus-Projekt-Synchronisierte und energieadaptive Produktionstechnik zur flexiblen Ausrichtung von Industrieprozessen auf eine fluktuierende Energieversorgung (SynErgie).* Stuttgart: Fraunhofer Verlag, pp. 537-558. ISBN: 978-3-8396-1479-2
Weeber et al. 2019	Weeber, Max, El-Mokadem, Mahmoud & Sauer, Alexander 2019. Assessment of Energy Related Planning Goals in Factory Design using Simulation Experiments. *Procedia CIRP*, **84**, pp. 550-557. DOI: 10.1016/j.procir.2019.03.264
Weeber et al. 2018	Weeber, Max, Ghisi, Enedir & Sauer, Alexander 2018. Applying Energy Building Simulation in the Assessment of Energy Efficiency Measures in Factories. *Procedia CIRP*, **69**, pp. 336-341. DOI: 10.1016/j.procir.2017.11.148
Weeber and Sauer 2018	Weeber, Max & Sauer, Alexander 2018. Total Energy Planning – A Working Paper. *Procedia CIRP*, **72**, pp. 820-825. DOI: 10.1016/j.procir.2018.03.286
Steinhilper et al. 2017	Steinhilper, Rolf, Weeber, Max, Lehmann, Christian, Christian, Bay, Küfner, Thomas, Thorenz, Benjamin & Böhner, Johannes. 2017. Die Energieeffiziente Fabrik - Wechselwirkungen von Produktkion und Technischer Gebäudeausrüstung. bayme - Bayerischer Unternehmensverband Metall und Elektro e. V. & vbm - Verband der Bayerischen Metall- und Elektro-Industrie e. V. München: Universität Bayreuth - Lehrstuhl für Umweltgerechte Produktionstechnik, Fraunhofer Projektgruppe Regenerative Produktion. URL: https://eref.uni-bayreuth.de/id/eprint/67628 [Accessed 11.05.2022].
Weeber et al. 2017	Weeber, Max, Lehmann, Christian, Böhner, Johannes & Steinhilper, Rolf 2017. Augmenting Energy Flexibility in the Factory Environment. *Procedia CIRP*, **61**, pp. 434-439. DOI: 10.1016/j.procir.2016.12.004

Böhner et al. 2016	Böhner, Johannes, Lang-Koetz, Claus, Weeber, Max & Steinhilper, Rolf. Integrating Resource Efficiency in Learning Factories for Industrial Engineering. *In:* Dimitrov, Dimiter & Oosthuizen, Tiaan, eds. International Conference on Competetive Manufacturing, 2016 Stellenbosch.
Jahn et al. 2016	Jahn, Josefine, Weeber, Max, Boehner, Johannes & Steinhilper, Rolf 2016. Assessment Strategies for Composite-metal Joining Technologies – A Review. *Procedia CIRP*, **50**, pp. 689-694. DOI: 10.1016/j.procir.2016.05.034
Lehmann et al. 2016	Lehmann, Christian, Weeber, Max, Böhner, Johannes & Steinhilper, Rolf 2016. Techno-economical Analysis of Photovoltaic-battery Storage Systems for Peak-shaving Applications and Self-consumption Optimization in Existing Production Plants. *Procedia CIRP*, **48**, pp. 313-318. DOI: 10.1016/j.procir.2016.03.017
Reinhart et al. 2016	Reinhart, Gunther, Steinhilper, Rolf, Böhner, Johannes, Gebbe, Christian, Glasschröder, Johannes, Lothes, Gerald, Müller, Thiemo, Simon, Peter, Unterberger, Eric & Weeber, Max 2016. *Ressourceneffiziente Fabriken - Innovative Praxisbeispiele und zukünftige Handlungsfelder*. Stutgart: Fraunhofer Verlag. ISBN: 978-3-8396-1120-3
Weeber et al. 2016a	Weeber, Max, Frötschner, Björn, Böhner, Johannes & Steinhilper, Rolf 2016a. Energy Efficiency in Assembly Systems. *Procedia CIRP*, **44**, pp. 334-340. DOI: 10.1016/j.procir.2016.01.021
Weeber et al. 2016b	Weeber, Max, Gebbe, Christian, Lutter-Günther, Max, Böhner, J., Glasschroeder, J., Steinhilper, R. & Reinhart, G. 2016b. Extending the Scope of Future Learning Factories by Using Synergies Through an Interconnection of Sites and Process Chains. *Procedia CIRP*, **54**, pp. 124-129. DOI: 10.1016/j.procir.2016.04.102
Böhner et al. 2015	Böhner, Johannes, Weeber, Max, Kuebler, Frank & Steinhilper, Rolf 2015. Developing a Learning Factory to Increase Resource Efficiency in Composite Manufacturing Processes. *Procedia CIRP*, **32**, pp. 64-69. DOI: 10.1016/j.procir.2015.05.003
Bradshaw et al. 2015	Bradshaw, Ines, Weeber, Max & Böhner, Johannes. Integrating CFRP repair technologies in manufacturing processes: An approach for prepreg processes. International Conference on Solar Energy and Building (ICSoEB), 20-21 Jan., 2015 Piscataway, NY, USA. IEEE, pp. 1-5. DOI: 10.1109/ICSoEB.2015.7244938
Weeber et al. 2015	Weeber, Max, Böhner, Johannes & Steinhilper, Rolf. Towards integrated energy efficiency assessment of production machinery, auxiliary processes and technical building services. 23rd International Conference on Production Research (ICPR), 2015 Manila. p. 9.
Freiberger et al. 2014	Freiberger, Stefan, Ellert, Florian & Weeber, Max 2014. Energy Efficient Manufacturing of Lightweight Products Illustrated by a Structural Optimization of an Automatic Knife Cutting System. *Applied Mechanics and Materials*, **655**, pp. 75–81. DOI: doi:10.4028/www.scientific.net/AMM.655.75

A3 Student work oriented by the author

The student works listed below were created under the scientific, technical, and content-related guidance of the author between 2014 and 2019. The related research questions dealt with diverse aspects of energy use in manufacturing. Some of the results have been incorporated into this document. The author thanks all students for their commitment to supporting this scientific work.

El-Mokadem 2019	El-Mokadem, Mahmoud. 2019. *Assessment of Energy Consumption in Manufacturing Plants - A Design of Experiments based Simulation Approach.* Master Thesis, Technical University of Berlin.
Höne 2018	Höne, Carmen. 2018. *Techno-economic analysis of integrating storage technologies into an automobile manufacturing factory to enable energy flexibility.* Master Thesis, Karlsruhe Institute of Technology.
Schlegel 2018	Schlegel, Philipp. 2018. *Simulation-Based Assessment of Energy Use in Manufacturing Systems for Battery Cells.* Student Work, University of Stuttgart.
Hoffmann 2017	Hoffmann, Christoph. 2017. *Entwicklung einer integralen Methodik für den Aufwand-Nutzen optimierten Einsatz der energetischen Gebäudesimulation zur Modellierung von Energieeffizienzmaßnahmen im Rahmen der Fabrikplanung.* Master Thesis, Bayreuth University.
Koller 2017	Koller, Jan. 2017. *Modellierung und Bewertung Energetischer Wirkzusammenhänge im Umfeld der Produktion.* Master Thesis, Bayreuth University.
Bay 2016	Bay, Christian. 2016. *Bewertung energieeffizienzsteigernder Maßnahmen bei Bestands- und Neuplanungen von Produktionsgebäuden und Darstellung in Technologiesteckbriefen.* Master Thesis, Bayreuth University.
Walter 2016	Walter, Moritz. 2016. *Simulationsgestützte Evaluierung ausgewählter Energieeffizienzmaßnahmen zur Reduktion des Gebäudeenergiebedarfs im produzierenden Gewerbe.* Master Thesis, Bayreuth University.
Lehmann 2015	Lehmann, Christian. 2015. *Spitzenlastmanagement in der Produktion durch intelligente Nutzung dezentraler Energiequellen und Speicher.* Master Thesis, Universität Bayreuth.
Pietzonka 2015	Pietzonka, Markus. 2015. *Abwärmenutzung in der Produktion – Bewertung und Ableitung von Handlungsempfehlungen.* Master Thesis, Universität Bayreuth.
Frötschner 2014	Frötschner, Björn. 2014. *Energieeffiziente Handarbeitsplätze - Auslegung am Beispiel der CFK-Bauteile-Produktion und Überführung in ein Demonstrationskonzept.* Master Thesis, Bayreuth University.