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Bachelorarbeit

Exploration of autarky increasement in single family houses by smart energy balancing

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Abstract

With climate change well on its way and new armed conflicts in Europe rising, energy demands are increasing and its supply might not always be reliable. This work explores how to increase the level of autarky in the scope of single family homes by balancing the energy intelligently.

We model a single family home with a number of actors, such as solar panels on the roof, a heatpump, buffer storage and an electric vehicle, and simulate their behavior in 15 minute timesteps for one year. An algorithm then controls at which times to charge the electric vehicle and the buffer storage based on 24 hour forecasts of the behavior of all non controlled actors. The results are then compared to a naive, currently in most houses implemented, algorithm, which charges the car when it is plugged in.

The results show, depending on the setup, that a good increment in autarky can be achieved with an intelligent algorithm. Furthermore it is possible, with the right setup, to live almost fully autark, especially during the summer season.

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1 Introduction

Among many other research bodies, the NASA Goddard Institute for Space Studies examines the changes in temperature on earth. Concerning a base period of 1880 to 1920, they observed an increase of 1.62°C, in mean over land and sea until the year 2022[GISS22]. Many different factors contribute to this effect, such as agriculture, waste management, and industrial processes. By far one of the most significant is the energy sector, accounting for 84.2% of CO2 Emissions in Germany in 2021[CO222]. To address global warming, the G20 committed to carbon neutrality by the year 2050[G2021]. To achieve that, there has to be a switch to renewable energy sources such as solar and wind energy instead of coal and gas.

Renewable energy sources come with some serious challenges. They, very naturally, are subject to high fluctuations in their electrical power output. Neither sun nor wind is particularly consistent, nor predictable. There are several ideas on how to flatten the grid curve, such as dynamically storing the energy during peak times and resupplying it when the power output of the renewable energy sources is low. Unfortunately, battery storage of that size would not be practical for multiple reasons. Pumped hydroelectric energy storage is a viable option in several regions on earth, but for some, such as Germany, impossible to realize due to missing large bodies of water.

Another way to deal with high fluctuations in power output is shrinking the problem. According to E3DC, already 1.3 million solar power systems were installed in Germany by the end of 2020[E3DC-Solar21]. People start to live more self-sufficient in terms of power supply. By introducing buffer storage, energy can be saved for the night or other times when no sun is shining. This helps to simplify the nationwide problem of power spikes. Since some people are already able to use their own stored energy, the overall power demand curve flattens. To further increase this effect electric vehicles can also be used as energy storage. By intelligently balancing the power of private solar panels between the home buffer battery and the electric vehicle, autarky can be strongly improved for single-family houses. This leads to an even better curve, which is easier to compensate for. In general, increased autarky in private households helps to simplify the switch to renewable energy sources.

But there are more reasons to increase autarky, concerning the reliability of power supply. For example, the power mix of Germany consists of 15.2% natural gas[Gas-Germany22b], of which, as of 2020, 95% were imported[Gas-Germany22a]. This heavy dependence on imported gas gets problematic, if, for whatever reason, that gas would stop flowing.

In this Bachelor's thesis, we find out if we could increase autarky for single-family homes by intelligently balancing the electric energy output of solar panels on the roof to a buffer battery and electric vehicle with an advanced algorithm. This algorithm uses forecasts to predict the driving behavior and weather conditions in the next 24 hours to store energy in the right place at the right time to maximize autarky.

Please note, that in the same simulation framework my colleague Loïc Glandier developed an Algorithm that maximizes monetary benefits by buying and selling power at the right time.

2 Background Information

Since this work will explore autarky, a proper definition is required.

2.1 Autarky

The term autarky describes the ratio of bought to consumed power.

$$autarky = 1 - \frac{bought\_kWh}{consumed\_kWh} \tag{2.1}$$

2.2 Self-sufficiency

Self-sufficiency described how much of the consumed power was self-generated.

$$self\_sufficiency = \frac{consumed\_kWh}{produced\_kWh} \tag{2.2}$$

2.3 Bi-directional charging

Bi-directional charging is a technology, where an EV not only can be charged but also discharged to get its energy. This is by far not a standard yet but has already been implemented in some vehicles, such as the Ford F-150 Lightning[fordbidi22]. Not only the vehicle but also the installed wall box needs to support that feature. There already are some on the market[bidiwall22]. For every model we inspect in this work, we assume this technology to be installed. It is important to mention, that neither charging nor discharging ever happens without losses. The loss functions are not linear and depend on the used battery and electronics. They are respected in this work.

2.4 HP

A heat pump is a system to heat a building, using the heat energy of its surroundings to support the process. The heat energy can either be collected in the air, the water, or the ground. In this work, we will always use a heat pump, since it uses less energy than a traditional heating system.

3 Related Work

3.1 POTENTIAL OF DEMAND AND PRODUCTION SHIFTING IN RESIDENTIAL BUILDINGS BY USING HOME ENERGY MANAGEMENT SYSTEMS

This study[sota115] is very similar to our investigation. They do not focus on autarky meaning their home energy management system does not optimize for that, but they focus on monetary benefits. This is very similar since trying to save money works best by using your self-generated electricity.

Their methodology is to use simulation software, as we did, but a professional one called SimulationX[SimulationX22]. We, in contrast, designed the whole simulation software ourselves. Their setup in terms of actors was mostly the same. The main difference and with that our contribution to research in this field is the fact that we do use a bidirectional wall box with a capable electric vehicle, while they use a unidirectional wall box with an electric vehicle. Another difference in setup is, that they do control the time when certain devices, such as washing machines or dishwashers, run. They also use the boiler to store energy, which is something we did not do.
They investigated very few configurations, namely three, as seen in Figure 3.1.

Just like us, they have a reference run with a naive algorithm, which does no smart management. Let's have a look at their results.

The results are very similar to our values, see Table 5.1. Our reference run, as well as the autarky optimized run, are both higher than the respective run from the study. This can be explained by our 45.6% higher kWp of the PV system. Although they do not specify the maximum charging power of the battery, they state they use 3.68kW to charge the car, whereas we use 11kW.
Taking these factors into account, the results are validating each other.

Components	MC	SC	BC
Building configuration	~1970 not refurbished	EnEV2009	EnEV 2012
Heat Generation	x (CB)	x (HP)	x (HP)
Electric Vehicle	x	x	x
Battery [kWh]	-	5	10
PV [kWp]	1	3	5
DSM-Devices	x	x	x
Immersion Heater	-	x	x
Thermal Storage HS [l]	-	700	700
Thermal Storage DWW [l]	300	300	300
not optimized in HEMS, optimized in HEMS			

Figure 3.1: The configurations for the simulation of the study

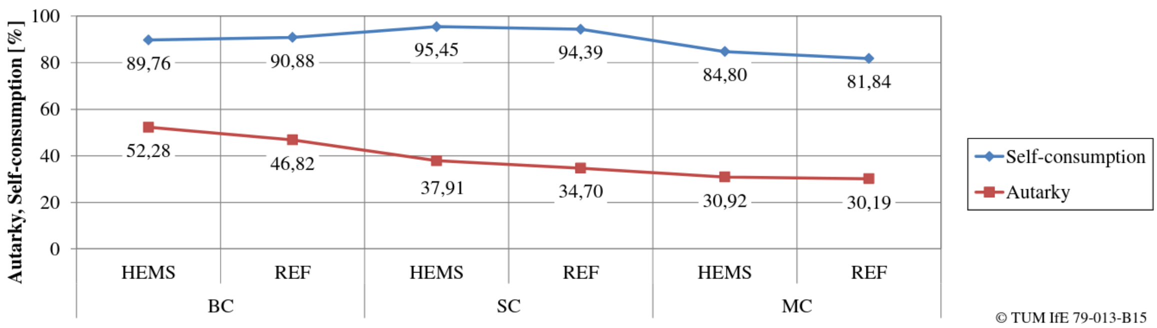

Figure 3.2: The results for the simulation of the study

3.2 Dezentrale Solarstromspeicher für die Energiewende

This study[Sota315] from the 'Hochschule fuer Technik und Wirtschaft', Berlin, analyzes, how we can use intelligent buffer storage charging to increase autarky in single-family homes. In contrast to our work, they do not include electric vehicles in their examination. Although, there are many similarities. They also use photovoltaic systems and heat pumps, as well as buffer storage.

Their approach is not simulation software, but a mathematical model, which they use to perform a linear numerical optimization.

Comparing the results is a challenge for several reasons. The models differ in the electric vehicle, which has an impact on the performance of the charging system. Apart from that, the input data is different. We use different datasets for the photovoltaic system, the house, and the heat pump consumption. Probably the most important factor is the amount of night usage of the electric vehicle we have available. It is not uncommon for a driver to use his vehicle after dark. This has a high impact on the autarky since there is no sunlight to charge in that case.

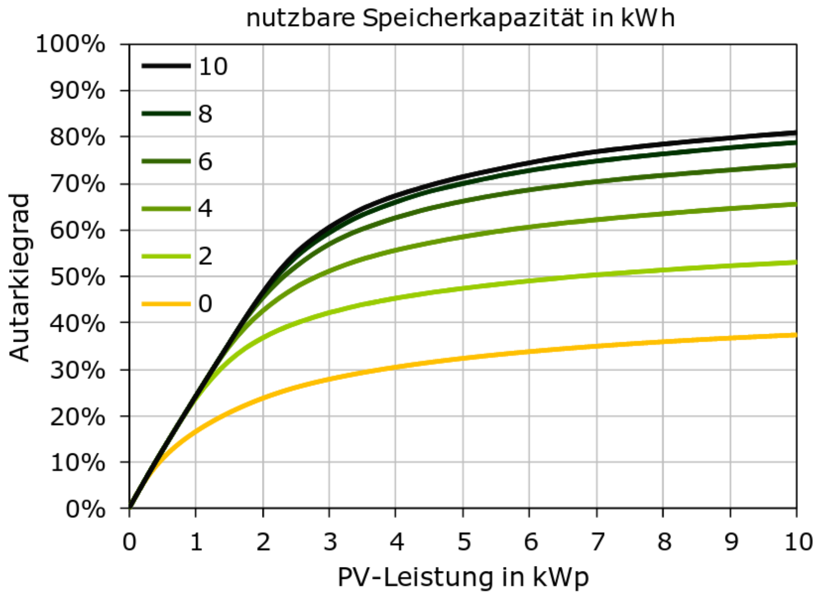

Figure 3.3: The results of the study

We can see, that they reach much higher degrees of autarky with significantly smaller configurations. We stated the reasons for this. Besides the offset, there are the same tendencies visible in this chart and Figure 5.17. In both charts, we can see, that upgrading the buffer storage has a higher impact than upgrading the PV system, at least from 3.64kWp onwards. Furthermore, we can observe, that both variables seem to reach a limit, meaning an infinite upgrade of the PV system would not result in 100% autarky.

3.3 Batteriespeicher in Haushalten unter Berücksichtigung von Photovoltaik, Elektrofahrzeugen und Nachfragesteuerung

This study[Sota217] was published at the 'Karlsruher Institut für Technologie' by Thomas Kaschub as his dissertation. Thomas Kaschub investigated how to maximize the capital value of a correctly sized PV system and buffer storage. This is different from our work since we try to maximize autarky. The study also includes measurements for autarky, which will help us to compare the results.

The approach was a mixed-integer linear program to simulate the very same household we simulated. Although he does not explicitly state the kind of heating system in the house.

		TRÄG	***REF***	***DYN***	***AKTUELL***
SOFORT, MLV^{SBS}	Zielwert^{SBS} in €	-24 840 ± 8 492	-28 520 ± 9 901	-30 729 ± 10 642	-26 984 ± 9 290
	NPV^{SBS} in €	19 ± 14	1 317 ± 568	5 179 ± 1 820	---
	NPV^{SBS} in €/kWh_{inst}	30 ± 22	341 ± 147	546 ± 192	---
	Kapa^{SBS} in kWh_{inst}	0,6 ± 0,5	3,9 ± 1,6	9,5 ± 4,4	---
	Komb. mit $NPV^{SBS} > 0$	250	250	250	0
	Ppeak^{PV} in kW_p	1,3 ± 0,8	3,7 ± 1,5	6,6 ± 2,4	6,2 ± 2,6
	Eigenverbrauchsanteil in %	85,4 ± 4,8	72,4 ± 2,9	63,3 ± 2,5	29,5 ± 3,8
	Eigendeckungsanteil in %	17,1 ± 6,8	41,6 ± 8,4	65,6 ± 5,4	28,7 ± 8,5
	Netzbezug in kWh	5 311 ± 1 830	3 880 ± 1 466	2 460 ± 869	4 556 ± 1 663
	Netzeinspeisung in kWh	-303 ± 208	-1 332 ± 547	-3 010 ± 1 076	-4 887 ± 2 032
	Ausnutzung zykl. Lebensd. in %	100 ± 0	82,0 ± 8,7	59,3 ± 4,3	---
OPTIMAL, MLV^{SBS}	Zielwert^{SBS} in €	23 055 ± 8 248	-25 696 ± 9 347	-27 283 ± 9 982	-23 416 ± 8 612
	NPV^{SBS} in €	16 ± 14	1 010 ± 521	3 793 ± 1 715	---
	NPV^{SBS} in €/kWh_{inst}	29 ± 26	292 ± 150	551 ± 249	---
	Kapa^{SBS} in kWh_{inst}	0,5 ± 0,5	3,5 ± 1,8	6,9 ± 3,8	---
	Komb. mit $NPV^{SBS} > 0$	246	250	250	0
	Ppeak^{PV} in kW_p	2,7 ± 1,2	4,6 ± 1,6	6,9 ± 2,4	8,6 ± 3,1
	Eigenverbrauchsanteil in %	79,4 ± 9,1	74,3 ± 4,1	65,1 ± 3,0	35,6 ± 4,7
	Eigendeckungsanteil in %	32,7 ± 9,5	52,1 ± 7,2	67,6 ± 4,1	46,0 ± 9,2
	Netzbezug in kWh	4 266 ± 1 665	3 069 ± 1 256	2 094 ± 799	3 364 ± 1 410
	Netzeinspeisung in kWh	-831 ± 477	-1 607 ± 614	-3 037 ± 1 123	-6 313 ± 2 393
	Ausnutzung zykl. Lebensd. in %	100 ± 0	74,1 ± 7,1	57,6 ± 4,5	---

Figure 3.4: The results of the study

For us, there are several interesting values in these results. Have a look at the REF column, which serves as a reference without further optimization. The lower half of the column has a row named 'Eigendeckungsanteil in %', which means autarky. In that field, we find the value 52.1 ± 7.2, which lines up very well with our value for the base case, which is 55.34%, see Table 5.1. The difference can be explained by a smaller BS ($3.6kWh \pm 1.8$ instead of 5.5kWh) and a smaller PV system ($4.6kWp \pm 1.6$ instead of 7.28kWh).

The DYN column describes one optimized case, where a greater BS comes into play, as well as a greater PV. Refer to the 'Ppeak^{PV} in kW$_p$' row for the size of the PV system and 'Kapa^{SBS} in kWh$_{inst}$' for the size of the BS. For this DYN case, we find an autarky of 67.6%, which is close to our autarky optimized base configuration case, which is 63.19%, as seen in Table 5.1.

The main difference is, that our study explicitly focuses on optimizing autarky with a smart algorithm, while the study from Thomas Kaschub has its main focus on economic aspects.

4 Methodology

4.1 General Approach

To explore the autarky increase in single-family houses by smart energy balancing, we built simulation software. The software simulates in time steps of 15 minutes, takes datasets as inputs to define the behavior of all noncontrolled actors, and produces datasets that can then be further analyzed. The backend is written in Python. To Visualize the generated data, grafana is used.

The timespan of one simulation is one year. This duration was chosen to not only simulate behavior during one season but all four. We simulated different setups, with several differently sized buffer batteries and electric vehicles and we tried out different

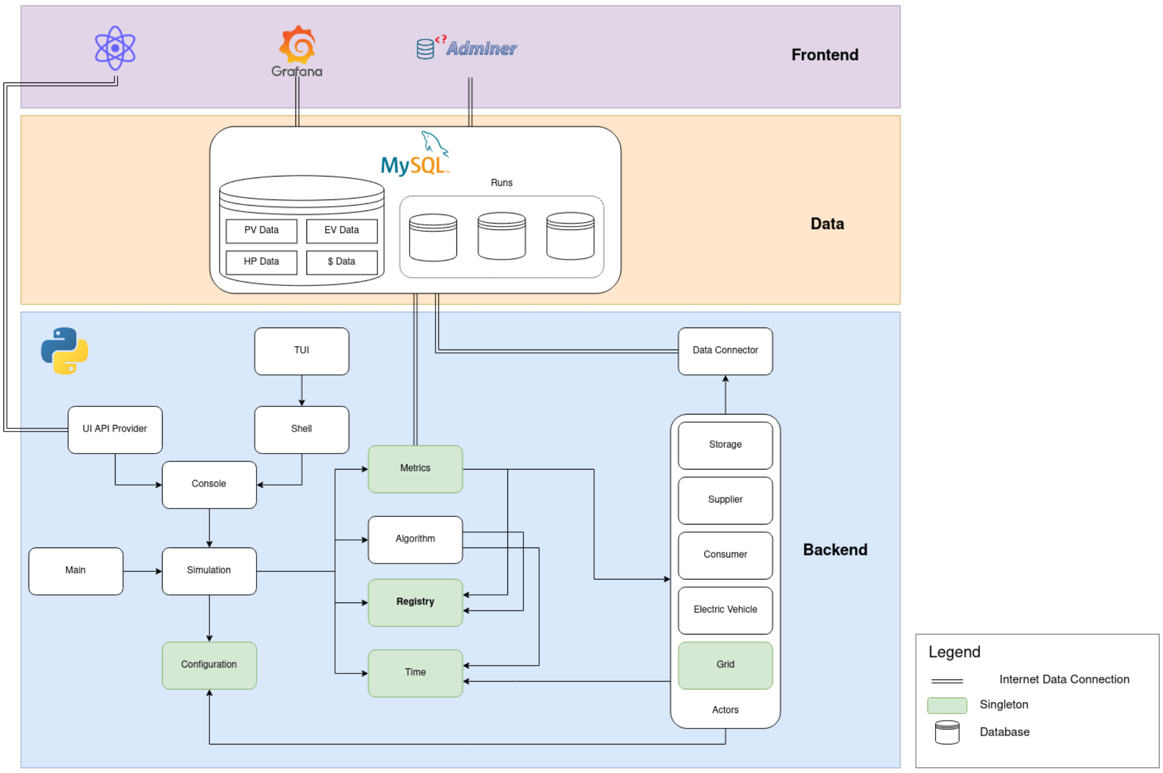

Figure 4.1: Simulation Software Architecture

driving profiles and different solar power systems. Which setups were used exactly and how well they performed is further described in Chapter 5 and Chapter 6.

All runs are compared to a run with the same setup but without intelligent energy balancing. This way we can see how well the algorithm performed.

4.2 Actors

We used the following actors in every simulation

actor	category
solar power system	supplier
electric vehicle	electric vehicle
buffer storage	storage
HP	consumer
house	consumer
grid	grid

Table 4.1: Actors used in every simulation, with different settings

In the following, every actor is described alongside the needed data.

4.2.1 Solar power system

The solar power system is a photovoltaic system that is installed on the roof of the virtual house. As a categorized supplier it supplies electric energy to the house.

Data

The used dataset for the solar power systems was generated by the professional simulation software PV*Sol[PVSol22]. The simulated PV model has a peak of 7.27kW and is assumed to be located in Berlin, Germany. The provided weather data was from the year 2020.

4.2.2 Electric Vehicle

The electric vehicle is in a special category. It can be connected to the house via a wall box. We assume the car and the wall box to be capable of bidirectional charging. The car has a dataset to define driving behavior. The car battery charging and discharging efficiency is implemented, respecting the measurements of Peter Rotenberger in his Bachelor's Thesis at the University Duisburg Essen. The vehicle board electronics consumption is also taken into account during charging and is assumed to be 200W. The car can never return with a higher SoC than the one it left with. This means the car is always charged at home.

Data

The driving profiles were generated using a sophisticated simulation tool from the DIW Berlin, called emobpy[emobpy21]. For this, we used three different driving profiles. One of a free-time driver 4.2, one of a part-time worker 4.3 and one of a full-time worker 4.4. The profiles differ mainly in their driving schedule. Figure 4.5 depicts the energy distribution in the EV model.

4.2.3 Buffer storage

The buffer storage is a battery that can store and release energy. It is fully controlled by the algorithm. It has the same efficiency curves for charging and discharging as the electric vehicle.

4.2.4 Heatpump

The HP is classified as a consumer. It decides for itself when to run at which power. This is defined in a dataset.

Data

The Data for the used heat pump is from a dataset recorded in Lower Saxony, Germany in a 15-minute resolution with the respective data for the consumption of the house [hpdata22]. We use the table 'sfh_12_heatpump_2020' for every simulation.

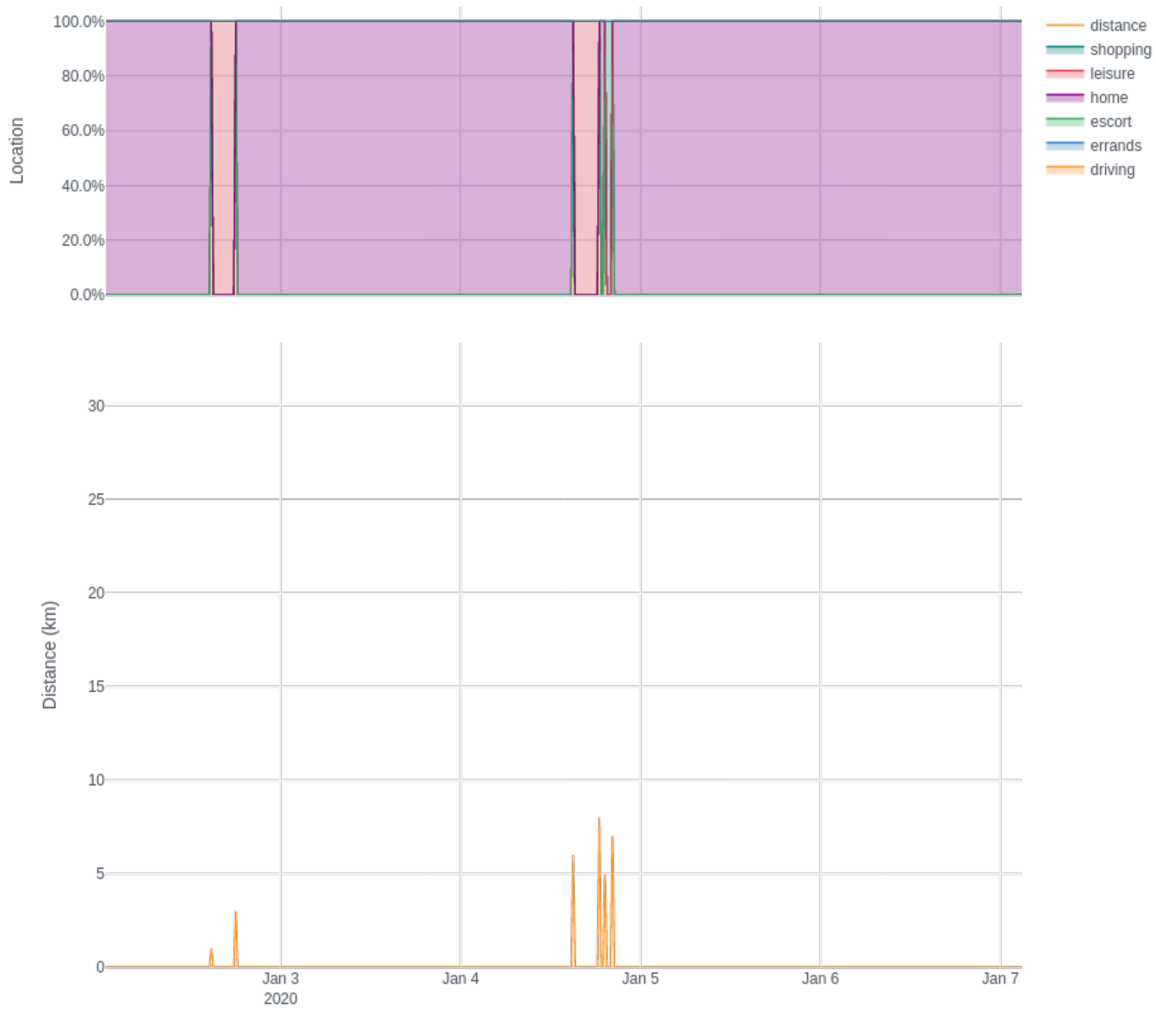

Figure 4.2: Example driving profile for a free-time driver

4.2.5 House

The house collects all remaining consumers, which in this case is everything but the HP. It is treated like a regular consumer, and all of its behaviors are defined in a dataset.

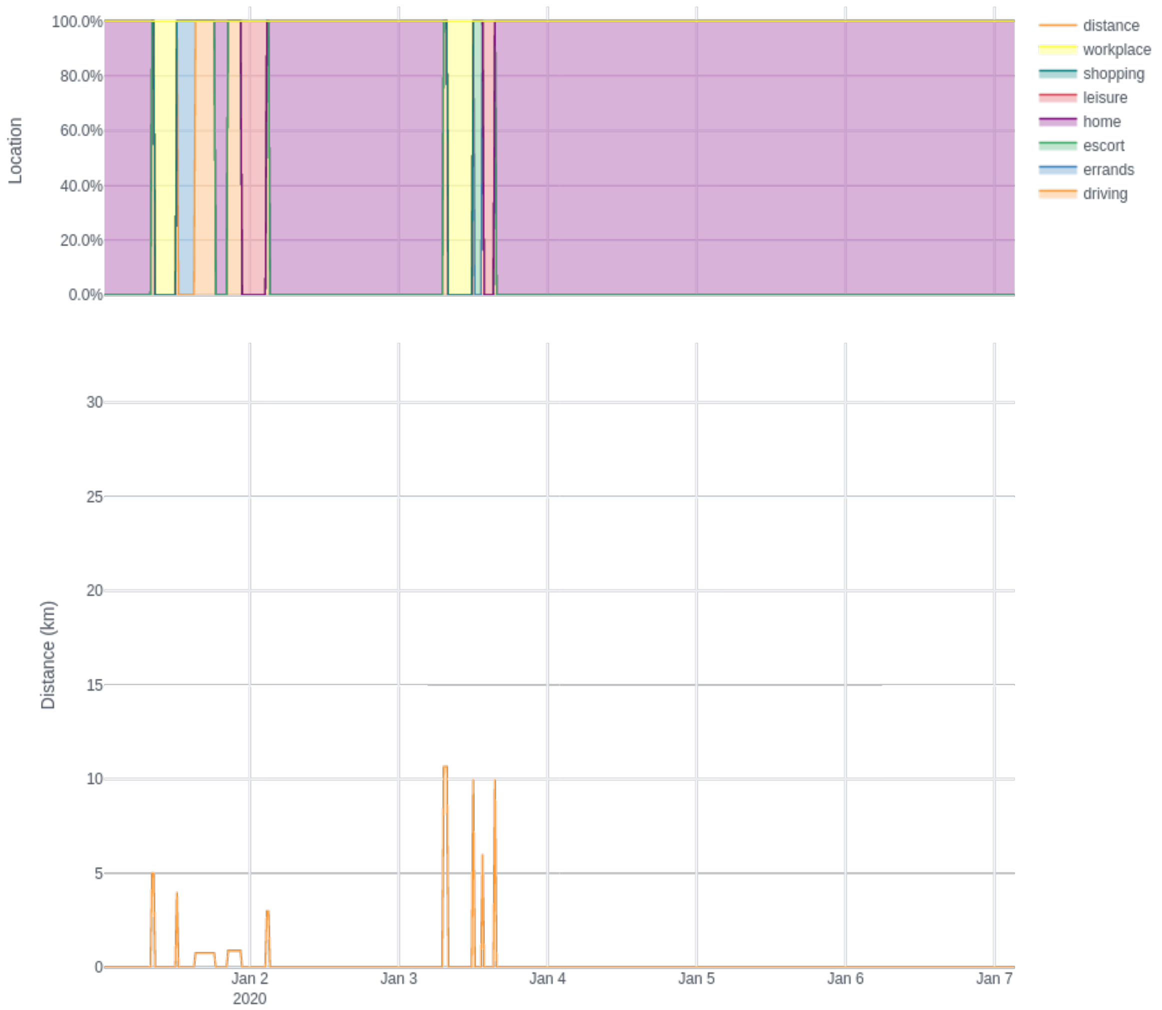

Figure 4.3: Example driving profile for a part-time worker

Data

The data for the house consumption comes from the same dataset as the data for the heat pump [hpdata22]. It is important to have these data match each other to model an accurate household. We use the table 'sfh_12_house_2020' for every simulation, which fits the data for house consumption.

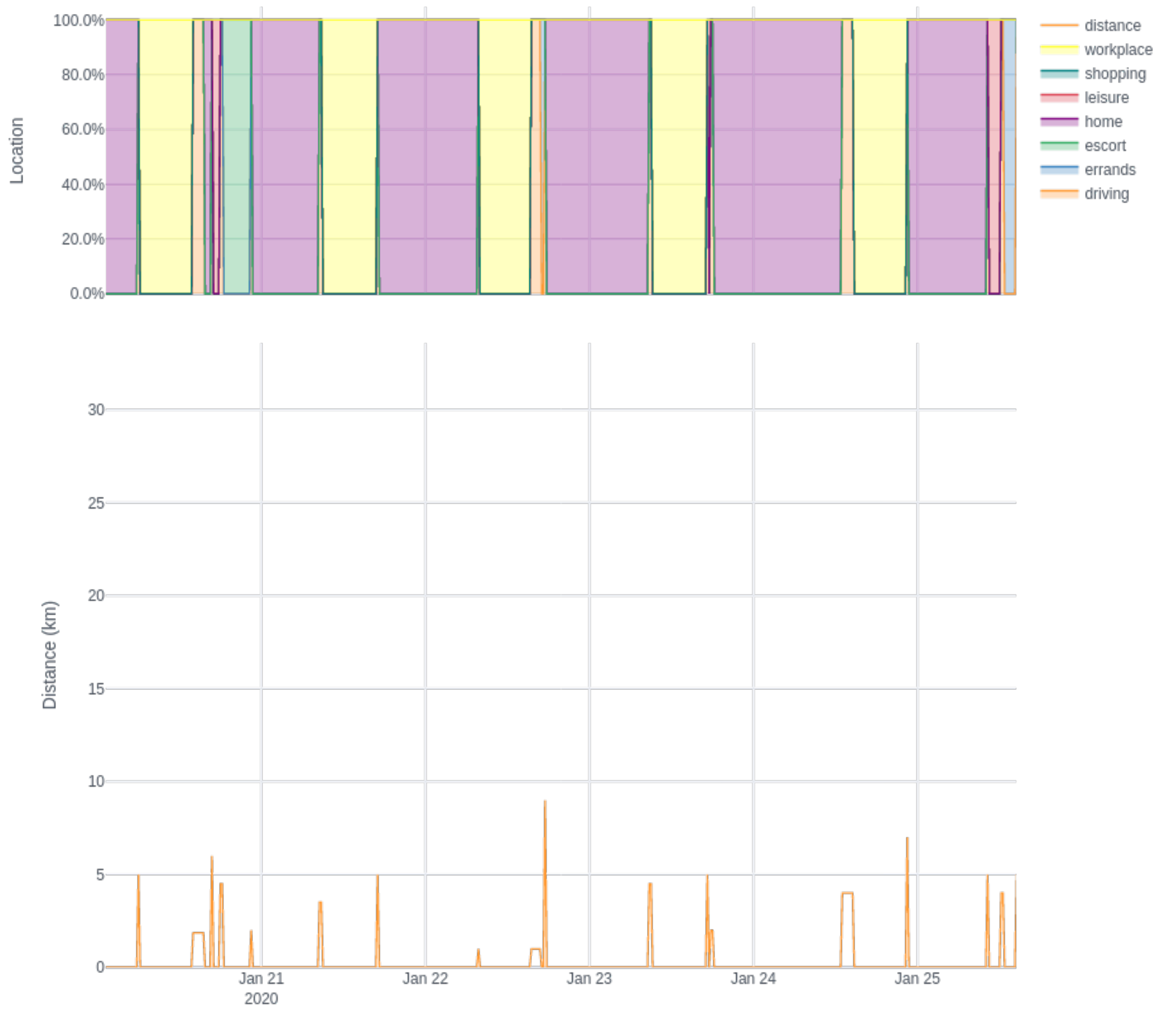

Figure 4.4: Example driving profile for a full-time worker

4.2.6 Grid

The grid is the simulated power grid the virtual house is connected to. We assume no power outages or shortages. We also assume that we can always feed power back into the grid. Our grid supports two payment models. One uses dynamic pricing, the other one is static.

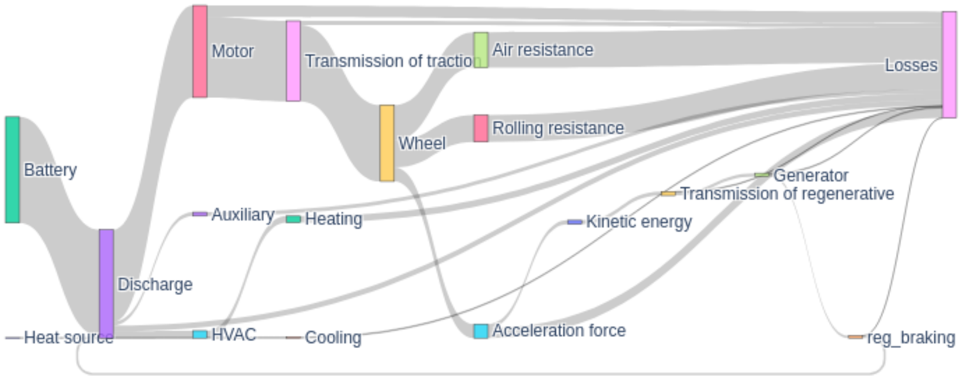

Figure 4.5: Example for the energy distribution and loss model in an electric vehicle

Data

For the dynamic pricing model, the day ahead prices from the Transparency Platform entsoe[entsoe22] are used. The time period is the year 2020, as in all other datasets as well. For static pricing, we assumed a fixed buy price of 0.35€and a selling price of 0.05€.

4.3 Simulation Framework

The simulation framework was developed from the ground up and uses very few libraries. We had a focus on extensibility. The software was written in Python 3.8. We built several interesting features, which we will highlight in the following. The whole architecture, for example, Grafana, Adminer, or the Database Server is collected in a docker-compose file to easily get started. The Python backend and the React frontend are not dockerized though. This decision was met for simpler development. Figure 4.6 gives a general overview of the backend.

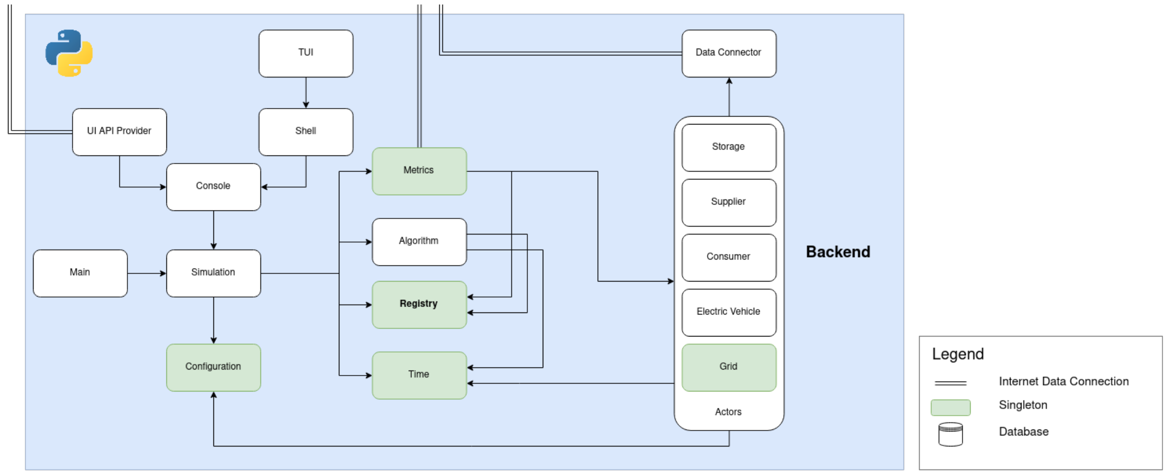

Figure 4.6: Simulation Software Backend Architecture

4.3.1 Console

The Console Structure allows for communication with the software. We built a shell on top with a small tui for convenience. There are several shortcuts to generate and register actors or to get the state of the current simulation, but you really can execute any Python code.

4.3.2 Metrics

The Metrics system allows exporting any data of any actor to a database. The data will be put in a clear structure, so you do not lose track when exporting many metrics. In Table 4.2 the tables inside the database of a simulation are visible. There is one table for every actor and an additional one for everything which is actor independent, such as values generated by the algorithm. Table 4.3 shows the content of one of these actor tables, specifically the Car table. We can see every recorded value for that actor listed with its time.
Besides data from actors, you can additionally export any other values which seem to be interesting to you. The data will automatically be readable by Grafana. To ensure fast access to the database, you can configure Save Intervals in which the metrics are exported. The metrics are recorded for every timestep, but kept in RAM and saved in clusters to save connection overheads to the database.

Tables
Grid
My_Battery
My_Car
My_House
My_Photovoltaic
My_Pump
states

Table 4.2: Tables for each actor in a database for one run

time	amount_consumed	current_charge	at_home
2020-01-01 00:00	0	30	1
2020-01-01 00:15	0	30	1
2020-01-01 00:30	0	30	1
2020-01-01 00:45	0	29.5148	1
2020-01-01 01:00	0	28.4527	1

Table 4.3: Example Table for Electric Vehicle Metrics

4.3.3 Configuration

The Configuration singleton holds every variable which should be easily configurable. See Listing 4.1 for some example values. Besides general configurations, there are also presets available. This adds convenience to the configuration process for actors such as cars. See Listing 4.2 for an example car configuration.

Listing 4.1 A few selected configuration options for general configuration options of the simulation framework

```
start_time = datetime(2020, 1, 1, 00, 00, 00) #Startdate
last_timestep = 34996   # the end of the simulation
db_url = "127.0.0.1"    # URL of database. Omit Port
db_user = "root"
db_pwd = "root"
db_save_interval = 1000 # Amount of steps to simulate until data gets written into the
    database
```

Listing 4.2 An electric vehicle preset

```
tesla_3 = {
   "max_capacity": 60,     #in kwh
   "charging_speed": 11,   #in kilowatt
   "discharging_speed": 11, #in kilowatt
   "required_min_charge_in_percent": 30, #the lowest battery percentage the car should
       have when returning home
   "initial_charge": 30,   #in kwh
   "consumption": 14,      #in kWh per 100km
   "base_consumption": 0.2 #in kW, consumption of the car when it is on but not
       driving, for example when charging or discharging
}
car_presets["tesla_3"] = tesla_3
```

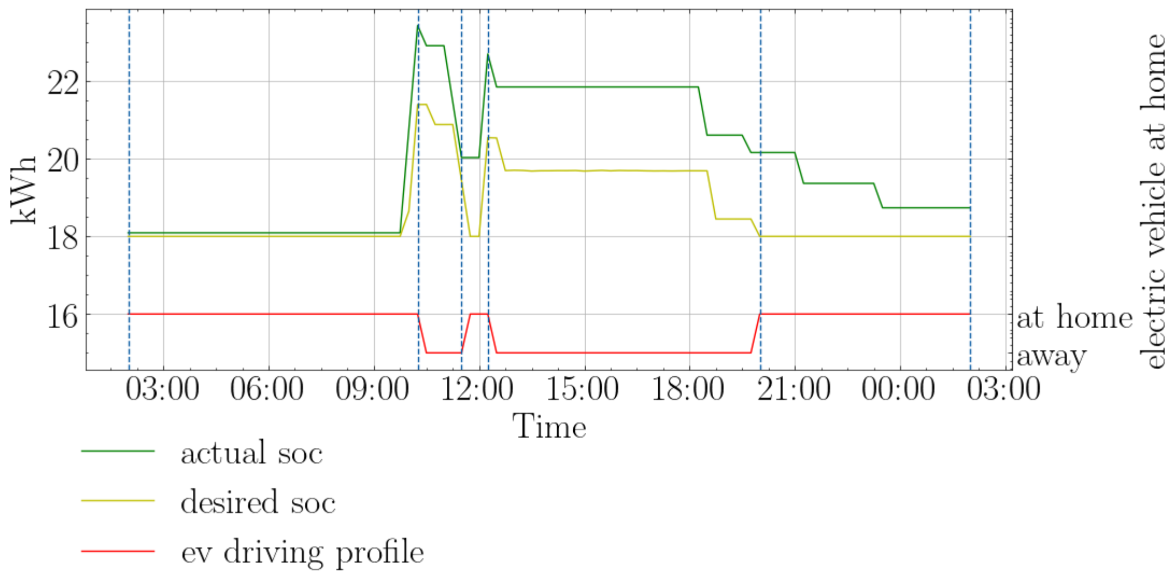

Figure 4.7: Visualization of the autarky algorithm

4.4 Autarky Algorithm

The autarky Algorithm works in three stages. For every single timestep, it performs the same analysis.

4.4.1 Stage 1

In this first stage, the following 24 hours get split into sections. In one section the driver is at home or away, but never both. This is indicated in Figure 4.7 by the vertical blue dashed lines.

We then go step by step through the away sections of the current 24 hours. At the end of each away section, we set the desired charge to be the specified minimum required charge. Usually about 30%.

Based on the forecast for each away section, we can estimate how much energy will be needed to drive the car in this section. This calculated value will be added to the minimum required charge and set as the desired start value for the away section.

We then calculate the desired State of Charge (SOC) during the home sections. This is usually the minimum required charge but goes up shortly before an away section. This is to charge the car at this point when it is needed, to guarantee, that it has enough energy to drive.

We now calculated the yellow line as seen in Figure 4.7.

4.4.2 Stage 2

Next, we work out the energy deltas in every section, meaning away and at home. To do that, first, we have a look at the away-Sections. Since the EV is not available, we only take into account the output of all suppliers combined minus the consumption of all consumers combined. In our setup, this means the delta at a specific timestep i is:

$$delta_i = pv_{out,i} - (house_{in,i} + hp_{in,i})$$

So a positive delta would mean, that there is more energy than we need, a negative delta indicates the opposite. Since we are calculating the delta for a whole section, we simply accumulate the supply and demand in every timestep of that section. Be s the start timestep and e the end timestep of a section, then

$$\hat{delta} = \sum_{i=s}^{e} delta_i = \sum_{i=s}^{e} pv_{out,i} - (house_{in,i} + hp_{in,i})$$

is the delta in one away-Section.

Home sections are more complex since we need to take into account, that the EV might need to charge. First, we calculate the same delta as in the away-Section. Then we figure out how much energy we need to charge into the EV. We do this by looking at the current SOC and at the desired SOC at the end of the section, which we computed in 4.4.1. If the current SOC is greater than the desired SOC at the end of the section, we ensure we do not discharge too much energy into the house. If the current SOC is smaller than the desired SOC at the end of the section, we add the calculated delta to the section delta, since this is the amount we need to charge in that section.

at home	current section delta	next section delta	charge satisfied	current delta	action
true	*	*	false	positive	+ car, + battery, sell
true	*	*	false	negative	- battery, buy
true	positive	positive	true	positive	+ car, + battery, sell
true	positive	positive	true	negative	- car, - battery, buy
true	positive	negative	true	positive	+ battery, + car, sell
true	positive	negative	true	negative	- battery, - car, buy
true	negative	positive	true	positive	+ car, + battery, sell
true	negative	positive	true	negative	- car, - battery, buy
true	negative	negative	true	positive	+ battery, + car, sell
true	negative	negative	true	negative	- car, - battery, buy
false	*	*	-	positive	+ battery, sell
false	*	*	-	negative	- battery, buy

Table 4.4: Action Table for different scenarios where '+' means charge, '-' means discharge and '*' means any

4.4.3 Stage 3

This brings us to the last stage. After calculating the sections, the desired charge at every point in time, and the deltas for every section, we have enough data to make decisions on when to charge and discharge the car. The following action table is used to determine an action:

The actions must be read from left to right with decreasing priority. Also, there are more mechanics in place. The loss reduction system assures, that we do not charge or discharge too little amounts of energy which would be shadowed by the loss of charging and discharging or the power needed to run the board electronics of the EV. Also charging and discharging are not binary operations as depicted in the table. In the case of a negative section delta, negative current delta, and the car not being above the desired SOC, the algorithm only charges the needed amount (taking losses into account) to get the EV SOC into the desired state. The same applies to discharging. Discharging the car will (including losses) never lead to the EV dropping below the desired SOC.

4.5 Naive Algorithm

The naive algorithm is much simpler and implemented like this:

Algorithmus 4.1 Naive algorithm

```
procedure ON_TICK
total_supply = 0
    for all supplier in suppliers do
        total_supply += supplier.current_supply()
    end fortotal_demand = 0
    for all consumer in consumers do
        total_demand += consumers.current_demand()
    end for
    for all car in cars do
        if car.at_home() then
            total_demand += car.max_ch_speed - car.charge(car.max_ch_speed)
        end if
    end for
delta = total_supply - total_demand
    if delta > 0 then
        for all storage in storages do
            remaining = storage.charge(delta)
            grid.sell(remaining)
        end for
    else if delta < 0 then
        for all storage in storages do
            missing = storage.discharge(delta)
            grid.buy(missing)
        end for
    end if
end procedure
```

Case: EV is not plugged in:
If there is a surplus of energy from the PV, it is charged into the battery and sold if there is too much. If the delta is negative, the battery will be discharged to meet the demand. If the battery is not sufficient, energy will be bought from the grid.

Case: EV is plugged in:
The car will immediately be fully charged. To meet this demand all available resources are used (energy from the PV, energy from the Buffer Storage (BS) and the grid, in that order). When the EV is at 100% SOC, the other case will be applied. The EV will never be discharged into the house.

We always use the naive algorithm to compare our benchmarks. This algorithm is currently used in most implementations.

5 Cases

Several runs of the simulation were performed to measure the performance of the algorithm in different scenarios. Four main variables are particularly interesting: The size and therefore the electrical output of the PV, the size of the battery in the EV, the driving pattern and therefore the availability of the EV and the size of the BS.

Performing simulations without an PV system would not make sense regarding autarky since if there is no self-produced electrical power, autarky is always zero. To see this, let's consider the formula to calculate autarky Equation (2.1) which would equal zero, if the amount of bought kWh equaled the amount of consumed kWh.

Performing without EV or BS would be a very simple optimization task, with simply always charging the available actor. This case will not be covered either. To make sure not to mix effects, only one variable is altered per case. One case always consists of a variable change with three values and a comparison to the naive case with the same variable changes. Have a look at the configuration scheme in Figure 5.1.

To realize a floating autarky calculation, we used the following formula, which is evaluated at every given point in time to generate the autarky graphs.

$$autarky_i = 1 - \frac{\sum_0^i bought\_kWh}{\sum_0^i consumed\_kWh} \tag{5.1}$$

Ultimately the very last value in the graph represents the overall autarky for that year.

Every case will be described and compared to the same case with the naive algorithm, which is described in Section 4.5

5.1 Base Case

The Base Case is done with the base configuration which is visible in Listing 5.1. In Figure 5.2 we can see how the level of autarky, with 1 meaning 100%, develops over time. As is evident from Table 5.1, the algorithm which was optimized for autarky performs 5% better at the end of the year with this configuration. In Figure 5.3 we can see how much power was bought from the grid by which algorithm. The graph is cumulative. With the autarky optimized algorithm buying 2648.65 kWh from the grid and the naive algorithm buying 3045.72 kWh, we can see, that the optimized algorithm only buys 86.96% of the power, the naive algorithm buys.

	autarky	bought from grid
naive	55.3417%	3321.76kWh
autarky optimized	63.1868%	2738.23kWh

Table 5.1: Performance table for the base case

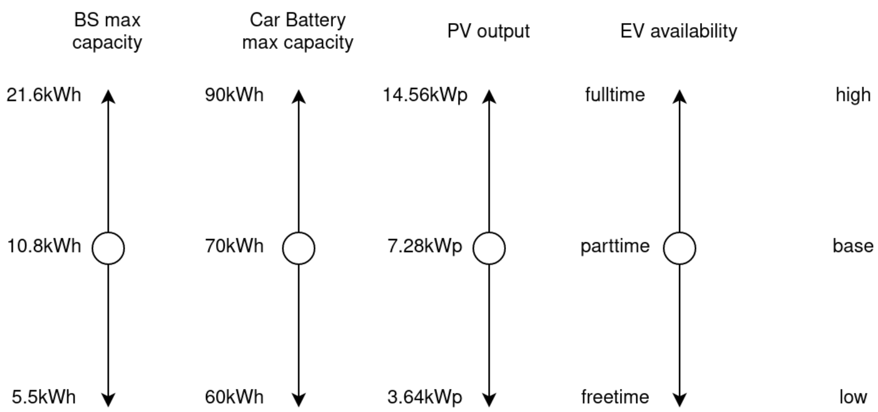

Figure 5.1: The state of the base configuration

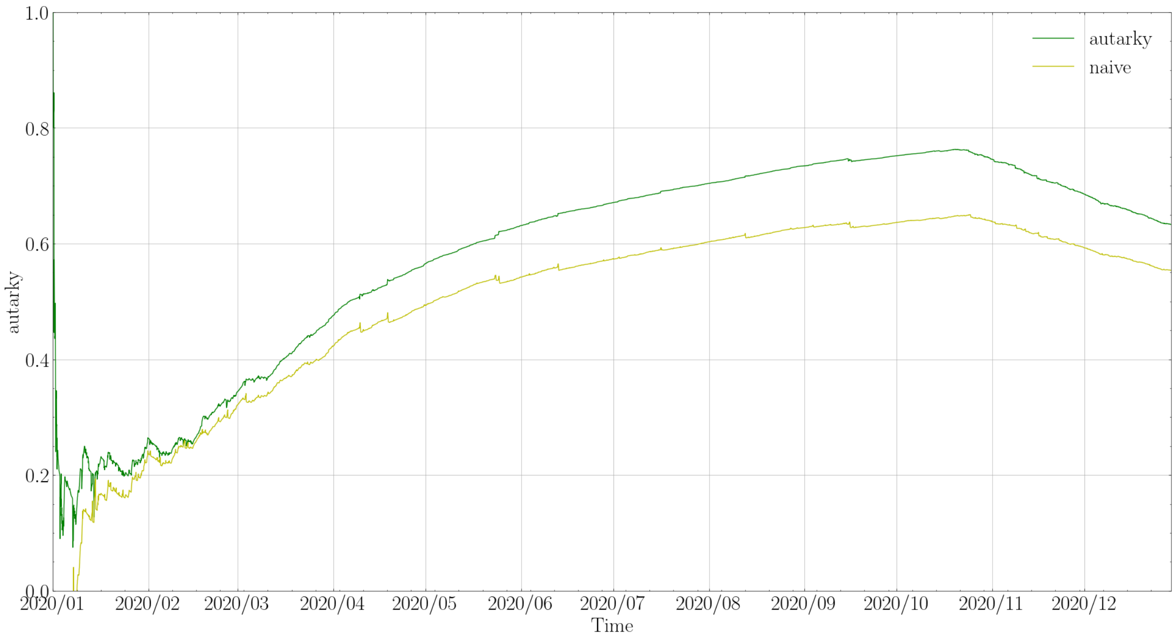

Figure 5.2: Base case autarky development of optimized vs naive algorithm

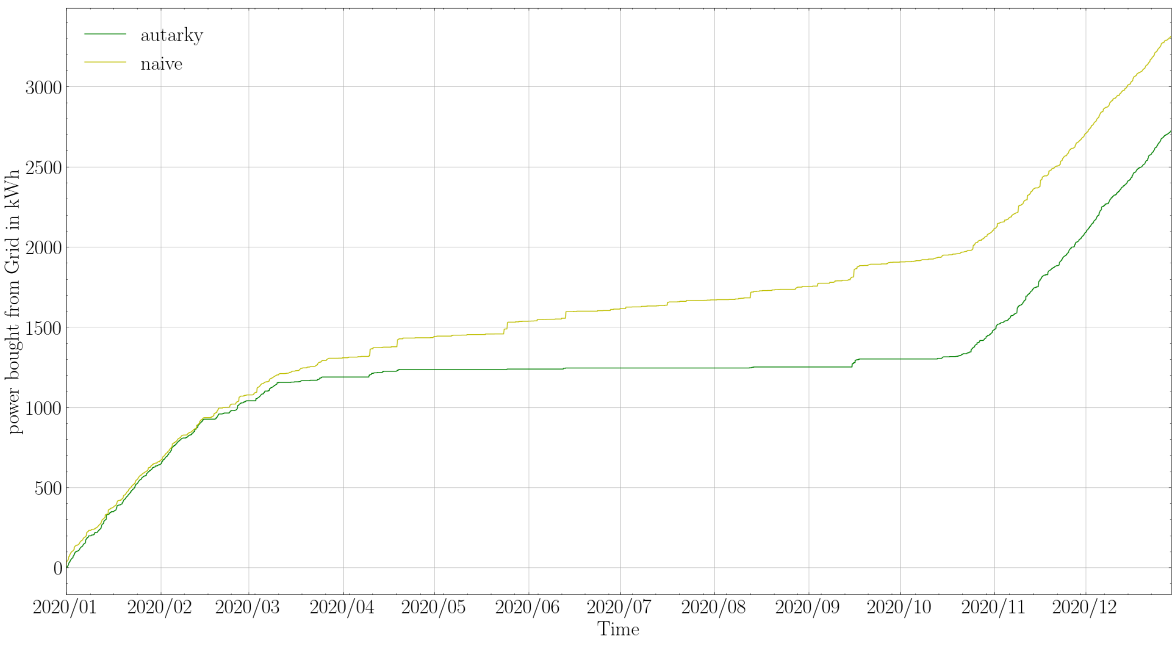

Figure 5.3: Base case amount of bought power from grid

Listing 5.1 Base Configuration

```
ev = {
   "max_capacity": 60,     #in kWh
   "charging_speed": 11,   #in kilowatt
   "discharging_speed": 11, #in kilowatt
   "required_min_charge_in_percent": 30, #the lowest battery percentage the car should
       have when returning home
   "initial_charge": 30,   #in kWh
   "consumption": 14,      #in kWh per 100km
   "base_consumption": 0.2 #in kW, consumption of the car when it is on but not
       driving, for example when charging or discharging
   "driving_profile": part_time
}
battery = {
   "battery_capacity": 10.8,  #in kWh
   "battery_charging_speed": 4.5 #in kilowatt
   "battery_discharging_speed": 4.5, #in kilowatt
   "battery_initial_charge": 5.4 #in kWh
   "lifetime": 1              #in years
}
pv = {
   "peak": 7.28,              #in kW
   "weather_year": 2020
   "scale": 1, #in kilowatt
   "weather_location": Berlin
   "size": 12.3               #in square meters
}
```

5.2 Battery max capacity Case

In this case, the max capacity of the BS is set to three different values, each doubling the lower one. All other values stay the same as in the base configuration 5.1. See Figure 5.4 for the new configuration. With this configuration, we will be able to see how the different configurations of maximum battery size impact the performance of the whole system. Also, we will be able to see how they perform in relation to each other.

We expect the autarky algorithm to greatly benefit from greater energy storage because it will have more capacity to compensate with.

In Figure 5.5 we can see, that a greater battery size resulted in a higher degree of autarky in all cases. The lowest configuration with the autarky optimized algorithm outperformed the highest configuration with the naive algorithm. We can also see in Table 5.2, that the battery size increment has a higher effect on the performance of the naive algorithm than the autarky optimized algorithm. For the low configuration, there is the greatest difference between the two algorithms in power bought from the grid. Which is $3823.1kWh - 2878.59kWh = 944.51kWh$. Meaning $944.51kWh$ can be saved by switching to a smarter algorithm.

The autarky optimized algorithm can almost reach full autarky during the summer season, see also Figure 5.6. This is the case even for the lowest configuration.

The key takeaways from this investigation are:
- Upgrading the BS has a greater impact on the naive algorithm than the autarky optimized algorithm
- The autarky optimized algorithm performs better in all investigated configurations, hinting, that a change in algorithm has a greater impact than new hardware
- The biggest tested BS in comparison to the smallest only brought a 5.27% higher degree of autarky, even though it is four times the size, which is insufficient to consider the upgrade

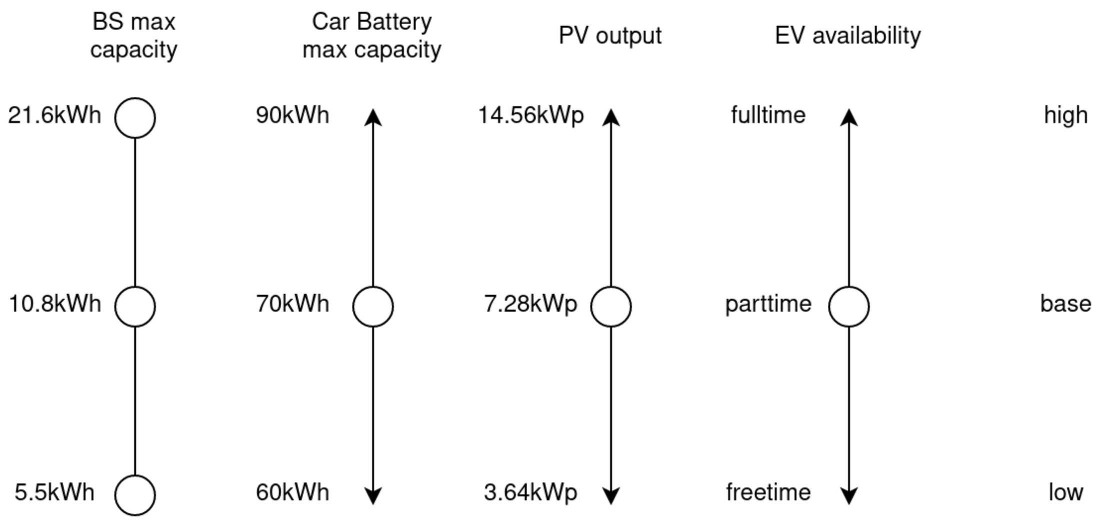

Figure 5.4: The state of the battery max capacity configuration scheme

Naive algorithm

	autarky absolute	autarky relative	bought absolute	bought relative	configuration absolute	configuration relative
high	59.8325%	+23.28%	2987.73kWh	-21.95%	21.6kWh	+292.72%
base	55.7365%	+14.84%	3292.39kWh	-13.99%	10.8kWh	+96.36%
low	48.5344%	-	3828.1kWh	-	5.5kWh	-

Autarky optimized algorithm

	autarky absolute	autarky relative	bought absolute	bought relative	configuration absolute	configuration relative
high	64.5235%	+5.27%	2638.8kWh	-8.33%	21.6kWh	+292.72%
base	63.1329%	+2.99%	2742.24kWh	-4.74%	10.8kWh	+96.36%
low	61.2998%	-	2878.59kWh	-	5.5kWh	-

Table 5.2: Performance table with different maximum BS capacities. The relative column is always relative to the lowest configuration

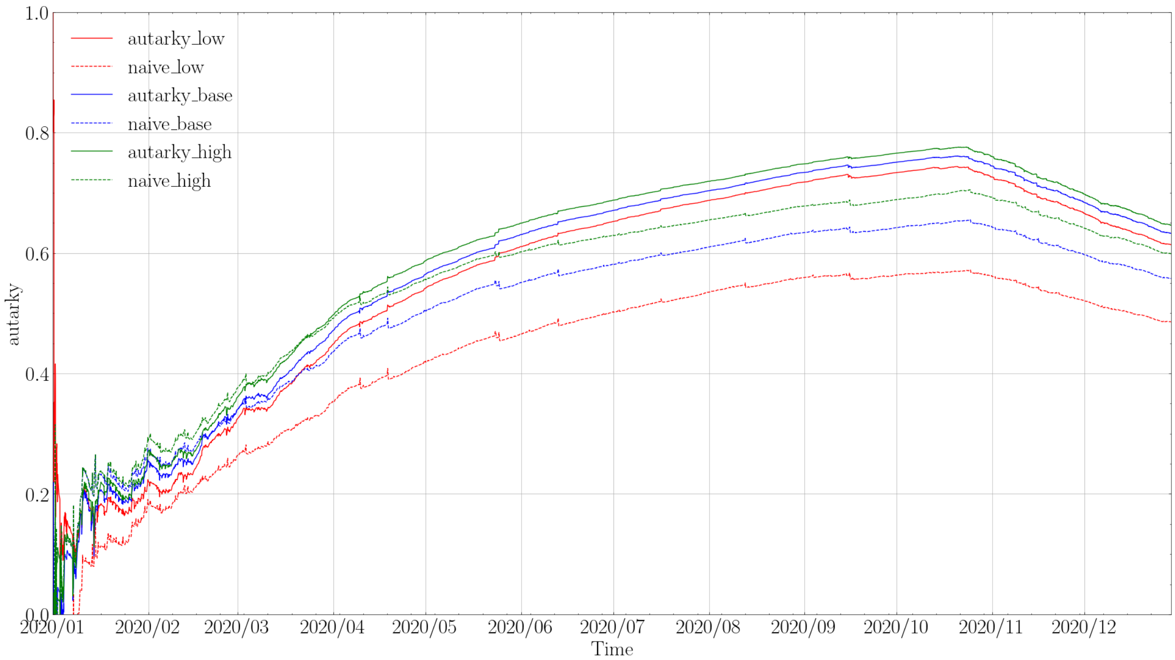

Figure 5.5: The degree of autarky achieved by each algorithm with different buffer storage capacities

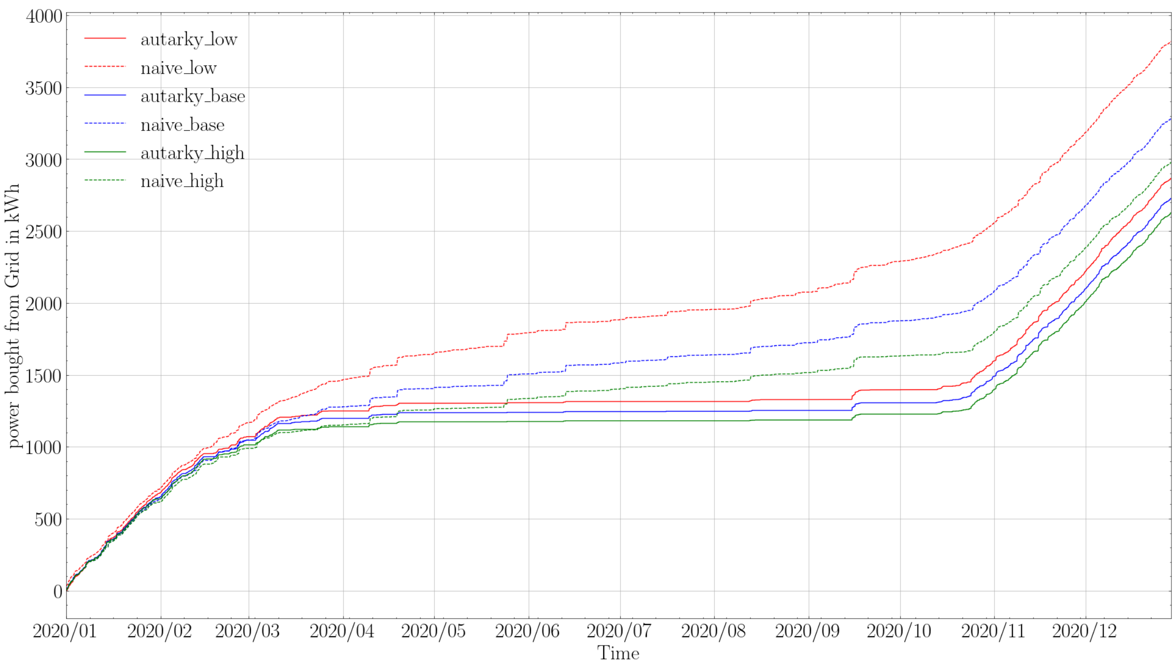

Figure 5.6: The amount of power bought by each algorithm with different buffer storage capacities

5.3 EV max capacity Case

For the EV max capacity Case we used three differently sized car batteries to investigate the difference in performance on this variable. We chose the three different configurations, as seen in Figure 5.7. We had to stick to the lower limit of 60kWh since our driving profiles were generated under that consumption, meaning, a smaller battery would lead to the car running out of power during a drive. The upper limit was oriented at the current maximum car batteries on the market which are typically at around 90kWh.

For the naive algorithm, we expect no change in performance since it is not making use of bidirectional charging. The autarky optimized algorithm on the other hand is using bidirectional charging which should help increase performance.

As expected, the naive algorithm has almost no change in performance, see Table 5.3. The existing differences can be explained by occurring randomness.
The autarky algorithm has a more significant change in performance, even though it is still very low. Even for a 50% bigger car battery, autarky is only increased by 1.56%, see Table 5.3. Looking at Figure 5.9 we can see, that the improvement happens during the summer when the car is sufficiently charged so it can be used to compensate.

The very low-performance boost for the autarky optimized algorithm can be explained by two influencing factors. The car has a set threshold, which can not be fallen short of by using the vehicle for compensation. This is to make sure, that in case of an emergency or other unexpected event, the driver can always drive his car. Refer to the base configuration, 'required_min_charge_in_percent' Listing 5.1, which is used as threshold. This leads to a lower effective capacity for optimization.
The second influencing factor is availability. The car is not available for optimization during driving sessions, since it is not connected to the house. Also, the car needs to get charged before driving sessions, which also leads to unavailability for discharging. These factors combined, the electric vehicle doesn't improve the overall performance of the system substantially.

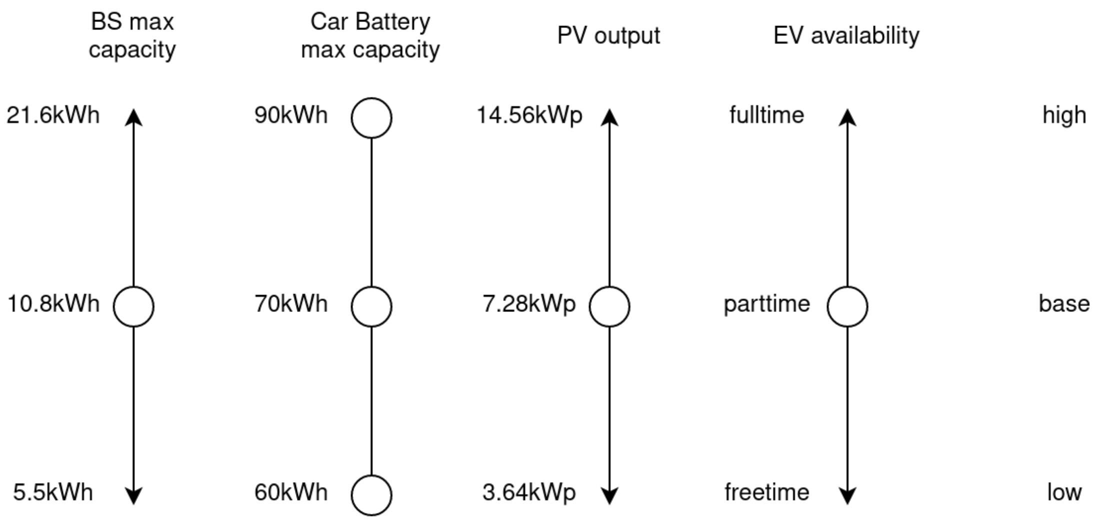

Figure 5.7: The state of the ev max capacity configuration scheme

Naive algorithm

	autarky		bought		configuration	
	absolute	relative	absolute	relative	absolute	relative
high	55.4581%	-0.04%	3313.1kWh	+0.05%	90kWh	+50%
base	55.5978%	+0.21%	3302.71kWh	-0.26%	70kWh	+16.6%
low	55.4814%	-	3311.37kWh	-	60kWh	-

Autarky optimized algorithm

	autarky		bought		configuration	
	absolute	relative	absolute	relative	absolute	relative
high	63.8387%	+1.56%	2689.74kWh	-3.16%	90kWh	+50%
base	62.8488%	+0.30%	2763.37kWh	-0.51%	70kWh	+16.6%
low	62.6585%	-	2777.53kWh	-	60kWh	-

Table 5.3: Performance table with different maximum EV battery capacities. The relative column is always relative to the lowest configuration

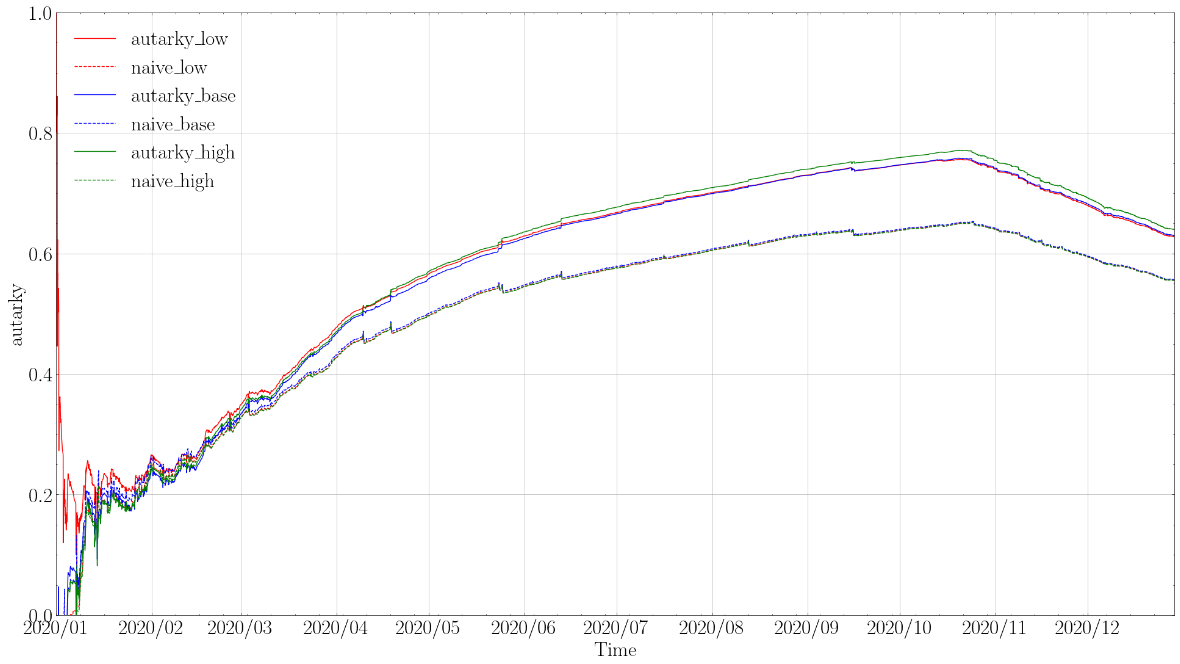

Figure 5.8: The degree of autarky achieved by each algorithm with different EV battery capacities

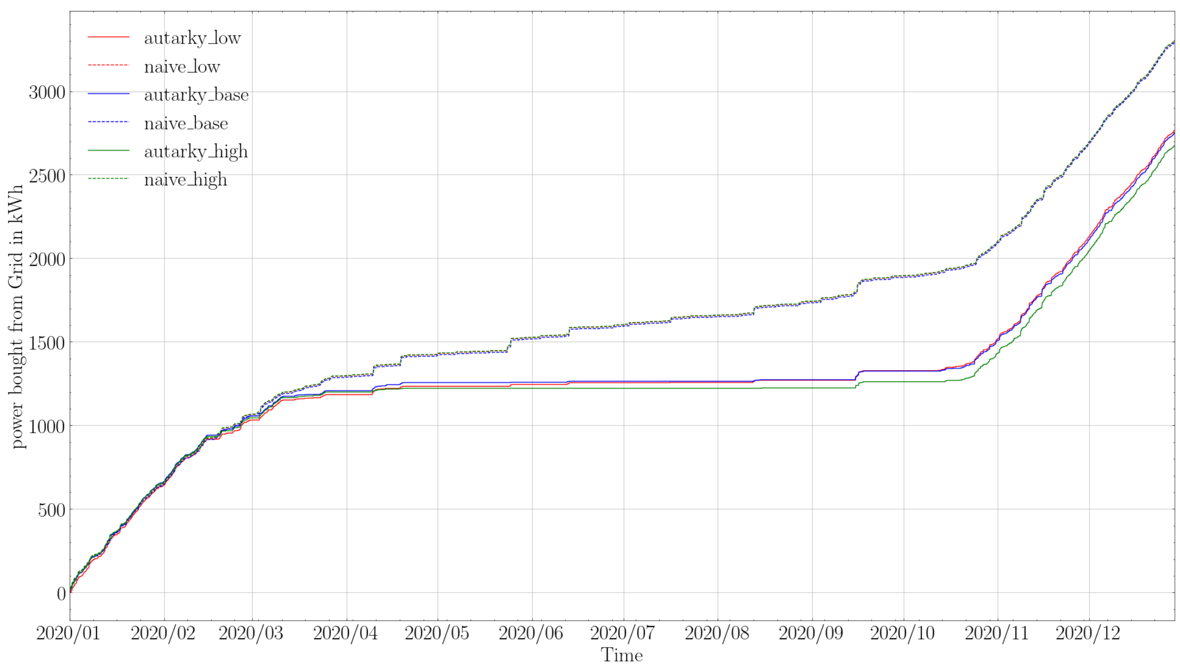

Figure 5.9: The amount of power bought by each algorithm with different EV battery capacities

5.4 PV peak case

For the PV peak case, we increased the output of the PV system to each doubling the next lower one. We did this to see the effects of the PV output on the algorithm performance. In practice the PV output can be increased with several methods, for example by increasing size, optimizing angle, or buying more effective panels. The used range, as seen in Figure 5.10 was chosen to have a small, medium, and very large configuration.

We expect the PV output to have a strong effect on the performance of both algorithms, but the autarky optimized algorithm should be able to make more use of the energy by balancing it correctly for later use.

As expected, both algorithms achieve significant performance improvements with a higher PV output. In Figure 5.11 we can see, that for the lowest configuration, the autarky of both algorithms is very similar. We can see the same effect in Figure 5.12. This makes sense since the difference in both algorithms should be 0 if there is no photovoltaic system. The same principle applies in the opposite direction. The greater the PV output, the greater the difference in performance. This, of course, only holds in our examined configuration range. The difference between both algorithms in power bought with the base configuration is 553.73kWh, the same difference for the high configuration is 774.64kWh, which is an increment of 39.89%. This shows that the autarky algorithm performs increasingly well with a higher PV output, compared to the naive algorithm.
We can also see, that in every tested case, the hardware upgrade had a higher effect on the performance, than switching from the naive to the autarky optimized algorithm. By looking at Figure 5.17 we can see, that especially for the high configuration with the autarky optimized algorithm, almost no power is bought from the grid, resulting in a high autarky. The naive algorithm on the other hand struggles to achieve similar levels of autarky, even during the summer, due to its inability to take forecasts into account and use the electric vehicle to compensate.

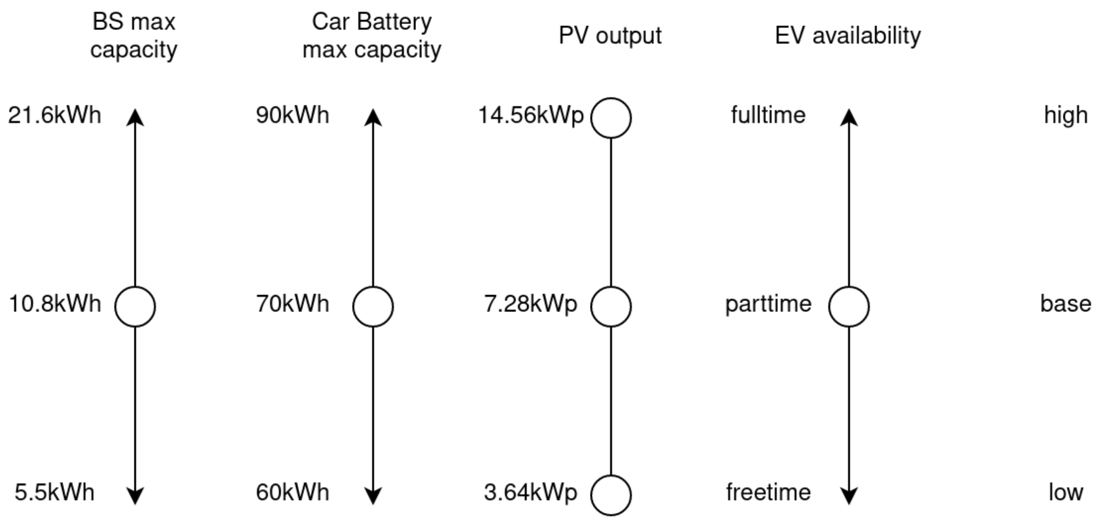

Figure 5.10: The state of the PV configuration scheme

Naive algorithm

	autarky		bought		configuration	
	absolute	relative	absolute	relative	absolute	relative
high	64.2305%	+49.08%	2660.6kWh	+37.15%	14.56kWp	+300%
base	55.5468%	+28.92%	3306.51kWh	-21.89%	7.28kWp	+100%
low	43.0854%	-	4233.41kWh	-	3.64kWp	-

Autarky optimized algorithm

	autarky		bought		configuration	
	absolute	relative	absolute	relative	absolute	relative
high	74.6448%	+68.03%	1885.96kWh	-54.37%	14.56kWp	+300%
base	62.9911%	+41.80%	2752.78kWh	-33.41%	7.28kWp	+100%
low	44.4234%	-	4133.89kWh	-	3.64kWp	-

Table 5.4: Performance table with different maximum EV battery capacities. The relative column is always relative to the lowest configuration

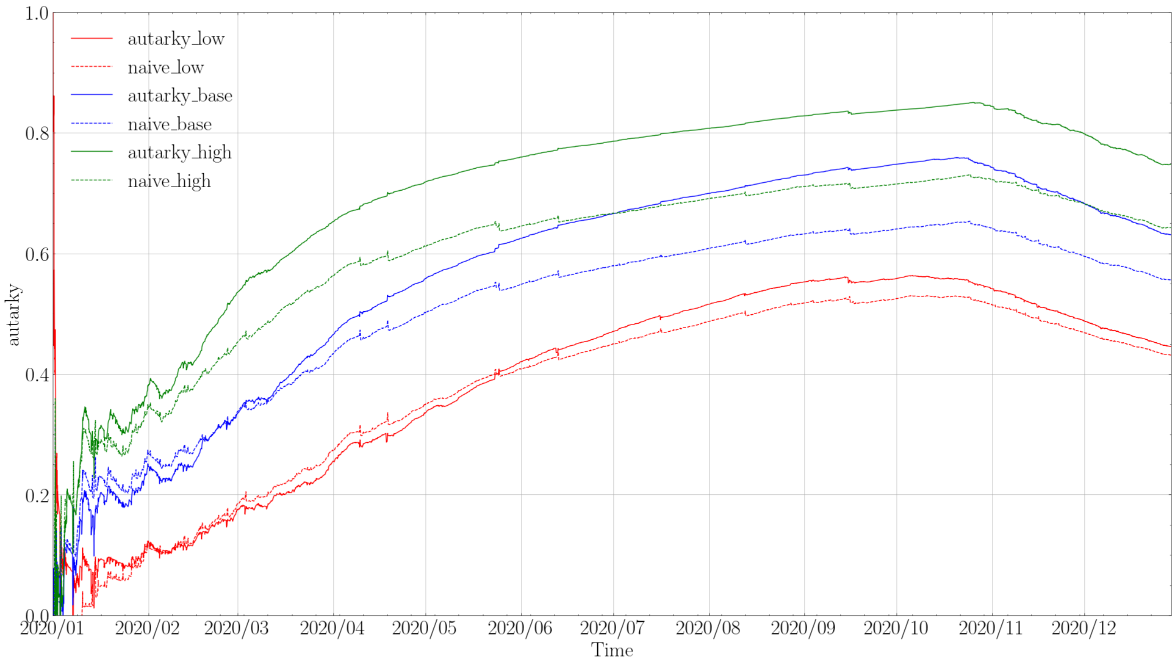

Figure 5.11: The degree of autarky reached by each algorithm with different PV output

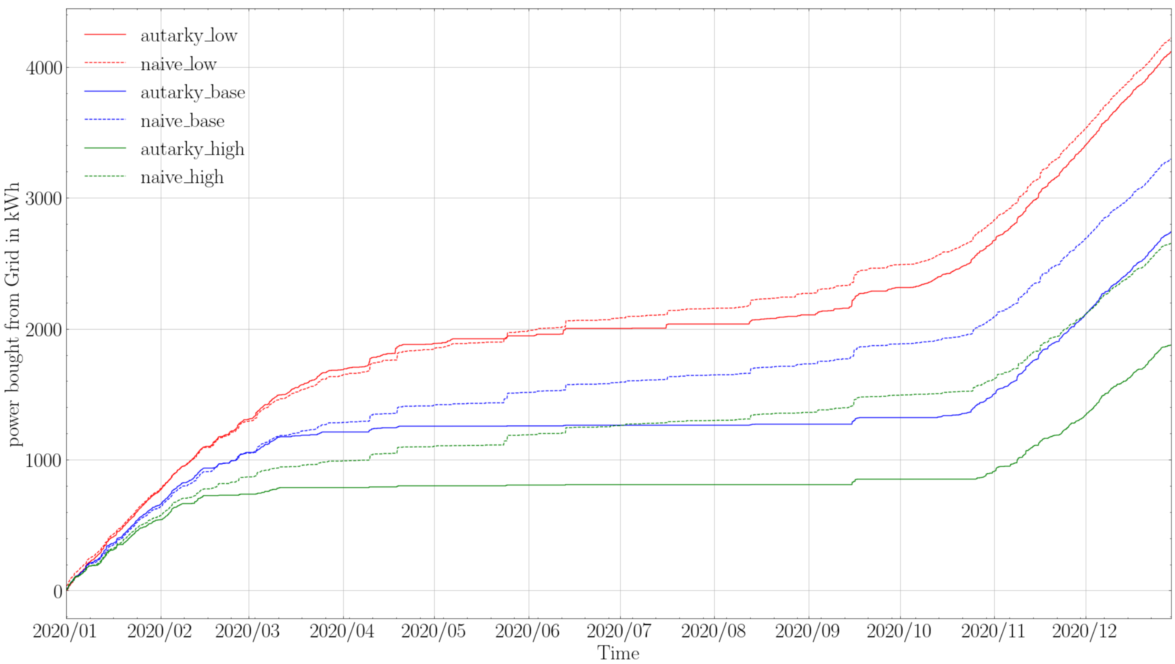

Figure 5.12: The amount of power bought by each algorithm with different PV output

5.5 EV driving profile case

For the EV driving profile case, we used three different driving profiles. Example slices of each profile can be found in Figure 4.2, Figure 4.3 and Figure 4.4. The difference in the profiles is not the driven distance, nor the overall time at home, but the time of the day when the driver mostly uses his electric vehicle. The full-time profile describes the driving behavior of a full-time worker, meaning the driver drives to work at the same time every day, a part-time worker, who goes to the office for a few days a week, as well as a free-time profile which describes the behavior of a non-working driver.

We expect a difference in performance for both algorithms with the three profiles since sunlight availability is fixed while the availability of the electric vehicle differs. Although the difference for the autarky optimized algorithm should be smaller since it will be able to compensate for the unavailability of the vehicle.

In Figure 5.14, Figure 5.15 as well as Table 5.5 it is indicated, that there is little to no difference in all three profiles.
For the naive algorithm, this can be explained by the missing vehicle-to-home feature and the size of the buffer battery. Since the car is never used to compensate for house consumption, its availability loses importance. This leads to the profiles generating very similar performance results.
When inspecting the performance over the year, for example in Figure 5.15, there is some deviation during the summer season. This is the time when there is the highest output of the PV system, meaning the availability of the car is more important. This effect is then minimized during the winter season, where all three profiles become similar in performance.

For the autarky optimized algorithm, we have already predicted a high similarity in performance, since the algorithm effectively tries to balance out these availability differences. Note that also, in this case, every single run with the autarky optimized algorithm outperforms the naive algorithm.

In conclusion, we can state, that changing the driving behavior, in terms of driving times during the day, will not affect the overall performance of the system.

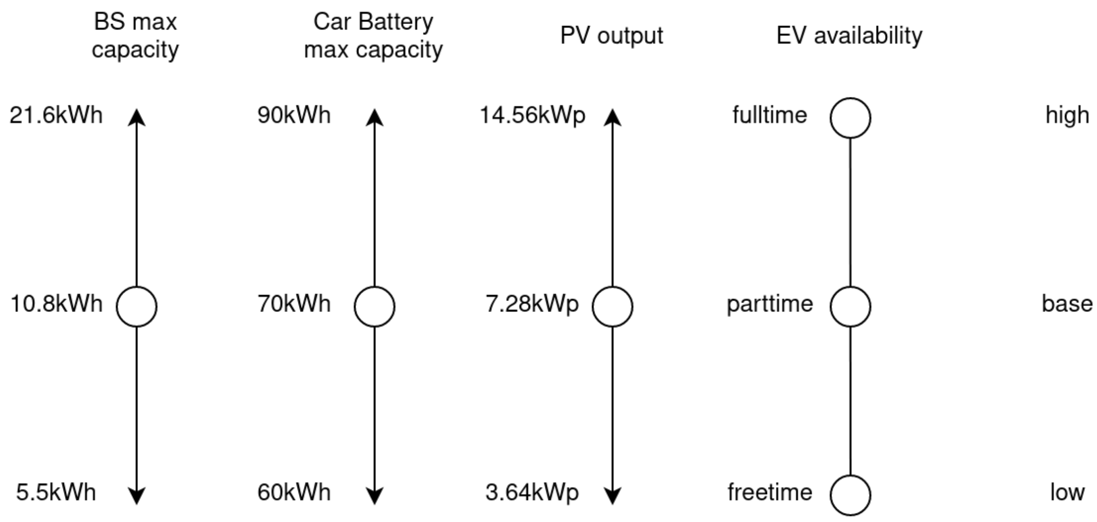

Figure 5.13: The state of the EV profile configuration scheme

Naive algorithm

	autarky absolute	autarky relative	bought absolute	bought relative	configuration
high	54.9831%	-0.52%	3382.47kWh	+0.11%	fulltime
base	55.1997%	-0.13%	3332.32kWh	-1.38%	parttime
low	55.2727%	-	3378.83kWh	-	freetime

Autarky optimized algorithm

	autarky absolute	autarky relative	bought absolute	bought relative	configuration
high	63.0419%	-0.11%	2749.01kWh	+0.18%	fulltime
base	63.2427%	+0.21%	2734.07kWh	-0.36%	parttime
low	63.1088%	-	2744.03kWh	-	freetime

Table 5.5: Performance table with different driving patterns. The relative column is always relative to the lowest configuration

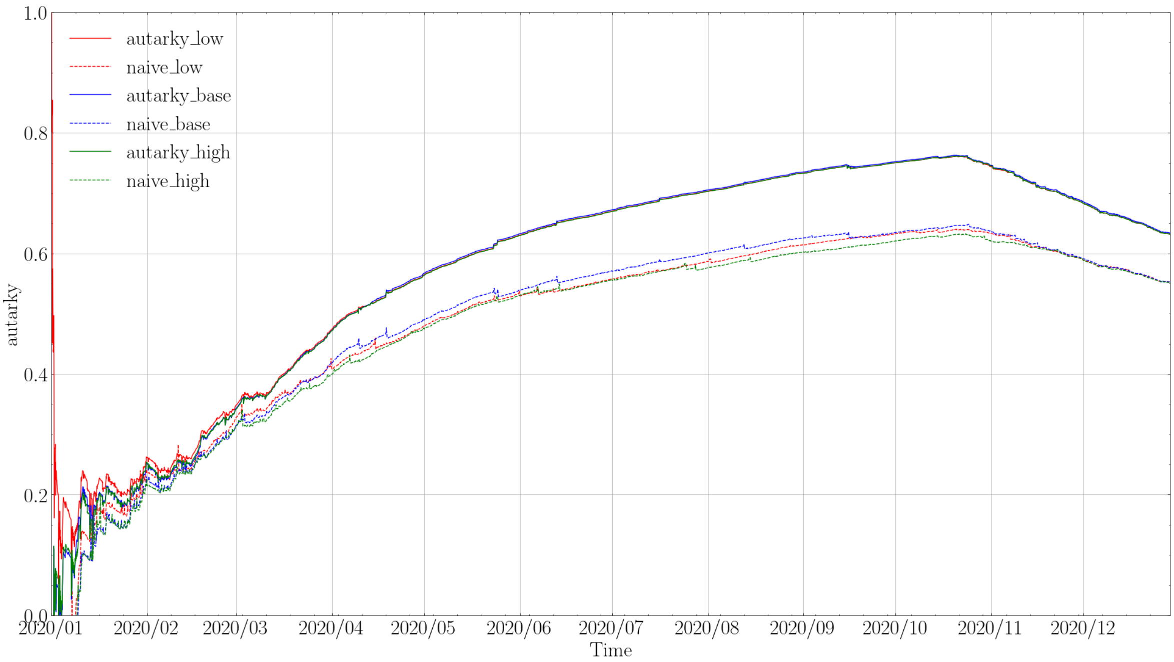

Figure 5.14: The degree of autarky reached by each algorithm with different EV driving profiles

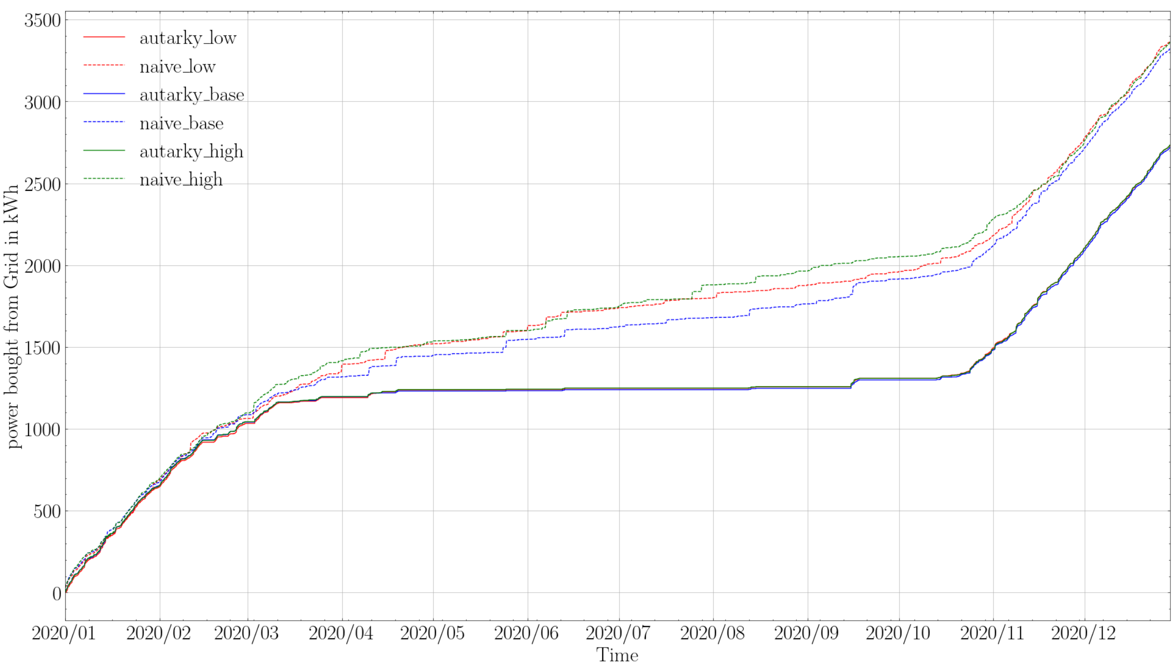

Figure 5.15: The amount of power bought by each algorithm with different EV driving profiles

5.6 PV-BS case

In the PV-BS Case, we performed 100 runs with different configurations. We did this, as in all cases, for the autarky optimized algorithm as well as the naive one. Find the respective configuration in Figure 5.16. This resulted in a three-dimensional graph that shows the performance of the algorithms measured in kWh bought from the grid, drawn on the Z-axis 5.17. On the X and Y axis, we have the variable PV kWp and BS size. There are two surfaces visible in this graph. The top one is from the naive algorithm, the bottom one is from the autarky optimized one. The fourth dimension, the color, shows the degree of autarky reached by that particular configuration.

The graph has many interesting features.

Layer segregation: The two layers are mostly segregated, but they do intersect for very low buffer storage capacities and very high PV output. This is because the autarky optimized algorithm was not designed for that particular case. In all other cases, the autarky optimized algorithm outperforms the naive one.

PV Curve: The top layer shows a significant curve on the PV axis. This indicates, that the naive algorithm performs better in terms of power bought from the grid when increasing the output of the PV system. The tendency is the same for the autarky optimized algorithm. This makes sense since a greater PV output helps to meet the consumption need of the consumers. The autarky optimized algorithm however doesn't profit greatly from this upgrade since the energy balancing can compensate for times of lower power output.

Autarky distribution: The lowest occurring autarky is already at 30% which is quite high for a minimal configuration without smart energy balancing. On the opposite side of the spectrum, there are values of up to 76% with a maximum configuration and the autarky optimized algorithm.

Steepness on axis: At the lower, autarky optimized, layer, there is a significant difference in steepness comparing the X and the Y direction. While there is a great increment in performance when increasing the size of the Buffer Storage, the output of the PV systems has a lower impact. It is important to say, that this holds only true for the tested configurations.

To summarize we can say, that upgrading to an autarky optimized algorithm, in most cases, has the greatest impact on performance. Generally speaking, upgrading the size of the buffer storage makes more sense than upgrading the PV system, for the autarky optimized algorithm. The naive algorithm profits from both upgrades.

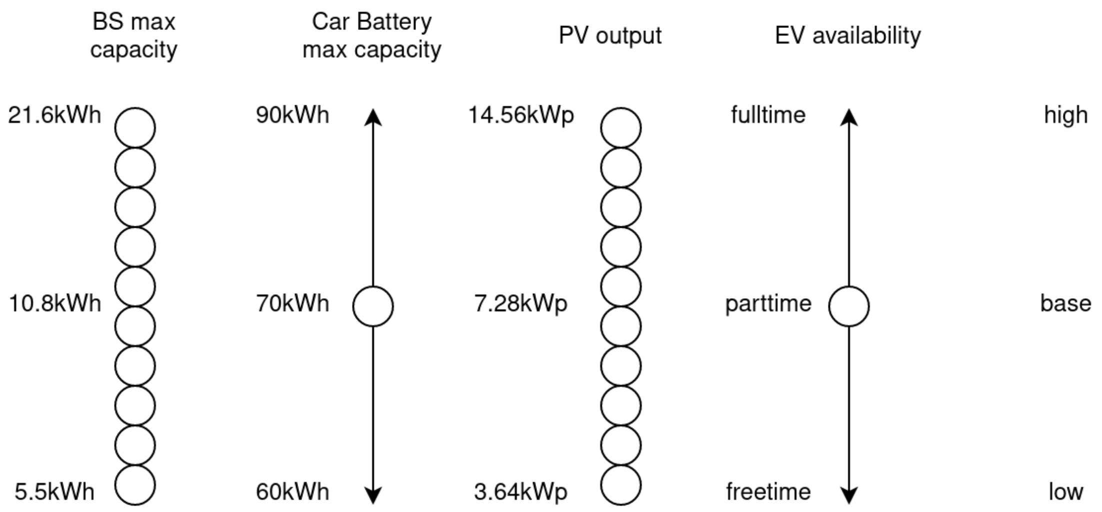

Figure 5.16: The state of the EV profile configuration scheme

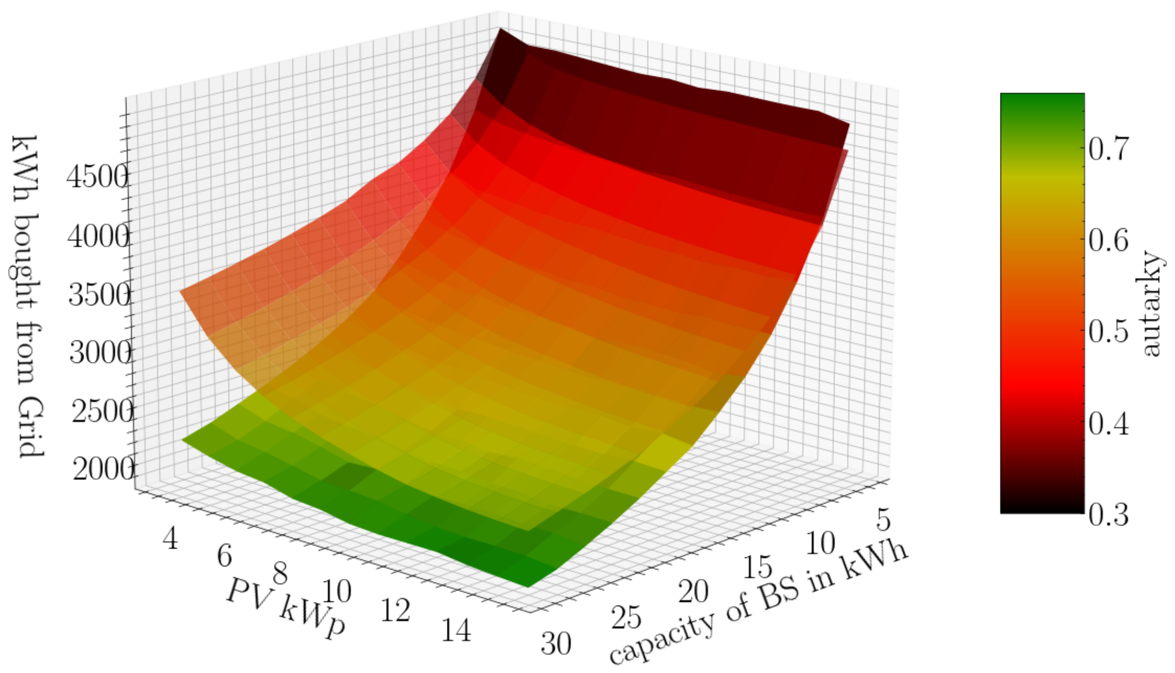

Figure 5.17: The amount of power bought by the two algorithms with 100 configurations applied. Autarky is colorcoded

6 Results

In this study, we investigated the autarky increment in single-family homes by smart energy balancing. We picked four different variables, the size and therefore the electrical output of the PV, the size of the battery inside the EV, the driving pattern and therefore the availability of the EV, and the size of the BS. We tried to find the impact of every variable on the performance of the algorithms.

We found, that the size of the electric vehicle and the driving behavior doesn't have much of an impact, on the tested cases.
A higher impact was found in the buffer storage capacity and the PV system. For the BS capacity, we can say, that an optimized algorithm can increase the performance with the existing storage quite well. For example, switching to an optimized algorithm with a 5.5kWh BS can save up to a quarter of the energy bought from the grid, see Table 5.2.

The output of the PV system was the second variable with a high impact on the performance. Although upgrading the PV system has a higher impact when using the naive algorithm instead of the autarky optimized one, seeFigure 5.17.

We can generally say, that the usage of a home energy management system with an intelligent, autarky optimized algorithm, can increase, depending on the current configuration, the degree of autarky a lot, compared to the same configuration without an intelligent algorithm.

7 Summary and Outlook

To conclude, we can say, that an autarky optimized algorithm, which intelligently balances the available energy, in all cases we looked at, proved to have a better performance concerning the degree of autarky as well as the amount of power bought from the grid, compared to the naive algorithm. In practice this could mean implementing such a balancing system could have a greater benefit than buying new hardware.

In the future, a system, such as the one we built in our simulation framework, could help to optimize hardware usage in single-family homes. Until that happens, more research is needed. There are way more variables we didn't include in this work, such as the overall amount of available minutes of the EV. Also, in our model, the EV was only charged at home, which is not necessarily the case for many people.

We need to mention, that these values can be improved in several ways. The optimization algorithm can be adjusted. We did not use the boiler as energy storage which might bring a significant advantage.
Another way to further optimize would be to actively control devices such as heating or washing machine. All of these aspects can be looked into in future studies.

Whatever path we choose regarding this technology, a further investigation could make sense when having climate change and its consequences in mind.

Bibliography

[bidiwall22] Bidirektionale Wallboxen. *Wallbox Chargers Quasar 2 (11,5 kW | 48 A)*. 2022. URL: https://bidirektionale-wallboxen.de/wallbox-chargers-quasar-2-11-kw/ (cit. on p. 19).

[CO222] Umweltbundesamt. *Treibhausgas-Emissionen in Deutschland*. 2022. URL: https://www.umweltbundesamt.de/daten/klima/treibhausgas-emissionen-in-deutschland#emissionsentwicklung (cit. on p. 17).

[E3DC-Solar21] E3DC. *89 Prozent des Solarpotenzials auf deutschen Ein- und Zweifamilienhäusern sind noch ungenutzt*. 2021. URL: https://www.e3dc.com/89-prozent-des-solarpotenzials-auf-deutschen-ein-und-zweifamilienhaeusern-sind-noch-ungenutzt/ (cit. on p. 17).

[emobpy21] Gaete-Morales, C., Kramer, H., Schill, WP. et al. *An open tool for creating battery-electric vehicle time series from empirical data*. 2021. URL: https://doi.org/10.1038/s41597-021-00932-9 (cit. on p. 29).

[entsoe22] ENTSO-E. *Central collection and publication of electricity generation, transportation and consumption data and information for the pan-European market*. 2022. URL: https://transparency.entsoe.eu/dashboard/show (cit. on p. 33).

[fordbidi22] Ford Motor Company. *Ford F-150 Lightning*. 2022. URL: http://ode.apache.org (cit. on p. 19).

[G2021] ZDF. *Ringen um Abschlusserklärung : G20-Klimaziele: Es bleibt schwammig*. 2021. URL: https://www.zdf.de/nachrichten/politik/klima-g20-gipfel-abschlusserklaerung-100.html (cit. on p. 17).

[Gas-Germany22a] Julian Wettengel. *Germany and the EU remain heavily dependent on imported fossil fuels*. 2022. URL: https://www.cleanenergywire.org/factsheets/germanys-dependence-imported-fossil-fuels (cit. on p. 17).

[Gas-Germany22b] Statistisches Bundesamt. *Gross electricity production1 in Germany from 2019 to 2021*. 2022. URL: https://www.destatis.de/EN/Themes/Economic-Sectors-Enterprises/Energy/Production/Tables/gross-electricity-production.html (cit. on p. 17).

[GISS22] GISTEMP Team. *GISS Surface Temperature Analysis (GISTEMP), version 4. NASA Goddard Institute for Space Studies*. 2022. URL: https://data.giss.nasa.gov/gistemp/ (cit. on p. 17).

[hpdata22] Schlemminger, M., Ohrdes, T., Schneider, E. et al. *Dataset on electrical single-family house and heat pump load profiles in Germany*. 2022. URL: https://doi.org/10.1038/s41597-022-01156-1/ (cit. on pp. 29, 31).

[PVSol22] Valentin Software. *The design and simulation software for photovoltaic systems*. 2022. URL: https://valentin-software.com/en/products/pvsol-premium/ (cit. on p. 28).

[SimulationX22] ESI Group. *Design and Analyze Your Multi-Physics System with Simulation Software*. 2022. URL: https://www.esi-group.com/products/system-simulation (cit. on p. 21).

[sota115] Patrick Wimmer1, Christian Kandler1, Johannes Honold. *POTENTIAL OF DEMAND AND PRODUCTION SHIFTING IN RESIDENTIAL BUILDINGS BY USING HOME ENERGY MANAGEMENT SYSTEMS*. 2015. URL: http://www.ibpsa.org/proceedings/BS2015/p2821.pdf (cit. on p. 21).

[Sota217] Thomas Kaschub. *Batteriespeicher in Haushalten unter Berücksichtigung von Photovoltaik, Elektrofahrzeugen und Nachfragesteuerung*. 2017. URL: https://publikationen.bibliothek.kit.edu/1000071259 (cit. on p. 23).

[Sota315] ohannes Weniger, Joseph Bergner, Tjarko Tjaden, Volker Quaschning. *Dezentrale Solarstromspeicher für die Energiewende*. 2015. URL: https://solar.htw-berlin.de/studien/solarspeicherstudie/ (cit. on p. 22).

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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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