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Bachelorarbeit

Carbon flow assessment and analysis in European countries: potential benefits of CO_2 - efficient Demand Response programs in interconnected electricity markets

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Abstract

The CO_2 emission intensity of electricity use in a country is determined by the combination of generation technologies used to satisfy the demand. In an interconnected electricity network, imports and exports between countries can be a significant contributor to the combination. In this thesis, we employ the Flow Tracing method to assess the carbon flow in the European electricity network based on the information made available by the European Network of Transmission System Operators for Electricity (ENTSO-E). The resulting data serves as basis for the employment statistical analysis methods, such as correlation, to ascertain whether a connection between electricity prices, CO_2 emission intensity, and electricity trade can be identified. Analysis results imply a correlation between price and emissions and determine that trade has a large impact on a countries emission intensity. Moreover, we present a simple optimal scheduling problem with the goal of minimising CO_2 emissions caused by a simple daily task in different European countries. The optimisation is able to reduce the caused CO_2 emissions by between 5% and 40%, meaning that there is potential for a Demand Response program to lessen the environmental impact of electricity use.

Contents

1 Introduction

The generation of electricity is a significant contributor to the emission of greenhouse gases. To assess the country specific environmental impact of electricity use is not enough to just consider the country's production technologies. Electricity imports are influencing the composition of consumed power and thus the emission intensity in these countries. For this reason it is interesting to examine the impact this trade has on the emission intensity of European countries. Identifying potential patterns in their generation, trade and consumption could produce interesting data. Additionally, resulting information may then be used to investigate the potential for demand side management based on CO_2 values.

Little research available in literature focuses on the analysis of the correlation between CO_2 intensity and trade, price, or energy mix. While several articles examine the impact of Demand response using CO_2 signals in single countries, a comparison between them and the impact of a different electricity consumption mix is not as well researched. The main research questions this project addresses are:

1. What patterns and correlations can be identified among European countries regarding their electricity trade and emission intensity?
2. Can this data then be used as an input for Demand Response?
3. How does the impact of Demand Response using CO_2 signals vary in countries with different consumption mixes?

To fulfil the main goals of this project we develop a Python application with the ability to calculate the hourly CO_2 -emission of European countries. This will take the electricity generation in Europe, the trade between European countries into account. Further, we analyse the results with statistical measures like correlation. Key questions are if energy prices and CO_2 emissions are connected or how electricity trade affects the importing country's emission intensity. The obtained emission data will be used as input for an optimal scheduling problem. Hourly CO_2 intensity will serve as the input to create an example of the emission impact of a daily task in households in different European countries.

2 Background Information

Electricity can be generated by a wide variety of technologies. The CO_2 emissions produced during the generation differ significantly between them. For this thesis we consider the lifecycle CO_2 emission intensity of generation technologies. Not only the emissions during operations are considered, but also the emission during other lifecycles, such as during manufacture. For example, the emission during operation of solar technologies is close to 0 grams of CO_2 per kilowatt-hour, but when the full lifecycle is considered it increases to a value between 70 and 100. This example is based on the emission intensities presented by Tranberg *et al.* (2019).

The flow of electricity can not be physically traced. This means it is not possible to determine the electricity source by any physical measurement. Instead, to assess the distribution of electricity of a specific source throughout a network a mathematical method is needed. Flow Tracing is such a method. According to Hörsch *et al.* (2018), "flow tracing follows the power flow from net-generating sources through the network to the net-consuming sinks"[P.1].

According to Albadi and El-Saadany (2007), the idea of Demand Response is to influence the electricity consumption behaviour of the end user. They describe that Demand Response encompasses äll intentional modifications to consumption patterns of electricity of enduse customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption"[p.1]. For example, when a network is operating near capacity, a high electricity price could be used to discourage further electricity use. Change on the consumer side has the advantage, that it is more flexible than on the generation side. This is especially the case for renewable electricity production, as it often relies on wind or sunlight.

3 State of the Art

Here we provide a brief overview of the available literature on the two main topics, namely methods for carbon emission assessment in interconnected networks and Demand Response programs based on CO_2 signals.

3.1 Assessment of carbon emissions

Hörsch *et al.* (2018) present a flow tracing formulation that can be applied in large electricity networks with a diverse technology composition. There it is used to analyse an example network with different types of generation methods and trade. Li *et al.* (2013) also detail flow tracing in electricity networks. The focus here is on carbon flow rather than power flow. The electricity trade between Chinese regions is used as a case study finding a significant impact of trade on CO_2 emission intensity in the regions. Tranberg *et al.* (2019) use the flow tracing method to examine carbon emissions in Europe. They assign the specific CO_2 emission intensity to the traced power. This means similar results to the research by Li *et al.* (2013) are presented, only for a different region. The data is then used to explore the differences between emission intensities of production and consumption but no further statistical analysis is done. Tao Sun *et al.* (2016) take a directed graph-based approach to flow tracing instead of the usual version with linear equations. It achieves the same goal as the usual version while being much less calculation intensive. They demonstrate with sample calculations that it is a massive improvement for networks with many nodes. For few nodes the difference between methods is too small to be relevant (saving 0.1s for 300 nodes).

3.2 Demand Response Programs

Not only the price of and demand for electricity are subject to hourly change but also its emission intensity. This makes Demand Response measures based on the CO_2 emissions interesting. Most research available on Demand Response based on CO_2 signals focuses on single, especially northern European countries. The way CO_2 emissions are calculated also changes from article to article. For instance, Song *et al.* (2014) develop a simulation model for Demand Response programs based on a combination of price and CO_2 signals. Sweden is used as an example in a case study. It comes to the conclusion that using the presented technique would be more interesting in environments with higher shares of fossil electricity generation since then the possible CO_2 emission reduction would possibly be more significant. For several countries, a dynamic CO_2 intensity is introduced and their correlation with electricity price is examined by Stoll *et al.* (2014). Although this takes different generation technologies into account, the impact of imported electricity on emissions is not fully calculated. The paper concludes that dynamic CO_2 intensity can be used in Demand Response to improve environmental impact while also enabling the consumer to choose between reduced cost or reduced carbon footprint if there is a negative correlation between electricity price and CO_2 intensity. The articles above concentrate on single countries without evaluating the impact of Demand Response measures on their neighbours. Multiple scenarios with different Demand Response measures in European countries are analysed by Bergaentzlé *et al.* (2014) They find that measures in one country can have an impact on its neighbours by influencing marginal electricity costs and the way power is traded. Their primary focus is on electricity price and efficiency and only indirectly on CO_2 emissions.

4 Data Gathering

A central requirement to examine the research question is to gather information on European electricity network. For this, we develop a Python application. Its implementation is presented in this chapter. The resulting data provides the basis on which the analysis and CO_2 - efficient demand response depend. Section 4.2 describes where the information on the European electricity network is obtained from and how it is processed for further use. Furthermore, Section 4.2.5 is concerned with gathering CO_2 emission intensity values for electricity generation technologies. In Section 4.3, the method to assess the electricity mix and CO_2 emission intensity for each country is explained. Immediately following is a more thorough summary of the application.

4.1 Application Introduction

The main goal of the Python application is to provide easy access to information on the European market, specifically on the energy composition, emission impact, import and export balance as well price. Moreover, it will allow for several statistical analysis methods to be used on this data directly through the application. To further increase the accessibility it should also be possible to expand the provided analysis methods. To achieve this the data format and application structure should be as flexible as possible.

4.1.1 Overview

The ENTSO-E transparency platform (European Network of Transmission System Operators, 2020) was chosen as the core information source because it offers an accessible API, with which extensive data on European electricity production, consumption as well as trade can be accessed. Other required information, such as CO_2 emission intensity values, is not offered by the ENTSO-E platform and needs another source. See the Section 4.2 for details on ENTSO-E and Section 4.2.5 for the other sources.

The European electricity market is very interconnected. Imports and exports can have a significant influence on a country's power balance. Therefore, simply considering a country's generation as a basis for the assessment of the local CO_2 emissions caused by electricity consumption can be misleading. For instance, the CO_2 emission intensity in a country with low carbon production but high carbon imports would be significantly lower without considering the imports. That is the reason the Flow Tracing technique is applied to the data. It enables a more accurate evaluation of local electricity consumption by taking the trade throughout the network into account. Section 4.3 illustrates the method and its application.

To realize this application the Python programming language was chosen since many libraries and tools are available for data analyses. All of the application is written in Python using Anaconda 2020.2. The "pandas python library", 2020 provides the internal data format and the foundation for the implementation of most analysis methods such as Spearman correlations.

An outline of the central components of the Python implementation is shown in Figure 4.1. A short explanation of the components follows.

- *demandResponse*: Contains the linear optimization concerning CO_2 efficient demand response programs. More information on this component can be found in Chapter 6.
- *statisticAnalysis*: Provides several statistic analysis methods based on the information offered by *flowTracing*. The employed methods and results are presented in Chapter 5.
- *flowTracing*: Uses the aforementioned Flow Tracing technique to calculate the networks electricity composition. Requires the *download* component for data access. Further explained in Section 4.3.
- *download*: Uses the *entsoe-py* library to download the required data and processes it for further use by other components. See Section 4.2.
- *entsoe*: Integrated library enabling ENTSO-E API downloads. Details in Subsection 4.2.2

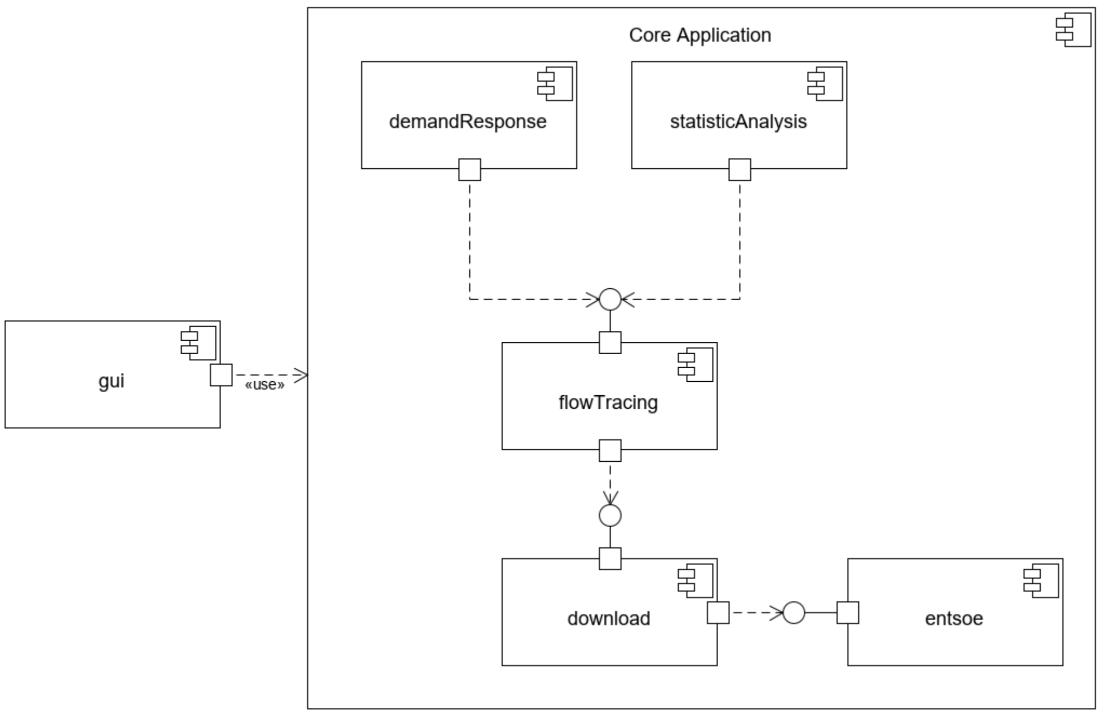


Figure 4.1: Component Diagram

AT	BE	BG	CH	CZ
DE	DK	EE	ES	FI
FR	GR	HU	IT	LT
LV	NL	NO	PL	PT
RO	RS	SE	SI	SK
UK				

Table 4.1: Countries with enough available data in 2019

4.2 Data Sources

The following section explains how the information required for this thesis is obtained. First, the data download and processing from the ENTSO-E API is explained. Then, other data sources are introduced. They concern information on CO_2 emissions, which can not be obtained from ENTSO-E.

4.2.1 ENTSO-E transparency platform

ENTSO-E, the European Network of Transmission System Operators, aggregates and publishes data regarding electricity generation, consumption, and trade in the European market. A REST API through which said information can be accessed is available for public use. This is the main source of data. For this thesis four categories of information are obtained from ENTSO-E:

- total load
- generation by production type
- cross-border physical flows
- 24h price forecast data

From 2015 onward this type of information is available on ENTSOE-E. Before 2015 only limited data is published, which is also not accessible via the API. Hence, this legacy data will not be used in this thesis.

Information regarding all EU members and a number of other adjacent countries is published. However, the quality of data can differ significantly between countries. While the data available concerning EU members, in general, is relatively complete, that can not be said about the other countries. For those, one or more of the aforementioned categories are often missing. Therefore they need to be excluded from most calculations. See Table 4.2.1 for a list of countries with sufficient data in 2019.

To be able to use the API, an access key needs to be requested from ENTSO-E. This is free and only requires an account on their website.

4.2.2 entsoe-py Library

The python library *entsoe-py* enables easy access to the API and is made available by EnergieID (2020). It offers a Python implementation to download all project-relevant data from the ENTSO-E API. By specifying the time frame, the country, and the requested information type (i.e. generation by production type) the appropriate request can be constructed by the library and send via the API. The response is also received by the library and converted into one of two data formats: a simple XML file or a pandas dataframe.

For this thesis, the pandas dataframe format is used since pandas offers a wide variety of functions concerning data manipulation and analysis.

A few changes were made to the client library.

First, the API mapping needed to be updated. It defines what strings the query types and countries are mapped to. These are used to construct the REST API queries. Some of them were obsolete while others were missing.

Secondly, the behaviour of the download client when encountering communication problems with the ENTSO-E servers was changed to allow for more retries with more time between them. This improved the stability of large downloads substantially. Before, the client tended to fail when used to download large successive information using the API, which is often required for this application.

The library is directly integrated into the project and can be found in the *entsoe* folder.

4.2.3 ENTSO-E Data Download

The data download of the application is implemented in the *download* folder, with the core function being located in the *datasetDownloader.py* file. There, a class is implemented, which offers functions to download a complete data set over a specified time frame. In this complete set all data concerning load, electricity generation per production type, price forecast, cross border physical flows, and load is contained for all available countries, representing most of the required input for the flow tracing calculations as well as for the statistical analyses.

The functions themselves are quite simple. To download generation, price, or load a request is sent to the API via the aforementioned client. The request contains a start and end date, the request type, and the country in question. Requesting data regarding the cross border physical flows works similar only that both countries of the exchange need to be specified. If the information is available the reply will contain it, otherwise, an error is reported, which is processed by setting this specific data to *None*. This process is then repeated for every country and request type. A maximum of one year of data can be downloaded in one request by the client.

The results are saved with the *dataSet* class. It implements a simple container for all data and some utility methods needed for the succeeding flow tracing calculation. Instances of this class can also be exported to xlsx (Excel) or CSV.

4.2.4 Data Processing

To clean up the data set several processing methods are used. Their main objective is to remove inconsistencies while impacting the actual values as little as possible. They are automatically applied after the downloads. The following subsections outline the processing methods used.

Data Point Frequency

For most countries, data points are reported every hour. Hence, the hourly information is taken as a basis for the flow tracing calculations. The data for countries reporting in shorter intervals is averaged to one-hour intervals. This is done via the pandas *resample* method. No countries report at intervals larger than 1 hour.

Special Cases

For multiple countries a further regional division of the data is available. This includes Norway, Denmark, Italy, and Sweden. For these countries, the price data is not available for the whole country, only for the sub-regions. The other information is available for both the country as a whole and the sub-regions. To obtain a singular price for these countries a weighted price average is calculated using the individual prices and their sub-regions share of the total load.

Another special case is the price data for Germany, Luxembourg, and Austria. Before 1.10.2018, they were considered to be one market zone with a single price. After said date, Austria split into its own zone while Germany and Luxembourg remained merged. The data can only be requested for those zones, not the individual countries. So, when individual price values are absent, the value of the market zone is used instead.

Missing Data

The data available from the ENTSO-E transparency platform is not without flaws. Values at specific timestamps or even whole data categories can be missing. In case a whole category is missing, the rest of the country's data becomes unusable for most further calculations. Hence, the application keeps a list of countries with fully available categories. In this list, all countries are found with load, generation, and cross-border flow data available. The price forecast is an exception. Because it is only needed in limited situations, countries with this price data missing are still included in the list. Calculations are only conducted for countries contained in this list. For example, countries such as Russia, Ukraine, and Turkey are excluded since no information on power generation is available.

Individual data points can also be missing. In this case, linear interpolation is used to infer missing information. This is done by using the *pandas* method *interpolate* with a maximum gap of two. So, larger intervals of missing data are kept unchanged while at most two successive values are inferred. Since most calculations run for every available timestamp in the data, when one of the remaining missing data points is encountered, the country is usually excluded at the specific timestamp of the gap.

Country	Missing Load Data (%)		Missing Generation Data (%)		Missing Cross-Border Flow Data (%)		Missing Price Data (%)	
	Interpolation	Unprocessed	Interpolation	Unprocessed	Interpolation	Unprocessed	Interpolation	Unprocessed
AT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BA	0.09	0.13	0.00	0.01	0.00	0.00	N/A	N/A
BE	0.00	0.00	4.06	4.07	0.00	0.00	0.00	0.00
BG	0.00	0.00	0.00	0.00	5.22	5.30	0.00	0.00
CH	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CZ	0.00	0.05	0.00	0.02	0.00	0.00	0.25	0.27
DE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
DK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EE	0.01	0.06	0.01	0.06	0.08	0.27	0.00	0.00
ES	0.00	0.00	0.03	0.06	0.00	0.00	0.00	0.00
FI	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00
FR	0.03	0.14	0.03	0.10	0.02	0.04	0.00	0.00
GR	0.00	0.02	0.04	0.08	0.00	0.00	0.00	0.00
HU	0.00	0.00	6.44	6.44	0.00	0.00	0.00	0.00
IE	0.00	0.10	0.00	0.14	0.00	0.00	N/A	N/A
IT	0.00	0.00	0.61	0.61	0.08	0.10	0.00	0.00
LT	0.00	0.03	0.27	0.34	0.22	0.28	0.00	0.00
LV	0.00	0.03	0.22	0.29	0.32	0.46	0.00	0.00
ME	0.00	0.00	0.00	0.00	0.00	0.00	N/A	N/A
MK	7.92	8.49	11.06	11.85	4.31	4.34	N/A	N/A
NL	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00
NO	1.07	1.11	0.00	0.01	0.00	0.00	1.11	1.11
PL	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PT	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RO	0.00	0.01	0.00	0.01	0.02	0.37	0.00	0.00
RS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SE	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01
SI	0.00	0.11	0.15	0.32	0.00	0.00	0.00	0.00
SK	0.00	0.02	0.00	0.00	0.13	0.14	0.00	0.00
UK	0.00	0.05	0.00	0.02	0.03	0.06	0.25	0.27

Table 4.2: Percentage of missing data points for unprocessed data and after linear interpolation in 2019

Frequency of Missing Data

Table 4.2 shows the percentage of missing entries belonging to the four data categories in the year 2019. Values are given for unprocessed data as well as after linear interpolation. The total number of values for load and price data is 8760, 1 entry for every hour. For generation and cross-border flow, the total number varies from country to country since the number of technologies or trade partners is country-specific. Generally, little to no data is missing for most available countries. 19 of the 30 countries report less than 0.1% of missing data for any category, while all but 4 countries report under 1%. The vast majority of missing values are clustered together in larger continuous gaps. For example, all of the missing Hungarian power generation values result from a month's long gap concerning solar power. Therefore, values inferred by linear interpolation only make up a small fraction of the total data. They never account for more than 0.79% of a category's values. Even this ratio is an outlier. It is found in the information concerning North Macedonia, the available country with the most incomplete data.

4.2.5 Other Data Sources

CO_2 Data Source

For the assessment of the carbon flow in the European electricity network the CO_2 emission intensity for each generation technology is required. Optimally the emission impact of the technologies is also specific for the generating country.

The main source used for this information is the article Tranberg *et al.* (2019). There, a table can be found detailing the life cycle CO_2 emissions for many generation technologies for each EU28 country. Where a value for a country technology pair is not available the EU28 average is used.

The electricity generation data from ENTSO-E contains several different variants of coal and oil generation technologies. For the sake of this thesis, all variants are considered with the same emission impact. Generation with offshore and onshore wind turbines are also assigned the same value. A similar approach is commonly used in literature, e.g. Tranberg *et al.* (2019), where differences in CO_2 emission factors among technologies using the same primary energy source are neglected.

For all technologies in Table A.3, except the following, the values are available from Tranberg *et al.* (2019).

The CO_2 emission intensity for generation with *fossil peat* is taken from Murphy *et al.* (2015). The authors calculate the life cycle impact for Ireland specifically. Noteworthy *fossil peat* use is only recorded in Ireland and Finland. For the *marine* generation type a general emission intensity value is taken from Intergovernmental Panel on Climate Change (2014). The generation type *other* is assumed to be a mixture of oil, coal, and gas generation. Generation from waste is considered part of *other*. Therefore, the emission intensity is an average of the three. The emission intensity of the *other renewable* type is an average of each countries renewable technology emission intensities.

4.3 Flow Tracing Implementation

Flow Tracing is a method to trace the electricity flow through interconnected networks from the producing node to the consuming node. Every node in the network is assigned its specific composition of electricity by source. Not only direct imports from neighbouring nodes are considered but also indirect flows through intermediary nodes. The electricity flow can be further differentiated into the specific technologies used in the source country. For example, this means the circulation of French nuclear power throughout the European electricity network can be tracked individually. Thus, the complete realisation of this method results in the calculation of the share of every generation technology in every country. This provides more accurate information on the actual composition of the consumed electricity. By multiplying a technology's share of the total load with its specific CO_2 emission impact, the carbon flow in the network can be assessed. The application of this method enables interesting analyses options in the highly interconnected European electricity market, as further presented in Chapter 5.

To illustrate the underlying principle of the method a simple example follows. Figure 4.2 describes a four-node network with electricity flow in between the nodes. Nodes C and D produce no own electricity while node A generates with technology α and node B with technology β. A and B are

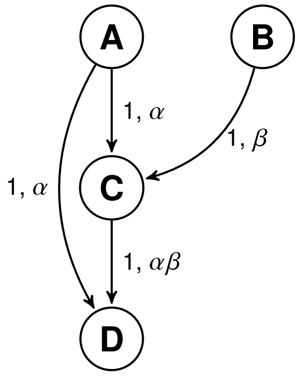


Figure 4.2: Flow through sample network

both exporting 1 unit of electricity to C. Therefore the total power composition in C is 50% α and β with a total value of 2. Now, C exports 1 unit to D. The same 50/50 split persists in the export volume. This is one of the core assumptions of the Flow Tracing method. Besides this import, D also receives 1 unit from A, resulting in a mix of 75% α and 25% β, again with a total value of 2. The generation technologies are traced through the network.

4.3.1 Method Formulation

The two papers Tranberg *et al.* (2019) and Hörsch *et al.* (2018) are the sources for the Flow Tracing method used in this project. Hereinafter the core concept of the method is introduced, without going into details. The interested reader is referred to the aforementioned papers.

Following variables are used in the calculation:

- $q_{n,\alpha}$ the ratio of technology α in node n
- L_n the total load in node n
- $F_{n\to x}$ the electricity flow from n to x
- $G_{n,\alpha}$ the electricity generation of technology α in n
- $c_{n,\alpha}$ the CO_2 emission intensity of technology α employed in country n

A fundamental assumption is that the electricity input from different sources is mixed proportionally in the nodes. This means that a technologies share $q_{x,\alpha}$ in incoming flows is equal to its share in outgoing flows. With this assumption the electricity balance of a certain technology α in country n can be expressed in this formula:

$$q_{n,\alpha} L_n + \sum_x q_{x,\alpha} F_{n\to x} = G_{n,\alpha} + \sum_x q_{x,\alpha} F_{x\to n} \tag{4.1}$$

The left side of the equation is the sum of electric flow leaving the node n and the right side all flow entering the node at one point in time. All variables are known through the data obtained from ENTSO-E except the ratio $q_{x,\alpha}$. For the calculation of the ratio, Equation 4.1 can be transformed as follows:

$$\sum_{x}\left[\delta_{n,x}\left(L_m+\sum_{k}F_{x\to k}\right)-F_{x\to n}\right]q_{x,\alpha}=G_{n,\alpha} \tag{4.2}$$

This can be interpreted as the definition of a system of linear equations. There are α different systems with x individual equations. So a single system describes a solution for the ratios of a technology in every country at one point in time. The calculated ratios $q_{n,\alpha}$ determine a technology's percentage of the node's total load and are the primary result. Based on this, three additional calculations are done for every node n, which produce interesting results for further statistical analysis.

First, the absolute electricity share $L_{n,\alpha}$ of a technology in MWh is calculated according to Equation 4.3.

$$q_{n,\alpha}L_n = L_{n,\alpha} \tag{4.3}$$

Next, Equation 4.4 is used for the calculation of the absolute CO_2 emissions of a technology $E_{n,\alpha}$ in kg/MW. $E_{n,\alpha}$ describes how many kg of CO_2 emission are caused by consumption of electricity generated by technology α in node n.

$$q_{n,\alpha}L_n c_\alpha = E_{n,\alpha} \tag{4.4}$$

Finally, the CO_2 emission intensity C_n in $kgCO_2/MWh$ is ascertained by Equation 4.5. C_n expresses how much CO_2 is emitted per MW of electricity consumption on average. It can be used as a measure of how clean a country's use is, regardless of the total amount. Therefore it is a crucial value for the assessment and analysis of carbon flow as well as the exploration of demand response programs based on CO_2 emissions.

$$\frac{\sum_\alpha E_{n,\alpha}}{L_n} = C_n \tag{4.5}$$

4.3.2 Implementation

The implementation of the flow tracing technique is found in the *flowTracing* folder of the application with the *flowTracingCalculator* as the central component.

The calculation of $q_{n,\alpha}$ for every technology α, country n and point in the time interval is implemented in two functions. First *calculateTechnology* solves the linear equation system for a specific α and t. The result, a series of $q_{x,\alpha}$ values, is returned to the caller.

The second function *calculateFlowTracing* is concerned with the calculation of the complete result. It iterates through the whole data set calling the first function for every α, t combination found.

Result data is saved in individual dataframes for every node with the index being a timestamp. A dataframe is a pandas data structure realising a two-dimensional matrix with labelled columns and rows. Every possible technology α has a corresponding column, while each row corresponds to a timestamp. The return values of *calculateTechnology* are inserted into the dataframes at the appropriate row column combination. With every finished calculation of *calculateTechnology* one entry is added to each of the dataframes.

After the main calculation is finished irrelevant columns are dropped from the dataframes to save memory space and calculation time of analysis methods. A column is deemed irrelevant when no entry exceeds a ratio of 0.001. For the same reason, individual values smaller than 0.001 are also discarded and further considered to be 0. This is done because the flow tracing calculation in electricity nets as interconnected as the European one leads to almost every technology being present in every node with the ratio being so small that it would correspond to single-digit watts. Without optimisations like this working with the full flow tracing data for a year requires vast amounts of memory and time while their impact is negligible.

The *flowTracingData* class defined in the correspondingly named file acts as a container for the resulting data. With the now available $q_{n,\alpha}$ values the absolute electricity share $L_{n,\alpha}$, the absolute CO_2 emissions $E_{n,\alpha}$ and the CO_2 emission intensity C_n can be now be determined by the application according to their formulation in Subsection 4.3.1 for every country at every timestamp. The implementation is found directly in the *flowTracingData* class, where the results are again saved in dataframes.

4.3.3 Example Calculation

The implementation, which is presented in Subsection 4.3.2, is now applied to an example network. A four-node network is described in Table 4.3 and figure 4.3. Each node produces power with two different technologies, α and β. Table 4.4 contains the power composition for all nodes, which is the main result of the flow tracing calculation. Other results, like the CO_2 emission intensity, are not shown.

Node A is a major exporter, crucial for the electricity supply of the network, as all other nodes have a negative balance without imports. Subsequently, the electricity generated by node A is present on a significant level throughout the whole network. Although no direct connection exists, node D relies on imports from A for about 9% of its supply. This is the result of the assumption that electricity mixes proportionally in the nodes. Since the power composition of node C, the sole trade partner of D, features A heavily as a source, it is also present in the trade between them. Thus, the flow tracing method has demonstrated its merits in assessing the electricity balance in networks, taking indirect flows into account.

Fundamentally, the European electricity network, defined by the data available from ENTSO-E, is not different from this example. The key difference being, that the number of nodes increases to about 30 and the number of technologies to 20.

4.3.4 Flawed Data and Methodical Problems

In a perfect system, the sum of all $q_{x,\alpha}$ should add up to 1 for each node x at any time t Unfortunately, this is generally not the case. Sums smaller than 1 can be caused by missing data, namely technologies or complete countries being excluded from the flow tracing calculation. Moreover, it was observed that the electricity balance, expressed by Equation 4.1, is not true at all points in time, according to

Node	Generation		Load	Balance without Trade
	α	β		
A	100	50	100	+50
B	25	25	70	-20
C	15	30	50	-5
D	25	75	125	-25

Table 4.3: Power generation, total load and node balance for example network in MW

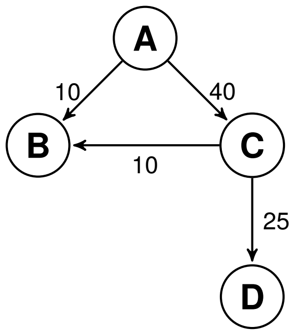


Figure 4.3: Power flow through Example Network in MW

the data from ENTSO-E. This means that either too much or too little power is present in the node. A negative balance shifts the sum lower, while a positive one higher. In Table 4.5 the average sum of $q_{x,\alpha}$ for every country in 2019 can be found. Most countries have values close to 1. Only certain countries differ more significantly, caused by the above mentioned reasons.

The application offers the possibility to adjust the sum of ratios to 1. This is done according to the following formula:

$$q_{n,\alpha,new} = \frac{q_{n,\alpha}}{\sum_\beta q_{n,\beta}} \tag{4.6}$$

It scales each $q_{x,\alpha}$ value according to its share of the original sum. This assumes that the electricity composition of the missing share is equivalent to the initially calculated one. All calculations relying on the Flow Tracing data are affected by this change. Employing this adjustment can have a

Node	Power composition by technologies with Source							
	A, α	A, β	B, α	B, β	C, α	C, β	D, α	D, β
A	0.667	0.333	0	0	0	0	0	0
B	0.140	0.070	0.357	0.357	0.025	0.051	0	0
C	0.314	0.157	0	0	0.176	0.353	0	0
D	0.063	0.031	0	0	0.035	0.071	0.2	0.6

Table 4.4: Flow Tracing result for example network

significant impact on their results since without it the missing composition share is not considered in any way. The larger the missing share, the larger the discrepancy between calculations using the adjusted values and calculations using the original ones.

Electricity losses in the network are not taken into consideration for the calculation. In Hörsch *et al.* (2018) the way to account for power losses between nodes is to treat the transmission loss as extra load at the exporting node. This method is not possible since in the ENTSO-E data the outgoing flow of the exporting node equals the incoming flow of the importing node. The only information available on transmission losses is a yearly published document by ENTSO-E detailing overall monthly transit losses for European countries. No information is given on exact losses between the individual countries on an hourly basis, making it unusable for the flow tracing calculation.

Power generation through Hydro Pumped Storage is distinct from the other technologies since it has a significant electricity consumption when it charges. This leads to negative generation values for this technology in the data. It is unclear whether this additional consumption is included in the general load value of the country or not. Either way would require special handling in the implementation of the core flow tracing Equation 4.2. If it is included, the negative $G_{n,\alpha}$ values for $\alpha = HydroPumpedStorage$ need to be replaced with 0. In case it is not included, negative values not only need to be replaced but their absolute value also needs to be added to the load L_m. We chose the latter approach for this thesis.

Country	Average sum of $q_{x,\alpha}$
AT	0.96
BA	0.93
BE	0.98
BG	1.02
CH	0.84
CZ	0.99
DE	0.96
DK	1.00
EE	0.82
ES	0.99
FI	0.86
FR	0.99
GR	0.90
HU	0.89
IE	0.82
IT	0.99
LT	0.64
LV	0.83
ME	1.20
MK	0.82
NL	0.80
NO	0.98
PL	0.90
PT	1.00
RO	0.96
RS	0.87
SE	0.97
SI	0.99
SK	0.99
UK	0.96

Table 4.5: Average sums of $q_{x,\alpha}$ in 2019

5 Data Analysis

This chapter is concerned with the analysis of the information obtained through the Python application, especially through the Flow Tracing method, described in Chapter 4. Possible relations in the data set are investigated. First, Section 5.1 outlines the employed analysis methods. Then, the results are presented and discussed in Section 5.2. 2019 was chosen as the year to base the analysis on because it was the most recent, fully available year at the time of writing this thesis. For all of the results calculated in this chapter data adjusted by the method outlined in Subsection 4.3.4 is used.

5.1 Analysis Methods

In this section the analysis methods used on the data are presented. No in depth formulation will be given in this thesis. Only the concepts are introduced to give an understanding of the results.

5.1.1 Correlation Coefficient

Correlation measures the relatedness of two variables through a coefficient. Related variables exhibit some sort of common behaviour when changing. Two ways to calculate such a coefficient are used in this thesis. The *Pearson correlation coefficient* r is determined by dividing the covariance by the standard derivation of the two variables. This is formulated in Equation 5.1. The *Spearman's rank correlation coefficient* r_{SP} is calculated in the same way as the Pearson coefficient, except not the actual variable value is considered but the rank. When the values of a variable are ordered after size, the rank of a value rg(x) is its the place in that order. For example, the rank of the smallest value would be 1, and of the largest value n, where n is the total number of values. The formulation is found in Equation 5.2. The source of both methods is the book by Fahrmeir *et al.* (2016). Their main difference is the kind of relationship between the variables they detect. The Spearman correlation coefficient detects monotonic relationships and the Pearson correlation coefficient only linear relationships. Linear relationships mean that a change in one variable is related to a proportional change in the other. Therefore a high Pearson coefficient value is achieved when the proportional change stays the similar. Monotonic relationships are not characterised by the proportions of the change. Only that the variables change together is of importance. So a high Spearman coefficient is present when both variables change in sync. For instance, if one usually rises when the other falls, but not necessarily according to a constant proportion, the result will be high. Neither of the two method are directly built into the application. Instead the robust and tested implementation of the the pandas library ("pandas python library", 2020) is used.

$$r = \frac{\sum(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{5.1}$$

$$r_{SP} = \frac{\sum(rg(x_i) - \overline{rg_X})(rg(y_i) - \overline{rg_Y})}{\sqrt{\sum(rg(x_i) - \overline{rg_X})^2(rg(y_i) - \overline{rg_Y})^2}} \tag{5.2}$$

The calculated coefficient of both methods has the same result range and meaning. It is a value between -1 and +1. Low values indicate a negative correlation, meaning that when one variable increases, the other decreases. High values are calculated when both variables change in the same direction. A value closer to 0 indicates no detectable relationship is present.

The relation between CO_2 emission intensity and other elements of the data set are investigated. Instead of calculating one coefficient for the whole year, the individual months are considered. If one or both of the values for a timestamp are missing, the specific timestamp is not included in the calculation. Possible categories include all results of the Flow Tracing calculation as well as the ones available from the ENTSO-E API, listed in Subsection 4.2.1.

Calculation of the correlation between CO_2 emission intensity and price

To investigate the correlation between the CO_2 emission intensity and the electricity price the Spearman correlation coefficient is determined. No linear relationship between both categories was expected. The emission intensity data points are provided by the flow tracing implementation outlined in Section 4.3. Only the 24h price forecast is available from ENTSO-E for price information. This means that the forecast from the day before is used instead of the actual price. Within 24 hours the actual value can change from the forecast. Still, this is the best data available for the whole network at hourly intervals. One correlation coefficient is calculated for each month.

Calculation of the correlation between CO_2 emission intensity and ratio of electricity imports

The impact electricity imports have on a country's CO_2 emission intensity is explored in this thesis. For this, the correlation coefficient between the ratio of imports in the electricity composition and the emission intensity is calculated. A linear relation was assumed, since electricity composition of the imports should stay similar. This would favour the use of the Pearson correlation coefficient. Nonetheless, both presented correlation calculation method were used to calculate a coefficient. Their differences were minimal. Like with the aforementioned calculation, the results are calculated for every month individually. They were obtained using the Pearson method.

5.1.2 Time-Delayed Correlation

The methods to calculate the correlation coefficient outlined in Subsection 5.1.1 assess whether the variables change at the same point in time. A potential delay between the two variable's behaviour is not considered. Such a relation would not be identified. For instance, it is conceivable that a price increase foreshadows a later increase in emission intensity, or vice versa. Thus, to investigate this possibility a time-delayed correlation method is implemented, based on the description by Wang (2013). Its difference to the aforementioned calculations is, that a time lag is taken into account by shifting one of the variables forwards or backwards a certain number of hours relative the other. To give an example, the value of the CO_2 emission intensity at 3PM would correspond to the electricity price at 5PM, if the first would be shifted forwards by 2 hours. With the adjusted variables, the Pearson or Spearman correlation coefficient is then determined. A maximum shift of 24 hours in either direction is considered. For every full hour within this range the correlation is calculated and the highest absolute value is reported as the result. Equation 5.3 is the formulation of the Spearman correlation coefficient with an delay of τ hours.

$$r_{SP,\tau} = \frac{\sum(rg(x_i) - \overline{rg_X})(rg(y_{i+\tau}) - \overline{rg_Y})}{\sqrt{\sum(rg(x_i) - \overline{rg_X})^2(rg(y_{i+\tau}) - \overline{rg_Y})^2}} \tag{5.3}$$

5.2 Analysis Results

An overview of the results for all countries will be presented first. Afterwards, a more in depth analysis and discussion for specific countries will be follow.

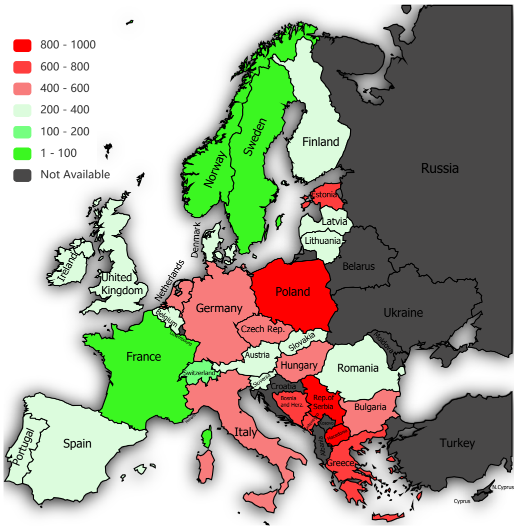
5.2.1 Overview

The ENTSO-E download and the Flow Tracing method produce a huge amount of data for every country. Thus, it is not feasible to go into detail for every country. Instead, a general summary will be presented in this chapter to provide insight about the nature of the results.

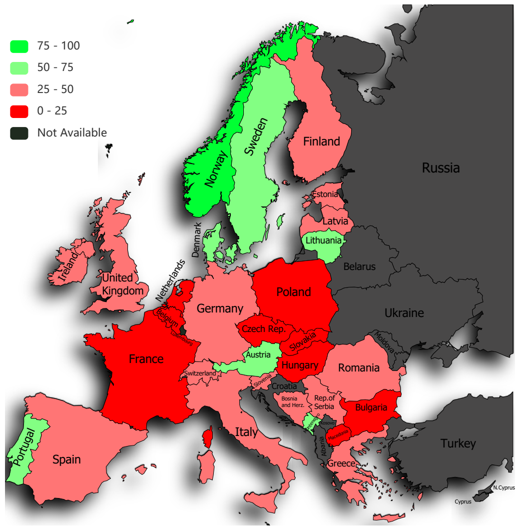
The CO_2 emission intensity is a key metric to assess the environmental impact of electricity consumption, stating how much CO_2 was emitted to produce a certain amount of power. Figure 5.1a displays the average CO_2 emission intensity in Europe in 2019. A full monthly breakdown of the information can be found in Table A.1. CO_2 emission intensity is determined by the composition of electricity. Not only the domestic production is considered but also the influence of trade. This is made possible by the Flow Tracing method. The figure clearly shows that the intensity can vary significantly between countries.

A key difference between the countries with high and low CO_2 emission intensity is the presence of renewable technologies, as they usually are the cleanest power source available. The following technologies appearing generation data obtained from ENTSO-E data are considered renewable:

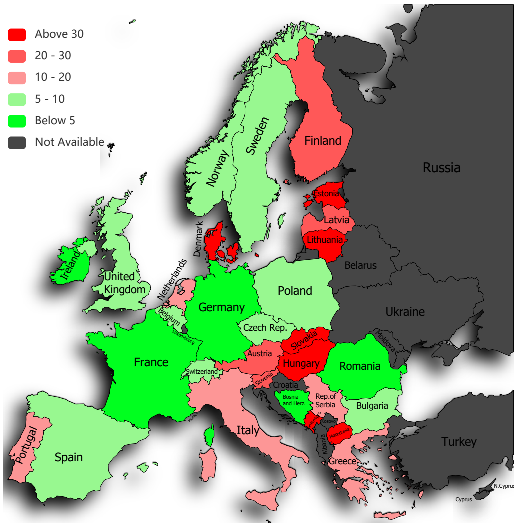
- Geothermal
- Biomass
- Hydro Water Reservoir
- Hydro Run-of-river and Poundage
- Marine
- Solar
- Wind Offshore and Onshore
- Other Renewable



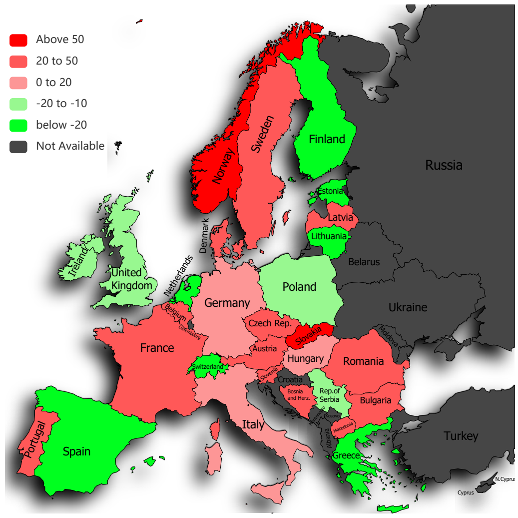
(a) CO_2 emission intensity in $kgCO_2/MWh$, 2019



(b) Share of domestic electricity production from renewable sources in %, 2019



(c) Share of imports in electricity composition in %, 2019



(d) Change from domestic to complete CO_2 emission intensity in %, 2019

Figure 5.1: Overview of results for European countries.

Only nuclear power presents a major exception, producing very little emissions while not being renewable. Similar to the proceeding map, Figure 5.1b presents the average share of electricity produced by renewable sources in the country itself. Data regarding the individual months can be found in Table A.2. While it is generally true that a high ratio of renewable energy in domestic production coincides with a low emission intensity, it is not a complete match for most countries. This can be explained by two factors.

One the one hand, there are large differences within the category of renewable and fossil generation. Solar panels for instance have a far larger emission impact than hydroelectric generation and gas power plants are significantly cleaner ones burning coal. Table A.3 provides more detailed information on the emission values of specific technologies. This means that a country can produce little renewable energy while still retaining a low CO_2 emission intensity. France is the prime example of this since nuclear power dominates the production.

On the other hand, imports are a central component for the power supply of many countries. Depending on the volume, this can have a large impact on the emission intensity since it is possible for import to be far cleaner or dirtier compared to the local generation. Subsequently, the CO_2 emission intensity of adjacent countries, from which power can be imported, becomes increasingly relevant to the environmental impact. Figure 5.1c displays how large the share of imports is in the electricity composition of European countries in 2019. The full monthly information is available in Table A.4. Several countries rely on trade for over a third of their supply. Such a large influx can significantly shift the local CO_2 emission intensity but even smaller amounts are not negligible. The effect of this is visualized in Figure 5.1d. There the change of CO_2 emission intensity can be seen, when imports are also factored in. For example in Norway the intensity increases by more than 50% when considering imports wheres in the Netherlands it decreases by more than 20%. The difference for most countries is significant, highlighting the importance taking the impact trade has into account. In Table A.5 the information for individual months can be found.

In the following subsections the data concerning certain countries will be examined more thoroughly. For example by employing the correlation methods among other things. Presenting data on such a level of detail would not have been possible for all countries.

5.2.2 Norway

The CO_2 emission intensity in Norway is the lowest of all considered countries. Figure 5.2 contains the average monthly CO_2 emission intensity. The detailed data can be found in Table A.1. Relatively speaking, the intensity change throughout the year is considerable. While the lowest intensity, in September, is 18.8 $kgCO_2/MWh$, the highest intensity is 38.5 $kgCO_2/MWh$ in March. Overall, in the months between May and September a lower intensity can be noted than in the rest of the year. A high ratio of renewable technologies is present in the electricity composition. Hydroelectricity, especially water reservoirs, account for the vast majority of domestic production. On average, these generation technologies produce more than 75% of the consumed power. The electricity mix is presented in Figure 5.3

It is noteworthy that the correlation coefficient between the CO_2 emission intensity and electricity price is negative for every month. This is very rare, as the only other country with the same result is Serbia. The most negative correlation is found in late autumn and early winter, reaching as low as -0.87 in November. In the rest of the year coefficients hover around -0.3, implying a less definitive relation between CO_2 emission intensity and price. June presents an outlier in this period, since with a value of -0.77. On the other and, a possible cause for the negative correlation presents itself when analysing the relation between electricity price and composition. Norway's key generation technology is water reservoirs, on average making up more than 60% of the electricity composition. Furthermore, it is a very clean generation method, being responsible for very little CO_2 emission per MWh of generated power. A positive correlation between the ratio of generation by water reservoirs and price can be determined. The coefficients are displayed in Figure 5.4. This means that when a

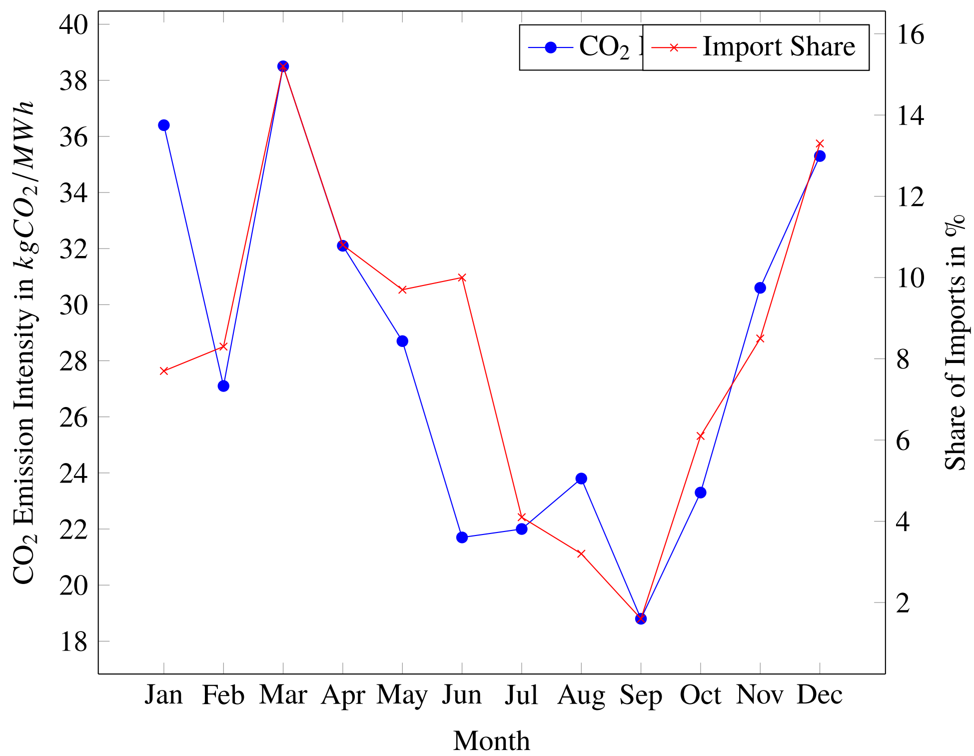


Figure 5.2: Average monthly CO_2 emission intensity and import share for Norway in 2019

high percentage of the electricity is produced by it, the price tends to be high as well. At the same time the CO_2 emission intensity will be low because a high ratio of the clean technology is used. That could explain why high prices tend to coincide with low CO_2 emissions.

Results of the time-delayed correlation method, described in the Subsection 5.1.2, are presented in Table 5.1. The delay corresponding to the highest correlation coefficient between the hourly CO_2 emission intensity and electricity price was always 0 hours. This means no delayed relation between the two variables could be identified with the method.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Optimal Delay	0	0	0	0	0	0	0	0	0	0	0	0
Correlation with delay	0.83	0.35	0.47	0.39	0.46	0.78	0.27	0.28	0.53	0.67	0.87	0.75
Correlation without delay	0.83	0.35	0.47	0.39	0.46	0.78	0.27	0.28	0.53	0.67	0.87	0.75
Difference	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5.1: Results of the time-delayed correlation method for a correlation between electricity price and CO_2 emission intensity for Norway in 2019

A consistently high and positive correlation can be found between the hourly CO_2 emission intensity and ratio of electricity imports. Since Norway's power generation is one of the cleanest in Europe, it is not surprising that a higher ratio of imports leads to an increase in emissions. The Norwegian trade partners are Denmark, Finland, Germany, the Netherlands and Sweden. Even the relatively clean Swedish generation causes more than double the CO_2 emissions per MWh produced when compared to Norway. For the other partners, this is even more pronounced. The high difference

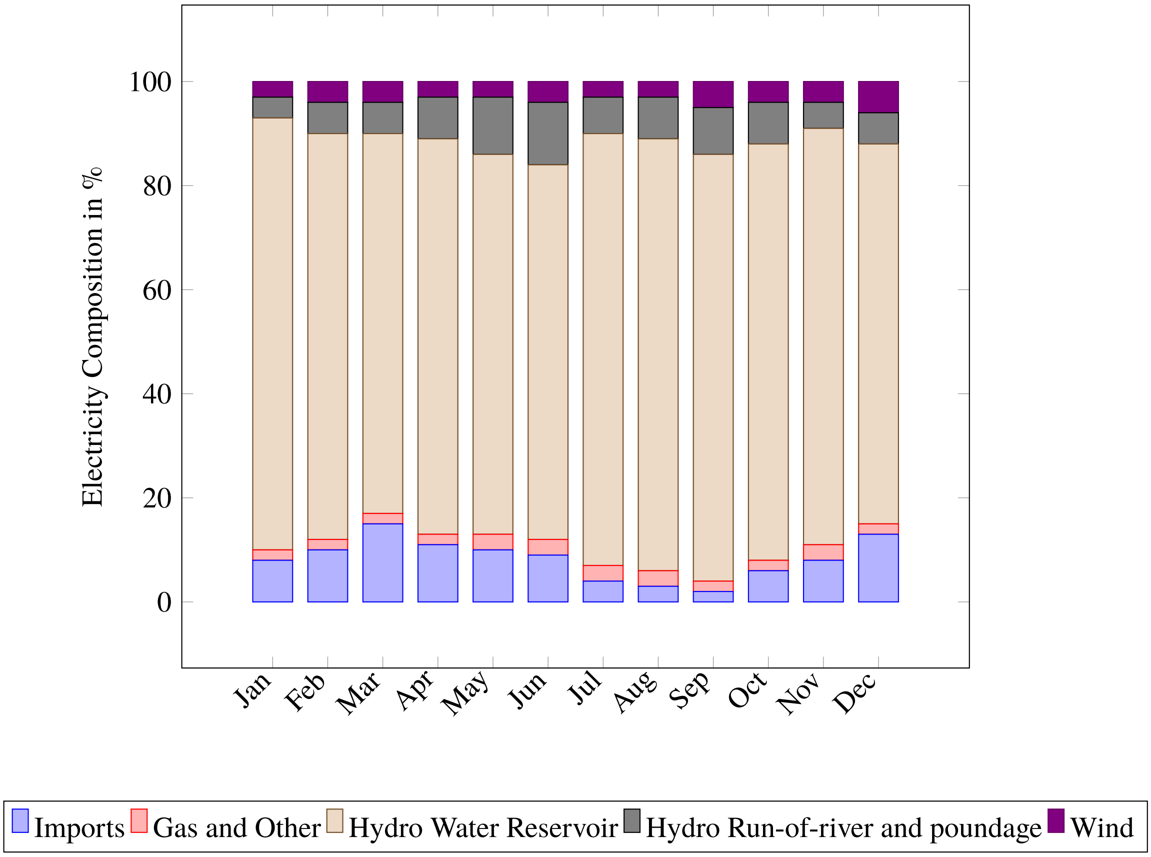


Figure 5.3: Norwegian Electricity Composition in 2019. Other includes Gas.

between the intensity of electricity generation and consumption seen in Table A.5 also indicate an influx of power with an high degree of CO_2 emission. Imported electricity is comparatively dirty. This leads to the question, whether high emission intensity values in several months can be explained by a larger presence of imports. The ratio of imports in the electricity composition of Norway is not insignificant, varying between 1.6% in September and 15.2 % in March. When comparing the average hourly emission intensity with the ratio of import, the data resembles each other noticeably. This can be seen in Figure 5.2. In months with a large import volume compared to domestic production the intensity of CO_2 emissions is high. Together with the aforementioned correlation data, this would indicate that a key reason for higher emission intensity values observed in certain months are caused by a larger dependence on imports.

5.2.3 Germany

The German electricity production is diverse. Renewable as well as fossil generation technologies are both employed on a significant scale, especially coal and wind power. Figure 5.5 shows the composition of the electricity mix in Germany. Overall the average share of renewables in the production composition is between 30% and 50%. Still, the CO_2 emission intensity especially compared to countries western and northern Europe is high, as can be seen in Table A.1. Generally, the intensity between April and October is relatively stable at a value slightly above 400 $kgCO_2/MWh$.

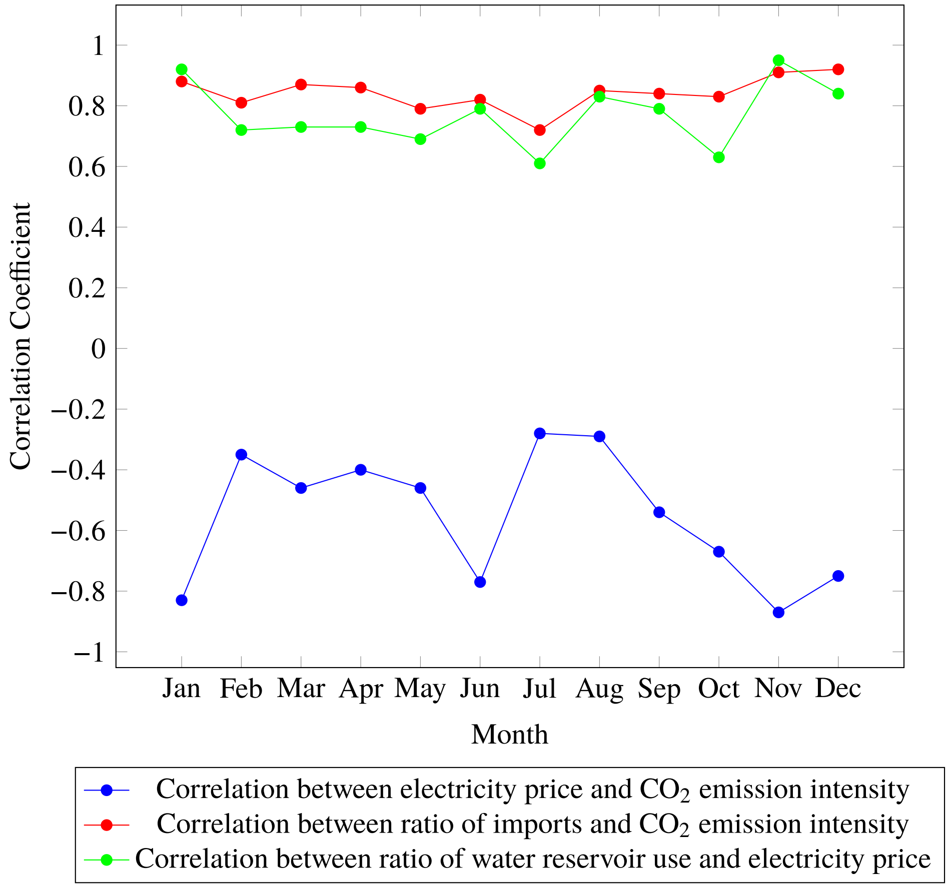


Figure 5.4: Correlation Coefficients in Norway, 2019

In January, February and November the intensity is notably higher than in the rest of the year, while for March and December the lowest values are reported. In the following paragraphs the reason for these differences in intensity will be investigated.

Another similarity between March and December, besides the low CO_2 emission intensity, is that in both months wind power is responsible for an above the ordinary share of the electricity composition. In turn, other technologies must be present at a diminished rate. Primarily a decline in coal based generation is noticeable, while other technologies remain at a share similar to adjacent months. Two possible explanations for this are presented. First, the consumption in March and December could be lower compared to the other months. Assuming renewable technologies generate as much power as possible in the environmental conditions this would mean that less fossil technologies are required. Consequently, the generation of one or multiple of these technologies would be throttled with the choice most likely depending on (economic) feasibility. Since the only reduction is notable in coal power, it was apparently the preferred choice. The idea behind the second explanation is similar. Key difference is that instead of a low consumption in Germany, a high production of wind energy is assumed. Parallel to the before, it would reduce the need for other technologies. The same throttling would take place. A further investigation of the data in Table 5.2 reveals that while the consumption is relatively high, onshore wind power is produced in a huge amount, reinforcing the second explanation. Regardless of the definitive reason for the shift in electricity composition, it is most likely the central reason for the low emission intensity

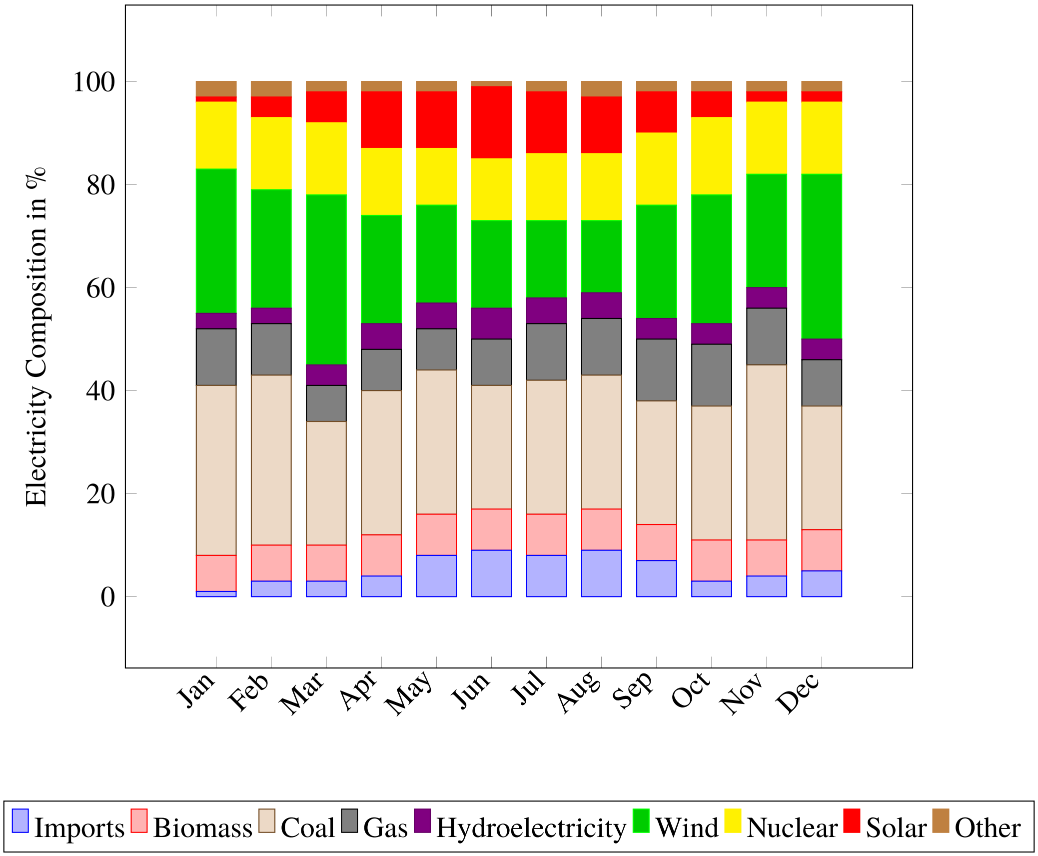


Figure 5.5: German Electricity Composition in 2019. Other includes Oil and Waste as well.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Consumption	61579	60612	58027	54527	54466	53267	54438	52184	53254	55654	58468	55718
Onshore Wind generation	16780	13164	18415	10102	8623	7097	6583	5966	9897	12549	10899	16350

Table 5.2: Power generation by Onshore wind and load in Germany in MW, 2019

The months January, February and November, where an increased CO_2 emission intensity is noted are also characterised by the highest level of electricity consumption. This puts extra strain on electricity supply. A comparison to the aforementioned low intensity months reveals a key difference. Whereas the consumption is only marginally lower in November and March, no as accentuated increase in renewable production is present. This leads to an inverse effect as before, meaning fossil fuels needs to be relied on more heavily, increasing the emission intensity. In the same way as before the coal power output is adjusting to the different requirement. It seems as though coal is the preferred technology to react to changes in the supply.

The correlation between price and CO_2 emission intensity was investigated as well. In contrast to Norway, a positive coefficient is calculated for each month. This means a higher electricity price tends to coincide with higher emission intensity. A reason for this could lie in the composition of electricity. Onshore wind power has a significant negative correlation with price, while coal has a positive one. This means, when prices are high, coal tends to be present in an increased way. For wind power it is the other way around. The mentioned correlation coefficients can be seen

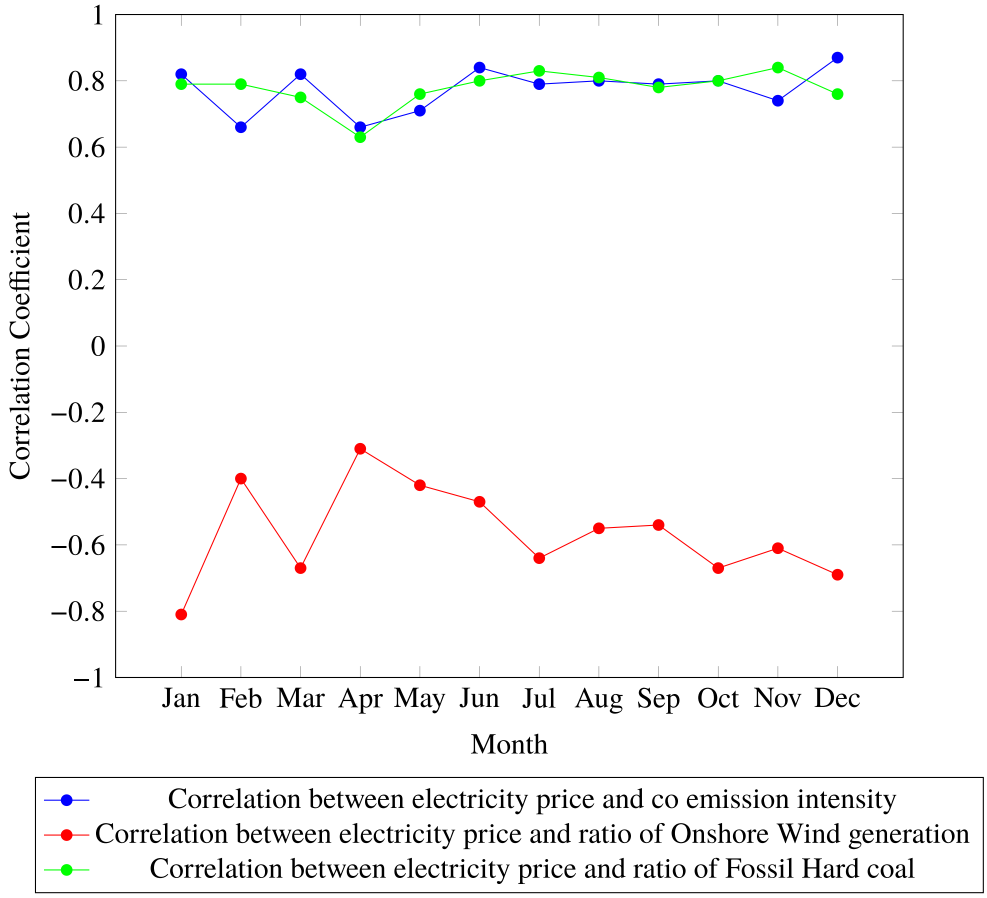


Figure 5.6: Different Correlations in Germany, 2019

in Figure 5.6. As coal is one of the dirtiest generation technology and wind of the cleanest ones, the positive correlation could be caused by this. The time-delayed correlation method was again employed to investigate a delayed relation between price and CO_2 emission intensity. Results are displayed in Table 5.3 Similar to Norway no noteworthy lag could be identified. Only in April a higher correlation coefficient was calculated when shifting the intensity forward one hour compared to the price. This would imply that a price increase predicts a intensity increase one hour later. However the margin of difference is practically negligible. Combined with the fact that a delay was only identified in one month, it can not be said that a delayed relation is present in a significant manner.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Optimal Delay	0	0	0	1	0	0	0	0	0	0	0	0
Correlation with delay	0.82	0.65	0.82	0.66	0.71	0.85	0.80	0.80	0.78	0.80	0.75	0.88
Correlation without delay	0.82	0.65	0.82	0.66	0.71	0.85	0.80	0.80	0.78	0.80	0.75	0.88
Difference	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5.3: Results of the time-delayed Correlation method for a correlation between electricity price and CO_2 emission intensity for Germany in 2019

5.2.4 Netherlands

Of the three examined countries, the Netherlands has the highest CO_2 emission intensity. This can in part be explained by the small presence of renewable technologies in the country. In no month more than 12% of generation are attributed to them. Most electricity supply is covered by domestic gas and oil power plants. Figure 5.7 details the composition of Dutch electricity. The three main trade partners are Norway, Germany and Belgium. All of which have considerably cleaner electricity compositions. Combined with an import share between 11% and 24% this means that the CO_2 emission intensity is lowered notably by the trade. This can be seen by the large difference between the intensity only considering local generation and the intensity taking imports into account as seen in Table A.5 and Figure 5.1d. The change of CO_2 emission intensity over the year is similar to Norway and Germany. In the colder months a higher intensity is calculated.

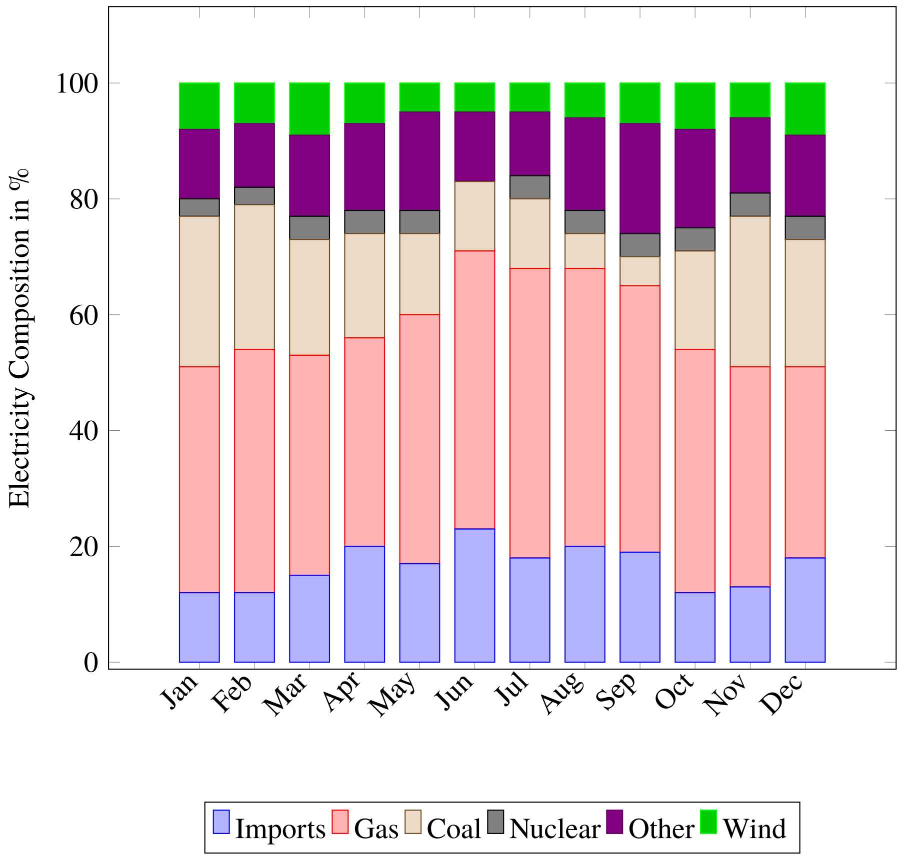


Figure 5.7: Dutch Electricity Composition in 2019. Components smaller than 2% are included in other.

A remarkable similarity between Germany and the Netherlands are the high CO_2 emission intensity values in January, February and November. For both countries the value is notably higher than in the surrounding months. Can a connection be identified in the data? As mentioned in Subsection 5.2.3, in Germany a high electricity consumption is accompanied by a comparably fossil heavy electricity composition. In the considered month, the majority of Dutch imports arrives from Germany. This is in contrast to the rest of the year, where Belgian and Norwegian imports are more relevant. Of the three trade partners, Germany has by far the dirtiest electricity composition. This suggests that one the reasons for high Dutch emission intensity is the increased ratio of German imports. A further factor can be identified in the domestic production in the Netherlands. Compared to the other Months, an unusually high ratio coal generation is noted.

In 2019 a positive correlation between the CO_2 emission intensity and electricity price can be observed in Figure 5.8 Although it must be said that the coefficient values are not consistent throughout the year. Especially till May the values are low, only weakly implying a relation between the variables. When comparing the data to Germany, it is clear that a far stronger connection between price and CO_2 emission intensity exists there.

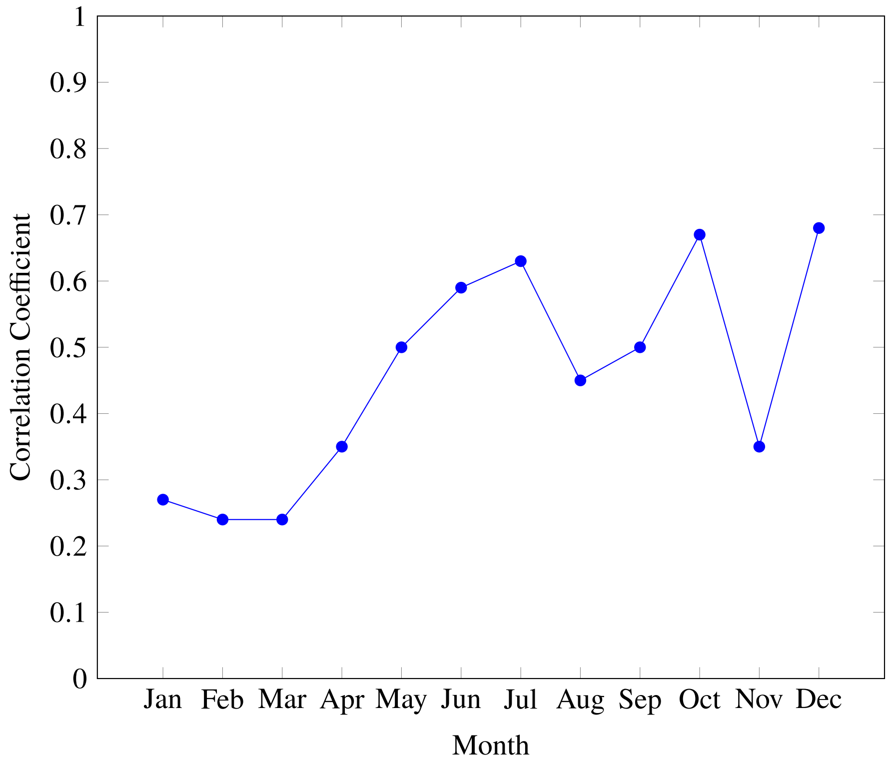


Figure 5.8: Correlation between electricity price and CO_2 emission intensity in the Netherlands, 2019

The results of the time-delayed correlation method are displayed in Table 5.4. Again, for most of the time no delayed relation was identified. The exception to this are the months of October to December and January. There, for a negative shift a higher correlation coefficient was calculated. A negative shift means that the CO_2 emission intensity is moved back in time compared to the price. This would imply that a change CO_2 emission intensity predict a change is price. Similar to the German results, the actual difference between the delayed and normal correlation calculation are minimal. In January a difference of 0.08 is recorded, by far the largest result observed. Considering the limited decisiveness of the change with the inconsistent delay for different months no delayed relationship can be assumed based on this data.

The presence of the *Other* technology introduced an uncertainty to the presented results. This category contains all power generation from unknown sources. Hence the exact emission intensity of the technology can only be estimated. For this, the source of the CO_2 emission data Tranberg *et al.* (2019) assumes a mixture of coal, oil and gas power generation. In the Netherlands this is especially relevant as *Other* is responsible for more than 10% of the electricity supply.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Optimal Delay	-5	0	0	0	0	0	0	0	0	-1	-2	-1
Correlation with delay	0.45	0.42	0.38	0.41	0.56	0.63	0.64	0.47	0.50	0.67	0.37	0.65
Correlation without delay	0.37	0.42	0.38	0.41	0.56	0.63	0.64	0.47	0.50	0.67	0.34	0.64
Difference	0.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01

Table 5.4: Results of the time-delayed Correlation method for a correlation between electricity price and CO_2 emission intensity for the Netherlands in 2019

6 Demand Response

We investigate the potential of using CO_2 efficient Demand Response by constructing a simple linear optimisation problem with the goal of minimising emissions of a simple daily task. Cooking pasta is the daily task to be examined. Fiorini *et al.* (2020) present a calculation to measure the emission of CO_2 when cooking a serving of pasta. We adapt their research to ascertain the emission impact of cooking for a range of times for every day in 2019. In addition to emissions, the monetary cost is also considered. The optimisation determines the best time to cook by either minimising the emissions, the cost, or a combination of both. We compare the change in cost and emissions when using different minimisation goals to ascertain their potential benefits. The information obtained from ENTSO-E and by the Flow Tracing method, described in Chapter 4, serves as a data basis.

6.1 Method Formulation

A mathematical formulation of the optimisation is presented in this subsection. The approach is based on the resources and information made available by Gurobi (2020) on their website. The goal is to find the time on a specific day at which it is optimal to cook the pasta. Following variables are used.

- T the set of all possible times of day
- $t \in T$ one specific time of day
- W_e the amount of electric power required by specific equipment to cook the pasta in Wh
- W_g the amount of gas power required by specific equipment to cook the pasta in Wh
- E_t the CO_2 emission intensity in gCo_2/Wh
- P_t the electricity cost in $€/Wh$
- X_t variable determining which time of day is chosen. A value of 1 indicates that t is chosen, otherwise it is 0.
- G_p the price of using gas power in $€/Wh$
- G_e the CO_2 emission intensity of using gas power in gCo_2/Wh

Values for E_t and P_t are obtained through the Python Application described in Chapter 4. The price of gas G_p is obtained from the information published by European Statistical Office (2020). The required power W_e and W_g is calculated based on the paper of Fiorini *et al.* (2020). There, the total amount of power required to heat up, boil, and cook 500 grams of pasta in 5 litres of water is determined. They calculate the efficiency of different types of cooking equipment. For instance, using an electric kettle to boil the water and then cook the pasta on a gas stove. The method formulation and implementation are able to operate with any of the cooking equipment combinations presented by Fiorini *et al.* (2020). This is done by splitting the total power required to cook with the equipment combination into an electric power part and a gas power part.

The goal of the optimisation is defined by an objective function. Depending on whether CO_2 emissions, electricity cost, or a combination of both is to be minimised a different objective function is used. Equation 6.1 is used when the goal is to minimise the cost of cooking the pasta and Equation 6.2 when minimising the caused emissions. Both are very similar. The first equation minimises the sum of $(W_e P_t + W_g G_p)X_t$ for every t. The sum is the total monetary cost of cooking. It includes the cost of electricity and the cost of gas. It is multiplied with X_t, which can be either 0 or 1. Obviously to achieve a minimal sum, X_t must be 1 for the smallest total cost. The second objective function is formulated in the same way, with the sole difference being that cost is replaced by CO_2 emission output.

$$\text{Min} \quad \text{Cost} = \sum_{t \in T} (W_e P_t + W_g G_p) X_t \tag{6.1}$$

$$\text{Min} \quad \text{Emissions} = \sum_{t \in T} (W_e E_t + W_g G_e) X_t \tag{6.2}$$

When both cost and emissions are to be considered, Equation 6.3 is employed. It differs from the previous equation since a simple addition of cost and CO_2 emissions can not be used because the numeric difference between the variables is too large. The smaller price values would have next to no impact on the objective function. The unit of the variables is also different. One is in €and the other in grams of CO_2 . Normalisation of both variables is required. For this, we first calculate the minimisation for cost and emission values independently, according to the two aforementioned formulas. O_P is defined as the minimal electricity cost and O_E as the minimal emission value. The individual objective functions are divided by their minimal value and then summed. So, the optimisation evaluates the sum based on how close the terms are to their individual optimum. A prerequisite for this normalisation to work as intended is that P_t and E_t must be positive for all t. Otherwise, the minimisation will produce wrong results. For prove this we assume, without loss of generality, that $P_t < 0$ for at one t, leading to an negative O_P. Thus, the value of the fraction $\frac{(W_e P_t + W_g G_p)X_t}{O_P}$ is negative for a positive numerator because the denominator is negative. The value of the fraction for the actual minimal price would be 1 (a division of O_P through itself). That means the optimisation would prioritise the maximum of P_t instead of the minimum. Unfortunately, this problem actually can occur since a few electricity prices obtained from ENTSO-E are negative. To solve it, we add a constant to all prices, which leads to $P_t > 0$ for any t. The constant is only used to determine the optimal time and not present in any of the resulting cost averages presented in Section 6.3. To the best of our knowledge, the introduction of the constant does not affect the optimisation in any other way than to resolve the negative value problem.

$$\text{Min} \quad \text{Combination} = \sum_{t \in T} \frac{(W_e P_t + W_g G_p) X_t}{O_P} + \frac{(W_e E_t + W_g G_e) X_t}{O_E} \tag{6.3}$$

We assume that pasta is only cooked once a day. Therefore only one time may be chosen. This means X_t must be 0 for all t except one. Equation 6.4 describes this additional constraint placed on the optimisation.

$$\sum_t X_t = 1 \tag{6.4}$$

6.2 Implementation

The mathematical optimisation solver of Gurobi (2020) is employed to solve the presented problem. With the provided Python interface, the mathematical formulation from Section 6.1 can be defined in code and solved by the application. The *flowTracingData* data container class described in Subsection 4.3.2 serves as source for the information regarding CO_2 emissions and electricity price. The results for all three presented objective functions are calculated. To achieve a more meaningful result we calculate the optimisation for every day in 2019. Additionally, not every time in the day is a possible solution. They are limited to full hours in one of the following intervals:

- between 06:00 and 09:00
- between 11:00 and 14:00
- between 17:00 and 20:00

The intervals are based around the time of breakfast, lunch and dinner. We assumed for this optimisation that considering times too distant from normal meal times would lead to questionable results. For example, there would little value in knowing that the least emissions are produced when cooking pasta at midnight, as it is not plausible to expect anyone to do so. The change to and from daylight saving time is also taken into account. This means we always consider the current local time.

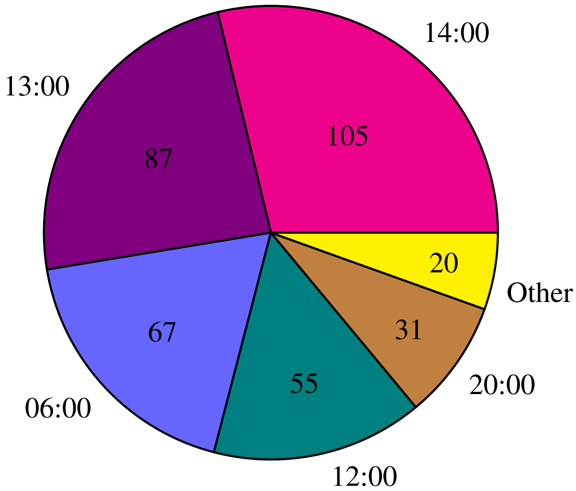
As outlined in Chapter 4, price or CO_2 emission values can be missing for various reasons. When the data is available for at least one of the mentioned hours in a day, we calculate the optimisation. Otherwise, the day is excluded from the result.

6.3 Optimisation Results

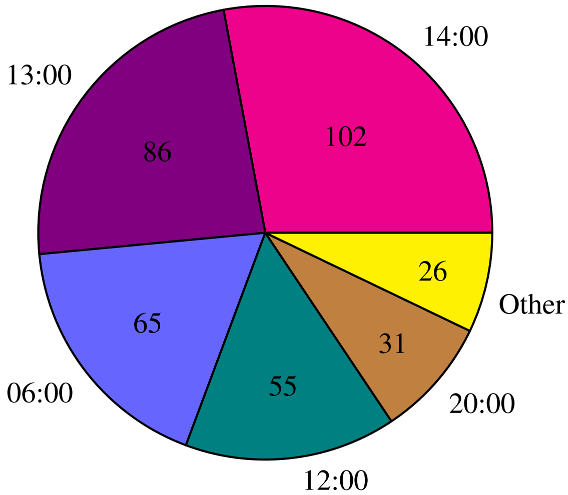
We present the results of the method for Germany, the Netherlands, and Norway in this section. First, the optimal time chosen by the optimisation is listed. Then, we compare the potential change in CO_2 emissions or electricity cost when cooking the pasta at the optimal time defined by the three objective functions. Instead of considering different equipment types, we take an average efficiency value of equipment using electric power. It amounts to 987.07 Watts.

6.3.1 Optimal Times

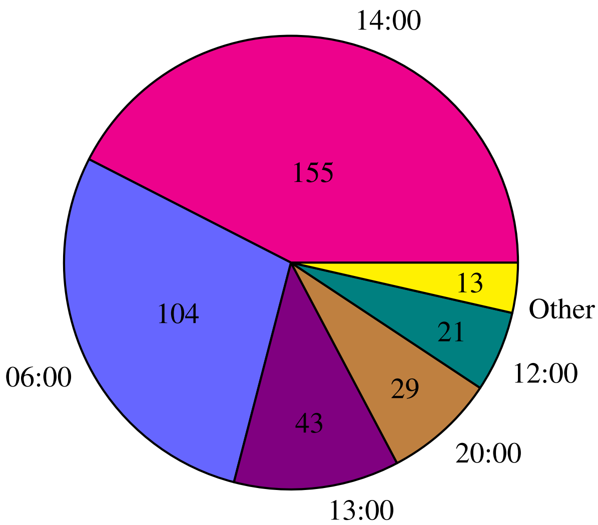
Figure 6.1 shows how often a certain time of day was deemed optimal by the three objective functions in Germany. 14:00 is the time chosen the most in all three functions. The difference between considering CO_2 emissions and electricity cost or only electricity cost is minimal. This can be observed as Figures 6.1a and 6.1b are almost identical. The choice of hours when minimising costs is displayed in Figure 6.1c. A greater difference to the previous results is evident. Then, 14:00 and 06:00 are chosen more often, mainly at the cost of 13:00 and 12:00. Furthermore, it is notable that out of the 12 possible times of day only the same 5 are chosen frequently, no matter the objective function.



(a) Optimal hours considering electricity cost and CO_2 emission intensity.



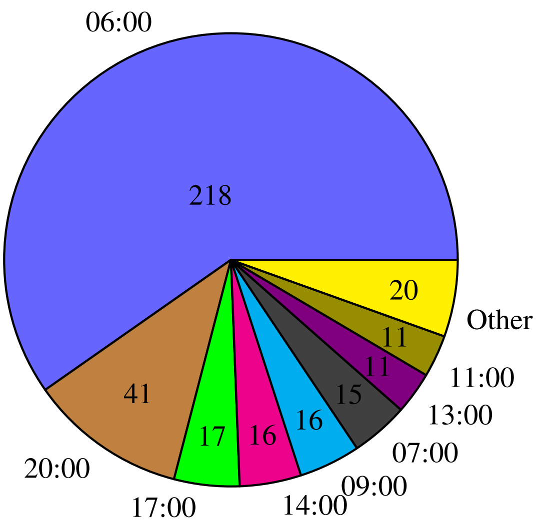
(b) Optimal hours only considering CO_2 emission intensity.



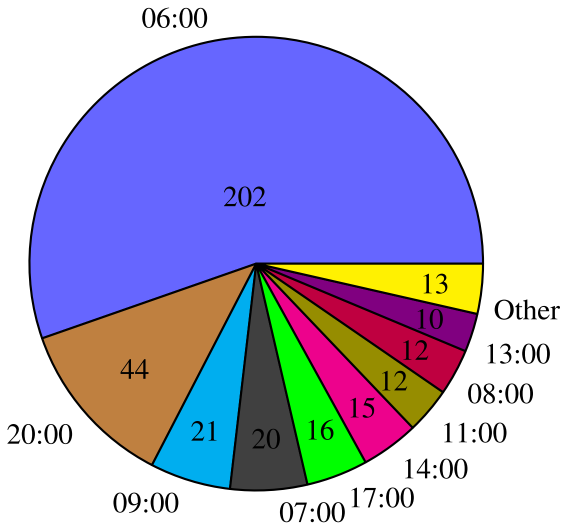
(c) Optimal hours only considering electricity cost.

Figure 6.1: Optimal hours chosen according to different objective functions in Germany in 2019.

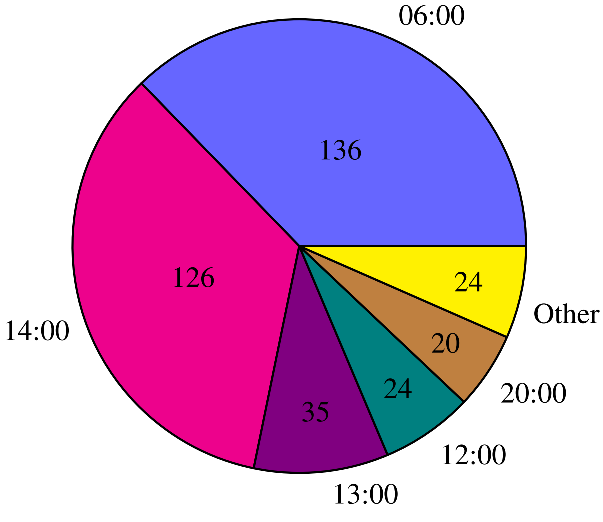
In the Netherlands, we reached a result with a comparable similarity between the times chosen by the combined objective function and the CO_2 emission focused one. This is presented in Figures 6.2a and 6.2b. For a majority of days the optimal time to cook pasta was either 06:00 or 20:00. When minimising costs instead, very different times are chosen. Primarily, the amount of times 14:00 is optimal increases drastically. In contrast to the German results a larger variety of times is identified as optimal. This is especially the case when the combination or emission oriented objective function is used. Despite this, for a large share of days the same hours are chosen. More than two thirds of optimal times are decided between two hours.



(a) Optimal hours considering electricity cost and CO_2 emission intensity.



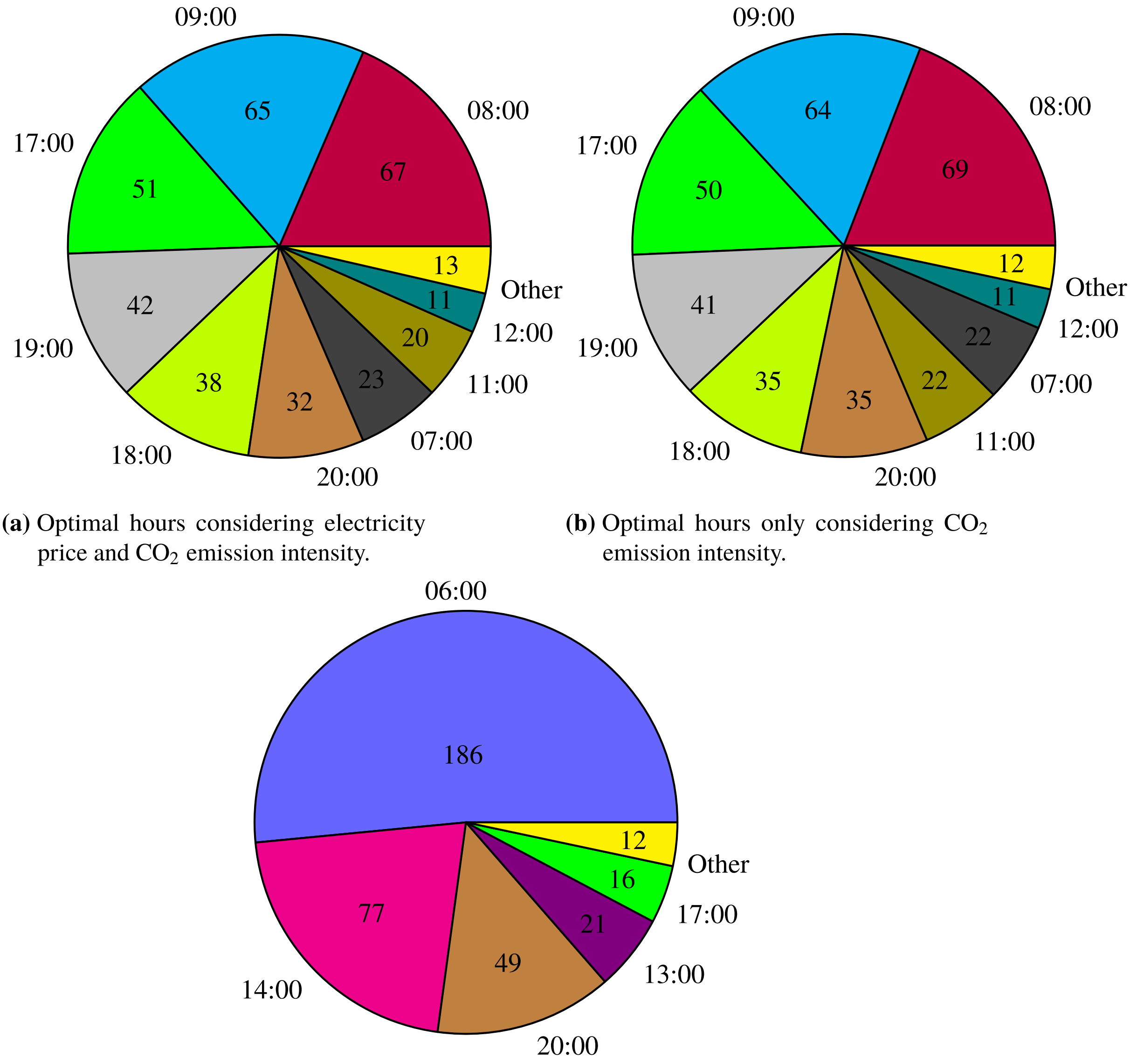
(b) Optimal hours only considering CO_2 emission intensity.



(c) Optimal hours only considering electricity cost.

Figure 6.2: Optimal hours chosen according to different objective functions in the Netherlands in 2019.

In Norway, the objective function minimising a combination of cost and emissions, shown in Figure 6.3a, and the function only minimising emissions, shown in Figure 6.3b, produce almost the same results again. However, the optimal times are more evenly dispersed over the day than for the other two countries. No single hour is deemed optimal for a large share of the days. Hours in the morning and evening are chosen the most. Similar to before, when the electricity cost objective function, the results differ significantly. 06:00 is optimal for over 50% of days and 14:00 for over 20%. This is a drastic change compared to the other objective functions, where both times are included in other. Note that only 362 days are considered in Norway because 4 are unavailable due to missing data.



(a) Optimal hours considering electricity price and CO_2 emission intensity.

(b) Optimal hours only considering CO_2 emission intensity.

(c) Optimal hours only considering electricity cost.

Figure 6.3: Optimal hours chosen according to different objective functions in Norway in 2019.

6.3.2 Emission and Cost Reduction

The CO_2 emissions by cooking the pasta at the time deemed optimal by the different objective functions is listed in Table 6.1. For the Netherlands there is only a marginal difference between the combined and emission objective function. In Germany and Norway the result is practically the same. This was to be expected, as very similar times are optimal, as seen in Subsection 6.3.1. In contrast, the emission values when considering cost-oriented objective function are significantly higher compared to combined function. The largest difference can be noted for Norway, where the emissions increased by 91.6%. In Germany and the Netherlands the increase only amounts to 2.3% and 5.9% respectively. The difference between the cost-oriented and the emission-oriented objective functions is identical to the just mentioned values with the exception of the Netherlands, where the increase raises to 6&. Table 6.2 lists the cost of cooking pasta. Although the difference in price values for the combined and CO_2 oriented approach is more pronounced compared to the emissions values it is still not very significant. For example the largest difference is found in Norway and amounts to circa 3%. Like before, when comparing the combined or CO_2 oriented optimisation to the price based one, a more definitive disparity is noticeable. Furthermore, any optimisation reduces emissions as well as the cost of cooking pasta when compared the average in Germany and the Netherlands. For Norway this is not the case. There, employing the cost-oriented optimisation actually increases the caused emissions. Compared to the average emission impact of cooking, employing an optimisation, which considers CO_2 emissions intensity, leads to a significant reduction of emissions when cooking pasta for all three countries. The highest potential reduction can be found in Norway, followed by Germany.

Country	CO_2 emissions			
	Equal	Price	CO_2	Average
Germany	366.2	374.6	366.2	427.9
Netherlands	494.7	524.1	494.4	522.3
Norway	16.6	31.8	16.6	28.2

Table 6.1: Average CO_2 emissions of cooking pasta in grams. The first three columns consider the value at the optimal time according the noted objective function. The last column considers the country's average CO_2 emission intensity.

Country	Costs of cooking			
	Combined	Price	CO_2	Average
Germany	3.161	2.998	3.229	3.767
Netherlands	4.001	3.510	4.121	4.120
Norway	4.12	3.731	4.136	3.890

Table 6.2: Average cost of cooking pasta in Euro Cent. The first three columns consider the value at the optimal time according the noted objective function. The last column considers the country's average electricity price.

6.4 Discussion

A positive correlation between electricity price and CO_2 emissions indicates that when prices are high, emissions are also high. Consequently, minimising the cost or emissions of cooking pasta should lead to a similar result. On the other hand, when a negative correlation is present, the results should go in opposite directions. An examination of the assumption is possible based on the data presented in Section 6.3 and Chapter 5. In Germany and the Netherlands we find a positive correlation between price and CO_2 emission intensity. Of the two, Germany exhibits a stronger correlation. Therefore, we expect a smaller difference between the results of the optimisation than in the Netherlands, which supported by the result data. Furthermore, the largest optimisations result difference can be observed in Norway, where the correlation of price and CO_2 emissions is negative. These facts support the assumption, that the nature of the correlation indicates how different the optimisation outcomes of the objective functions are.

The share of electricity generated by renewable technologies could be a reason for the difference in CO_2 emission reduction compared to the average. Most renewable technologies are dependant on environmental factors for their generation and thus are subject to more significant change over time compared to fossil technologies. We assume that this also leads to an increased variance in CO_2 emission intensity values. When there is a larger difference between values, the optimisation has a greater potential to reduce emissions. In Norway and Germany, renewable technologies are utilised on a larger than in the Netherlands and the potential emission reduction is larger as well, supporting this hypothesis.

The optimal time of cooking pasta varies significantly depending on the used objective function. For instance, in Norway the majority the times determined by the price-oriented function are completely different to the times recommended by the CO_2 -oriented function. Thus the intended behaviour change of Demand Response programs can be go into opposite directions depending on the used function. For a large percentage of days the optimal time is decided between few specific hours. An example for are the times recommended by the combined objective functions in the Netherlands. There, on almost 60% of days 06:00 is the chosen time. Subsequently, a Demand Response program based on such functions do not need to be very dynamic. A static incentive to move consumption to the hours that represent the majority of optimal times could achieve a significant reduction in price or CO_2 emissions. For the possible times we chose a four hour interval around breakfast, lunch, and dinner. This limits the potential reductions of the optimisation as it is possible for the price or CO_2 emissions at the excluded hours to be lower than during the included hours. As mentioned before, we chose this limitation to produce more realistic results. Even within the limited intervals, the optimisation recommends hours that many consumers would probably dislike as a time to cook pasta. For instance, we assume that a Demand Response program trying to shift electricity consumption to 06:00 would encounter difficulties to convince the user to do so.

Examining the absolute emissions caused by cooking pasta in the three countries illustrates the effect a different electricity composition can have on daily tasks. Cooking pasta everyday for two to four weeks in Norway is responsible for an equal amount of CO_2 emissions as cooking once in the Netherlands. The difference is so drastic since clean renewable electricity is prominent in Norway while the Netherlands obtains most of its supply from fossil fuels.

We only consider the average electric equipment efficiency to calculate the power usage of cooking pasta. For several reasons, this average does not necessarily represent the actual equipment efficiencies in the three countries. First, gas-powered cooking equipment is also present in some European households. For instance, according to the Federal Statistical Office of Germany (2018), 6.1% of German households owned a gas cooker in 2018. This means that for a certain percentage of households, the optimisation changes as gas-powered cooking equipment is not subject to the same CO_2 emission intensity fluctuation as electricity. Furthermore, we calculate an equally weighted average efficiency. Every possible equipment combination has the same impact on the average. This calculation method assumes that every equipment combination is used in an equal amount of households. This assumption does almost certainly not reflect the actual situation. We chose this simplified way of calculating the average efficiency because we deemed an average efficiency calculation based on the actual technology used too extensive for the simple optimisation model.

7 Conclusion and Outlook

The application we developed provides an easy way to download the information required to assess flows in the European electricity network. Directly included is an implementation of the Flow Tracing method. The provided information serves as an extensive data basis for different analysis methods. As the application's data format is based on the widely used data analysis library pandas it is possible for other research projects to add additional calculations and methods. On the ENTSO-E transparency platform more data is available than is utilised by us. For instance, the stored energy value of water reservoirs and hydro storage plants is published and could be used in a further examination of variances in CO_2 emission intensities and electricity compositions. Furthermore, for a number of countries ENTSO-E offers electricity network information divided into sub-region. Utilising the more granular data could provide insight into intra-country differences.

The data analysis we conducted shows that electricity trade between countries has an impact on the CO_2 emission intensity of electricity consumption. Depending on the country, changes in excess of 50% are possible. Thus, only considering a country's domestic production to assess the emission intensity of electricity consumption can be very different and potentially misleading results. Furthermore, the data indicates a correlation between the CO_2 emission intensity and electricity price for the examined countries. Positive as well as negative correlations can be found, depending on the month and country. This relation has implications for possible Demand Response programs. According to Albadi and El-Saadany (2007), programs based around electricity price are one of the main forms of Demand Response. Such programs encourage or discourage electricity consumption based on high and low prices. In countries where a strong negative correlation between price and CO_2 emissions is present this could potentially increase the actual emission output.

The optimisation problem we presented indicates that CO_2 emission output can be reduced significantly by shifting the time of consumption. Therefore, a Demand Response program based on CO_2 emission signals has the potential to achieve a reduction in CO_2 emissions. The possible CO_2 emission reduction of such a program would certainly be smaller than the results achieved in the optimisation, as the optimisation results present the largest possible saving within the considered times of day. Further research is required to develop an actual Demand Response program based on CO_2 emission intensity as a signal.

Bibliography

Albadi, M. H., & El-Saadany, E. F. (2007). Demand response in electricity markets: An overview. *2007 IEEE power engineering society general meeting*, 1–5 (cit. on pp. 5, 43).

Bergaentzlé, C., Clastres, C., & Khalfallah, H. (2014). Demand-side management and european environmental and energy goals: An optimal complementary approach. *Energy Policy*, *67*, 858–869 (cit. on p. 7).

EnergieID. (2020). *Entsoe-py*. https://github.com/EnergieID/entsoe-py. (Cit. on p. 11)

European Network of Transmission System Operators. (2020). *Entso-e transparency plattform*. https://transparency.entsoe.eu/. (Cit. on p. 8)

European Statistical Office. (2020). *Gas prices for household consumers*. https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_pc_202&lang=en. (Cit. on p. 34)

Fahrmeir, Heumann, Pigeot, K., & Tutz. (2016). *Statistik, der weg zur datenanalyse*. Springer Spektrum. (Cit. on p. 21).

Federal Statistical Office of Germany. (2018). *Equipment of households with electrical household appliances and others*. https://www.destatis.de/EN/Themes/Society-Environment/Income-Consumption-Living-Conditions/Equipment-Consumer-Durables/Tables/liste-equipment-households-electrical--household-appliance-others-germany.html. (Cit. on p. 42)

Fiorini, L., Steg, L., & Aiello, M. (2020). Sustainability choices when cooking pasta. *Proceedings of the Eleventh ACM International Conference on Future Energy Systems*, 161–166 (cit. on pp. 34, 35).

Gurobi. (2020). *Gurobi mathematical optimization solver*. https://www.gurobi.com/. (Cit. on pp. 34, 36)

Hörsch, J., Schäfer, M., Becker, S., Schramm, S., & Greiner, M. (2018). Flow tracing as a tool set for the analysis of networked large-scale renewable electricity systems. *International Journal of Electrical Power and Energy Systems*, *96*, 390–397 (cit. on pp. 5, 6, 15, 19).

Intergovernmental Panel on Climate Change. (2014). *Climate change 2014: Mitigation of climate change*. Cambridge University Press. (Cit. on p. 14).

Li, B., Song, Y., & Hu, Z. (2013). Carbon flow tracing method for assessment of demand side carbon emissions obligation. *IEEE Transactions on Sustainable Energy*, *4*(4), 1100–1107 (cit. on p. 6).

Murphy, F., Devlin, G., & McDonnell, K. (2015). Benchmarking environmental impacts of peat use for electricity generation in ireland—a life cycle assessment. *Sustainability*, *7*(6), 6376–6393 (cit. on p. 14).

Pandas python library. (2020). https://pandas.pydata.org/. (Cit. on pp. 9, 21)

Song, M., Alvehag, K., Widén, J., & Parisio, A. (2014). Estimating the impacts of demand response by simulating household behaviours under price and co2 signals. *Electric Power Systems Research*, *111*, 103–114 (cit. on p. 6).

Stoll, P., Brandt, N., & Nordström, L. (2014). Including dynamic co2 intensity with demand response. *Energy Policy*, *65*, 490–500 (cit. on p. 6).

Tao Sun, Donghan Feng, Teng Ding, Lixia Chen, & Shi You. (2016). Directed graph based carbon flow tracing for demand side carbon obligation allocation. *2016 IEEE Power and Energy Society General Meeting (PESGM)*, 1–5 (cit. on p. 6).

Tranberg, B., Corradi, O., Lajoie, B., Gibon, T., Staffell, I., & Andresen, G. B. (2019). Real-time carbon accounting method for the european electricity markets. *Energy Strategy Reviews*, *26* (cit. on pp. 5, 6, 14, 15, 33).

Wang, J. (2013). Time-delay correlation. In W. Dubitzky, O. Wolkenhauer, K.-H. Cho, & H. Yokota (Eds.), *Encyclopedia of systems biology* (pp. 2170–2171). Springer New York. (Cit. on p. 22).

All links were last followed on November 30, 2020

A Tables

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
AT	314.1	314.3	213.9	188.3	135.2	127.4	210.8	208.4	254.8	309.2	282.5	283.1	236.8
BA	839.1	763.7	788.8	661.8	631.5	705.6	889.3	886.6	867.4	801.8	723.1	650.8	767.5
BE	309.0	273.6	219.1	204.2	184.0	182.8	194.6	176.3	189.8	247.4	269.0	213.7	222.0
BG	644.0	586.4	523.4	502.3	586.3	396.1	499.5	509.5	584.9	708.7	564.1	548.1	554.4
CH	226.2	224.4	158.9	154.7	109.7	156.3	131.0	132.0	129.8	156.1	189.8	145.9	159.6
CZ	658.1	636.3	620.8	607.9	555.4	534.4	575.6	596.5	611.2	577.2	601.9	615.9	599.3
DE	490.9	496.1	371.7	436.2	437.2	390.3	428.1	429.1	407.1	423.5	512.8	383.6	433.9
DK	365.2	327.0	267.1	288.7	205.1	123.1	151.4	226.7	189.2	264.6	315.5	267.8	249.3
EE	969.0	783.3	822.2	770.6	631.1	403.1	374.4	602.2	669.2	563.8	699.9	555.2	653.7
ES	297.6	270.0	186.3	202.7	206.5	235.5	263.7	254.5	235.7	257.7	198.5	170.0	231.6
FI	326.6	281.1	247.9	196.9	159.7	104.9	109.7	116.6	187.8	227.9	235.5	219.7	201.2
FR	92.4	76.8	57.2	49.9	45.0	44.6	63.0	53.8	65.9	67.6	101.0	71.8	65.7
GR	724.6	666.0	673.4	684.8	652.3	655.2	648.7	609.7	631.6	659.1	677.0	670.6	662.7
HU	451.4	453.2	434.6	352.7	321.5	362.8	414.8	396.1	434.9	434.7	407.3	384.7	404.1
IE	406.8	315.3	389.1	413.5	436.5	445.8	430.9	376.3	399.3	357.6	400.1	346.1	393.1
IT	456.0	424.0	413.0	420.0	366.7	363.5	392.1	402.9	427.6	435.3	400.1	382.0	406.9
LT	390.6	274.4	220.2	224.0	228.4	216.0	257.1	258.9	310.8	205.6	217.9	261.9	255.5
LV	546.1	447.3	320.1	381.5	386.2	372.9	376.2	438.1	448.6	368.4	347.2	321.9	396.2
ME	707.9	589.3	743.5	540.4	379.8	591.0	803.1	814.2	791.2	867.0	513.4	453.7	649.5
MK	819.9	783.4	791.1	811.6	705.2	864.9	820.4	843.0	911.5	850.3	807.8	772.3	815.1
NL	590.6	599.9	542.8	540.6	526.9	487.6	490.7	457.0	450.8	532.9	596.0	539.5	529.6
NO	36.4	27.1	38.5	32.1	28.7	21.7	22.0	23.8	18.8	23.3	30.6	35.3	28.2
PL	932.9	906.5	869.2	899.6	929.9	947.5	928.0	974.4	916.3	910.7	904.1	873.5	916.1
PT	379.5	344.2	299.7	298.5	274.9	373.2	409.6	272.2	251.3	299.9	218.4	186.6	300.7
RO	428.2	407.4	376.3	351.0	302.2	276.5	385.7	404.1	432.8	440.4	397.6	389.2	382.6
RS	932.4	877.3	930.7	860.3	755.3	752.0	935.4	1007.8	1010.0	1043.4	944.4	912.6	913.5
SE	113.6	100.9	97.3	87.4	69.0	52.3	56.6	60.1	63.6	73.7	85.3	85.9	78.8
SI	464.9	410.2	345.1	287.4	256.9	253.9	382.5	340.3	356.2	628.4	321.1	338.0	365.4
SK	420.0	364.8	325.5	351.2	305.4	312.1	356.1	323.2	371.4	382.6	305.9	345.5	347.0
UK	340.3	281.0	256.1	268.1	259.0	270.8	275.4	228.9	229.4	256.4	297.7	250.7	267.8

Table A.1: Average CO_2 emission intensity in 2019

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
AT	61.6	62.7	78.7	80.9	90.0	87.8	79.6	77.4	70.6	61.0	64.7	63.0	73.2
BA	27.6	34.1	32.3	43.2	45.3	38.8	23.5	23.8	25.5	31.8	37.3	43.9	33.9
BE	14.2	15.2	18.0	14.2	13.9	18.6	14.8	15.7	15.8	15.7	14.6	18.1	15.7
BG	8.5	13.3	12.8	12.6	20.0	22.6	13.0	13.1	10.8	9.1	9.7	10.4	13.0
CH	26.9	22.7	14.9	19.7	24.7	44.2	39.0	39.5	27.3	23.6	26.4	27.9	28.1
CZ	8.9	9.6	13.2	14.0	12.2	14.7	14.7	12.5	11.0	9.9	8.4	8.9	11.5
DE	39.0	38.1	49.6	44.5	45.3	47.3	41.7	40.4	42.7	41.4	34.7	46.3	42.6
DK	59.0	62.5	70.4	65.7	76.9	75.4	72.9	67.3	75.4	71.9	66.2	70.2	69.5
EE	12.7	23.3	22.1	17.3	22.3	31.5	30.9	26.3	26.9	30.2	25.4	35.3	25.3
ES	39.2	38.2	43.8	42.1	43.4	34.3	30.6	28.8	32.9	31.6	51.3	51.9	39.0
FI	31.2	35.5	38.0	39.3	50.7	48.0	39.8	39.4	38.4	32.4	34.6	38.8	38.8
FR	14.4	16.1	20.5	18.5	20.4	22.1	18.6	18.2	17.0	18.5	21.3	24.3	19.2
GR	23.0	30.0	34.3	29.5	32.5	30.0	28.1	34.8	30.1	26.2	28.2	32.4	29.9
HU	6.3	8.2	8.1	7.7	7.6	6.1	5.2	4.8	6.0	8.8	8.4	9.0	7.2
IE	37.6	54.7	45.4	41.4	27.7	30.6	26.0	40.1	39.1	47.8	41.2	52.1	40.3
IT	28.6	33.9	34.1	35.5	42.3	43.2	36.9	35.9	31.9	28.7	39.0	40.3	35.9
LT	69.4	76.8	75.7	70.7	64.3	58.4	55.1	47.6	55.7	58.8	69.1	69.5	64.3
LV	26.0	43.9	64.0	65.9	52.3	31.5	26.6	24.2	21.9	38.9	48.6	54.6	41.5
ME	43.5	54.4	38.1	100.0	100.0	53.9	34.3	37.0	35.4	18.7	69.3	75.9	55.0
MK	19.5	21.6	20.0	19.7	24.8	14.7	17.0	15.6	10.5	20.5	19.4	24.1	19.0
NL	9.0	7.6	10.8	8.6	7.0	6.8	5.4	7.6	9.6	10.0	7.5	11.3	8.4
NO	97.4	97.9	97.5	97.2	97.2	97.1	97.3	97.4	97.7	97.8	97.9	97.6	97.5
PL	13.3	15.1	17.1	13.0	10.7	9.2	10.1	7.4	12.7	11.9	13.3	15.7	12.5
PT	49.2	51.1	57.6	54.9	52.6	37.6	34.9	44.8	48.3	45.8	61.8	68.0	50.5
RO	33.4	36.8	41.1	45.1	60.2	57.3	39.8	36.8	34.4	29.9	36.5	36.5	40.7
RS	24.2	30.5	28.0	31.7	40.6	39.9	26.4	21.7	21.2	17.9	24.9	25.7	27.7
SE	51.8	52.9	53.5	52.3	55.1	50.6	52.3	47.7	55.4	54.0	54.3	55.4	52.9
SI	16.6	26.7	23.9	32.5	37.8	40.4	25.9	25.8	26.9	28.9	39.6	35.7	30.1
SK	18.7	21.5	27.4	26.0	28.1	31.0	21.2	19.3	16.7	17.3	19.5	18.3	22.1
UK	24.6	29.8	34.3	30.5	28.6	32.2	28.5	35.7	33.5	31.0	28.3	37.0	31.2

Table A.2: Share of renewable technologies in domestic electricity production in %, 2019

	AT	BE	BG	CZ	DE	DK	EE	ES	EU28	FI	FR	UK	GR
Nuclear	12.40	12.00	12.00	12.00	11.30	12.40	12.4	12.1	12.4	12.5	12.9	12.4	12.4
Geothermal	81.80	81.80	81.80	81.80	81.80	81.80	81.8	81.8	81.8	81.8	81.8	81.8	81.8
Biomass	53.80	53.80	56.80	53.80	53.80	53.80	56.8	53.8	53.9	53.8	53.8	53.8	53.9
Hydro Pumped Storage	452.00	378.00	901.00	1140.00	965.00	617.00	617.00	546	617	617	77.3	617	1420
Hydro Water Reservoir	6.97	14.7	14.7	51.4	51.4	14.7	14.7	51.4	14.7	51.4	6.97	14.7	14.7
Hydro Run-of-river and poundage	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42
Solar	107.00	112.00	77.9	118.00	110.00	94.6	94.6	71.4	94.6	94.6	90.9	94.6	76.3
Wind Offshore	17.8	16.2	19.5	19.4	20	13.8	19.8	14.2	16.8	23	15.6	16.8	15.1
Wind Onshore	17.8	16.2	19.5	19.4	20	13.8	19.8	14.2	16.8	23	15.6	16.8	15.1
Fossil Brown coal/Lignite	986.00	1120.00	1180.00	1190.00	1170.00	1160.00	1300.00	1210	1160	1080	1090	1140	1300
Fossil Coal-derived gas	986.00	1120.00	1180.00	1190.00	1170.00	1160.00	1300.00	1210.00	1160.00	1080.00	1090	1140	1300
Fossil Hard coal	986.00	1120.00	1180.00	1190.00	1170.00	1160.00	1300.00	1210.00	1160.00	1080.00	1090	1140	1300
Fossil Oil	1160.00	913.00	1670.00	1060.00	877.00	1240.00	1180.00	866.00	1020.00	447.00	953	1320	993
Fossil Oil shale	1160.00	913.00	1670.00	1060.00	877.00	1240.00	1180.00	866.00	1020.00	447.00	953	1320	993
Fossil Gas	614.00	472.00	746.00	697.00	533.00	513.00	513.00	492.00	513.00	839.00	588	521	682
Waste	920.00	835.00	1198.67	982.33	860.00	971.00	997.67	856.00	897.67	788.67	877.00	993.67	991.67
Fossil Peat	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00
Marine	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00
Other renewable	38.32	39.52	36.45	45.65	44.80	36.74	38.62	38.53	37.50	43.63	35.76	37.49	34.79
Other	920.00	835.00	1198.67	982.33	860.00	971.00	997.67	856.00	897.67	788.67	877.00	993.67	991.67

	HU	IE	IT	LT	LV	ME	NL	NO	PL	PT	RO	RS	SE	SI	SK
Nuclear	12	12.4	12.4	12.4	12.4	12.4	12	12.4	12.4	12.4	14.2	12.4	12.2	12	12
Geothermal	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8	81.8
Biomass	53.8	53.8	53.8	56.8	56.8	53.9	53.8	53.9	53.8	53.8	53.8	53.9	53.8	53.8	53.8
Hydro Pumped Storage	617	851	615	1040	617	617	617	41.7	1420	588	629	1220	617	617	684
Hydro Water Reservoir	14.7	14.7	6.97	14.7	14.7	14.7	14.7	6.97	14.7	51.4	14.7	6.97	51.4	14.7	51.4
Hydro Run-of-river and poundage	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42	4.42
Solar	94.6	94.6	81.3	109	94.6	94.6	109	94.6	94.6	69.3	88.1	82.8	110	83	90.7
Wind Offshore	13.6	13.7	19.7	13.3	18.2	16.8	16.3	14.4	16.5	13.7	25.3	16.8	16.2	16.8	16.8
Wind Onshore	13.6	13.7	19.7	13.3	18.2	16.8	16.3	14.4	16.5	13.7	25.3	16.8	16.2	16.8	16.8
Fossil Brown coal/Lignite	1410	1070	1150	1180	1160	1160	1030	1160	1160	1140	1140	1340	1180	1200	1160
Fossil Coal-derived gas	1410	1070	1150	1180	1160	1160	1030	1160	1160	1140	1140	1340	1180	1200	1160
Fossil Hard coal	1410	1070	1150	1180	1160	1160	1030	1160	1160	1140	1140	1340	1180	1200	1160
Fossil Oil	1130	919	1060	1020	1020	1020	1020	1020	1020	834	1000	1020	854	1390	960
Fossil Oil shale	1130	919	1060	1020	1020	1020	1020	1020	1020	834	1000	1020	854	1390	960
Fossil Gas	750	462	532	513	513	513	465	407	513	441	615	513	513	1090	694
Waste	1096.67	817.00	914.00	904.33	897.67	897.67	838.33	862.33	897.67	805.00	918.33	957.67	849.00	1226.67	938.00
Fossil Peat	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00	1120.00
Marine	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00	17.00
Other renewable	36.69	36.72	35.59	38.79	38.22	37.50	39.17	35.94	37.42	38.14	38.80	35.06	43.85	36.04	41.59
Other	1096.67	817.00	914.00	904.33	897.67	897.67	838.33	862.33	897.67	805.00	918.33	957.67	849.00	1226.67	938.00

Table A.3: Life cycle CO_2 Emission Impact

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
AT	30.5	31.8	28.5	20.5	18.3	15.1	25.1	25.2	30.7	36.1	25.7	31.6	26.6
BA	4.0	5.3	14.6	7.8	3.5	4.9	1.7	1.7	2.1	4.4	2.3	1.7	4.5
BE	13.3	16.7	11.9	10.9	14.1	16.5	8.1	5.4	2.4	5.3	9.0	12.4	10.5
BG	4.8	4.0	6.1	6.1	9.4	9.8	4.6	2.7	2.9	3.6	5.7	7.8	5.6
CH	41.8	48.8	47.2	28.5	30.7	26.4	12.7	14.8	32.2	36.4	37.3	42.0	33.2
CZ	12.8	9.5	11.4	10.2	6.7	9.7	18.0	9.1	9.8	8.9	6.6	11.5	10.4
DE	1.4	2.8	3.4	3.9	7.6	9.1	8.3	9.4	6.9	3.6	3.6	4.6	5.4
DK	23.7	24.8	25.2	38.8	34.2	55.0	49.7	51.9	41.2	38.4	31.9	30.1	37.1
EE	9.2	20.3	15.1	26.7	38.5	59.5	63.6	37.4	31.1	45.5	29.1	39.4	34.6
ES	4.7	7.8	9.1	7.6	6.4	4.5	4.3	4.8	5.1	6.2	3.4	6.5	5.9
FI	17.7	16.0	15.1	16.1	18.2	20.9	28.0	27.2	27.5	21.5	21.0	17.5	20.6
FR	3.0	0.9	0.6	1.1	0.2	0.2	1.1	0.9	1.7	1.7	4.0	2.8	1.5
GR	7.4	11.7	19.5	18.6	18.2	15.4	17.2	14.7	16.7	14.9	15.6	18.7	15.7
HU	33.0	35.5	38.5	34.7	38.9	33.6	26.8	33.8	36.0	30.6	24.6	29.8	33.0
IE	7.0	2.5	3.6	3.4	2.7	2.1	5.9	5.1	4.8	3.6	3.6	3.7	4.0
IT	11.8	16.5	15.7	11.5	13.2	11.9	11.9	9.1	12.2	15.7	13.1	14.7	13.1
LT	63.7	53.0	52.7	58.8	55.5	73.7	68.8	72.7	61.5	60.4	50.3	50.3	60.1
LV	30.6	31.7	18.5	35.5	35.6	42.3	46.9	26.8	24.2	26.4	19.6	24.8	30.2
ME	40.0	27.9	46.9	77.7	59.0	44.5	47.9	53.1	47.0	50.4	42.3	42.8	48.3
MK	36.7	44.8	59.8	45.9	63.9	34.0	41.4	39.4	34.9	49.2	53.0	56.2	46.6
NL	11.9	12.3	14.9	19.8	17.4	23.5	17.8	20.0	18.8	12.5	13.3	18.7	16.7
NO	7.7	8.3	15.2	10.8	9.7	10.0	4.1	3.2	1.6	6.1	8.5	13.3	8.2
PL	6.0	6.6	7.5	8.4	8.7	9.0	10.2	7.7	9.8	9.5	8.3	8.1	8.3
PT	10.7	18.3	20.2	13.9	16.4	12.1	10.8	17.9	19.2	15.3	7.5	4.2	13.9
RO	4.6	1.8	2.0	1.8	1.0	0.6	3.6	10.0	11.0	7.4	4.8	4.2	4.4
RS	15.3	10.9	5.0	11.5	10.2	14.1	12.1	11.3	12.4	10.2	15.2	17.3	12.1
SE	8.3	5.0	4.6	4.0	2.6	2.3	6.2	11.0	8.3	5.3	5.8	4.7	5.7
SI	32.7	19.6	29.7	31.9	23.2	27.6	31.0	32.4	36.2	47.9	8.3	13.1	27.8
SK	37.0	31.1	25.6	31.5	26.2	27.6	31.8	30.1	38.5	38.2	20.8	29.2	30.7
UK	5.6	10.0	10.5	6.7	9.7	8.7	8.4	8.2	7.2	6.2	7.8	7.9	8.1

Table A.4: Share of imports in electricity composition in %, 2019

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Average
AT	23.0	22.0	40.5	46.6	71.4	43.5	37.1	26.5	26.9	20.4	16.2	10.8	32.1
BA	16.9	43.1	52.0	10.4	21.5	40.1	39.9	43.7	32.8	20.1	55.5	56.4	36.0
BE	11.4	12.5	9.3	1.7	-11.3	-6.6	1.3	9.2	9.6	14.4	14.0	22.6	7.3
BG	14.8	12.1	27.6	26.1	13.6	21.6	25.1	26.6	23.0	19.5	26.0	17.3	21.1
CH	179.7	212.6	107.4	63.2	17.0	-13.2	35.3	39.3	79.0	106.6	176.1	130.3	94.4
CZ	36.3	36.6	28.4	33.0	34.8	27.9	31.3	32.4	40.7	42.2	34.1	36.1	34.5
DE	6.2	4.7	5.3	1.5	-5.4	-7.8	-4.7	-4.3	-0.5	1.8	0.9	0.9	-0.1
DK	28.4	22.6	36.3	12.7	24.1	-22.4	-7.6	-3.0	21.5	33.4	27.4	41.5	17.9
EE	9.5	-21.1	-20.2	-16.0	-28.0	-46.9	-45.1	-40.1	-28.9	-35.8	-33.0	-39.7	-28.8
ES	-34.0	-36.7	-36.5	-41.2	-39.7	-40.2	-39.9	-39.8	-38.8	-39.9	-37.3	-35.9	-38.3
FI	-23.9	-22.6	-22.9	-20.1	-19.7	-14.5	-15.2	-25.8	-28.7	-24.3	-24.5	-19.1	-21.8
FR	13.7	15.6	18.1	15.4	9.0	8.0	17.6	18.4	20.2	18.2	13.3	13.1	15.0
GR	-14.4	-23.0	-21.7	-24.8	-25.3	-20.0	-17.8	-14.2	-12.9	-16.3	-23.1	-26.3	-20.0
HU	1.3	-17.0	-8.4	1.3	-9.2	-17.5	-5.1	-5.1	7.5	18.1	-0.1	6.5	-2.3
IE	-18.3	-9.1	-14.5	-21.6	-20.0	-10.3	-22.5	-12.4	-11.6	-18.0	-13.6	-14.7	-15.6
IT	-5.1	-9.4	-10.0	-7.1	-9.4	-9.8	-9.1	-6.6	-8.0	-9.3	-7.8	-9.5	-8.4
LT	7.6	4.4	-12.2	-27.1	-50.0	-46.4	-44.0	-53.8	-36.6	-58.0	-50.0	-31.8	-33.2
LV	56.2	46.4	83.6	131.8	39.3	11.8	8.1	25.3	28.8	13.5	38.7	42.4	43.8
MK	2.4	5.1	21.7	-11.5	20.9	12.6	37.3	29.4	25.0	7.5	11.5	25.9	15.7
NL	-25.5	-34.1	-29.0	-35.3	-33.1	-41.7	-34.2	-36.3	-39.2	-26.7	-19.1	-23.4	-31.5
NO	84.1	49.7	90.1	92.8	39.6	36.1	49.6	62.4	33.9	27.0	75.0	123.2	63.6
PL	-7.3	-9.6	-11.6	-11.6	-11.5	-13.5	-12.4	-12.0	-12.2	-13.2	-12.2	-10.5	-11.5
PT	6.3	-3.5	-7.1	2.6	-0.2	-0.1	1.9	-0.1	1.9	2.4	10.6	19.5	2.8
RO	0.5	3.1	4.0	2.9	6.5	10.4	0.8	2.0	1.7	-1.0	3.7	1.3	3.0
RS	-28.5	-20.6	-5.4	-16.3	-17.5	-16.4	-19.4	-19.1	-22.1	-24.9	-19.4	-21.9	-19.3
SE	26.0	28.7	27.0	25.7	23.0	40.1	41.2	37.3	27.0	27.2	28.2	29.8	30.1
SI	7.7	13.5	8.9	26.8	33.2	27.0	44.7	62.4	60.8	-0.7	40.6	33.3	29.9
SK	126.5	110.1	94.9	104.0	117.5	84.6	108.7	141.4	155.3	137.0	78.1	101.5	113.3
UK	-17.4	-22.4	-24.1	-18.2	-20.9	-12.4	-17.2	-20.7	-21.1	-19.3	-19.3	-21.0	-19.5

Table A.5: Change between CO_2 emission intensity by domestic generation and consumption in %, 2019

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

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