

Impact of Parametrization of Battery Energy Storages on Multi-Agent Energy Systems with a High Share of Renewable Energy Sources

Jakob M. Fritz^a, André Xhonneux^b and Dirk Müller^{c,d}

^a IEK-10, Forschungszentrum Jülich, Jülich, Germany, j.fritz@fz-juelich.de

^b IEK-10, Forschungszentrum Jülich, Jülich, Germany, a.xhonneux@fz-juelich.de

^c IEK-10, Forschungszentrum Jülich, Jülich, Germany, dmueller@eonerc.rwth-aachen.de

^d EBC, Energy Research Center, RWTH Aachen University, Aachen, Germany, dmueller@eonerc.rwth-aachen.de

Abstract:

With the increasing share of distributed renewable energy sources not only the need for distributed energy storages rises, but also the need to coordinate those storages in the context of their local micro-grid. This publication illustrates the impact of battery energy storages on the overall performance of a district energy system. The energy system is controlled in a distributed way by using a multi-agent approach that is scheduled by a market-mechanism. This market-mechanism allows to coordinate many individual agents with only few restrictions. The individual agents are flexible in the internal approach to forecast power supply or demand, allowing easy development of agents using individual algorithms.

Besides pure consumer or producer agents, the battery storage forms a prosumer agent that can consume energy in some time-steps while supplying energy in others. By this, battery agents provide flexibility to the micro-grid while also aiming to generate profit for the owner. This approach is therefore attractive to both, the district energy system and the battery storage operator. The presented battery agents use model predictive control to determine the optimal operation strategy/bid for the upcoming time horizon. The determination of optimal strategy does not only assume losses but also takes the resulting degradation of the battery-cells into account.

In a case study, we show the impact of battery storages on the overall system performance. As a main part of the publication, a sensitivity study reveals the importance of the individual parameters and how the revenue of the storage agent is affected. By adapting the charging and discharging power by 20 %, the profit can be increased by 33 % for the presented case.

Keywords:

Battery Energy Storage (BES), District Energy System, Agent-Based, Model Predictive Control, Multi-Agent Systems

1. Introduction

The energy transition leads to an increasing share of renewable energy sources [1]. Renewable energy sources like photovoltaic or wind power plants constitute a fluctuating energy resource that cannot be controlled like conventional power plants with regard to power output. The power output can only be curtailed but not increased. Therefore, it becomes increasingly important to be able to shift energy demand over time, which is referred to as Demand Side Management (DSM) (see e.g. [2–4]). By shifting the demand over time, it can better match the times when renewable energy sources supply their power. Shifting demand to other time-steps can be done in multiple ways. One is to shift the demand of the main consumers. Another possibility is to utilize storages to create an artificial demand to match the supply of renewable energy surplus. In later time-steps, this energy can then be supplied according to the consumers' demands that cannot be shifted. This leads to a higher share of renewable energy supply that can be used although consumers did not adapt to the energy supply by renewable sources. Shifting the main consumer is the preferred approach, as it reduces losses that always occur when using storage technologies. Additionally, shifting the demand can be cheaper than using storages. However, the demand that can be shifted without e.g. negatively affecting comfort, is limited. Therefore, storages remain important, as they can fill this gap and provide additional flexibility. This publication focuses on short-term energy storages in district energy systems, where storages are used to shift demand and supply in the range of hours. For this, battery storages are employed.

The context of this battery storage is a district energy system, that is controlled in an agent-based, distributed fashion. The employment of agents offers flexibility in the development of each agent. It furthermore increases privacy, as less information needs to be transferred.

The paper is structured as follows. First, the methodology is described in section 2.. This section splits up into an overview of the scheduling-structure of the used micro-grid (2.1.), followed by a characterization of the agents employed in this publication (2.2.) as well as information on the model used in the battery agent (2.3.) and the main parameters that are examined afterwards (2.4.). The results of this examination are presented and discussed in section 3.. Section 4. concludes the publication and gives an outlook on further research aspects.

2. Methodology

In the following, we give a short introduction to the overall district energy system and the incorporated energy storage to underline the influence of the parameters studied in this paper.

2.1. Structure of district energy system

The district energy system outlined here consists of multiple agents, each representing a single building or unit. Therefore, the system at hand is a multi-agent system. Multi-agent systems are described in multiple publications, such as [5–7]. In the present case the main difference to the mentioned approaches is the management of the individual agents. In our work, each agent shares a forecast of the amount of power it wants to buy or sell over an upcoming horizon. The agents furthermore share a price they are willing to accept as trading price for each of the upcoming time-steps. One additional agent is used to coordinate the other agents, so that demand and supply match as good as possible, while maintaining a macro-optimal solution (maximizing social welfare). This specific agent is referred to as “central instance”. Matching demand and supply is done by means of market clearing. Further information on market-mechanisms in general as well as different applications can be found in [8–12]. In this work, all agents belong to the same market and trading restrictions as well as transportation losses and constraints of the micro-grid are neglected.

A visual representation of the structure can be found in Figure 1.

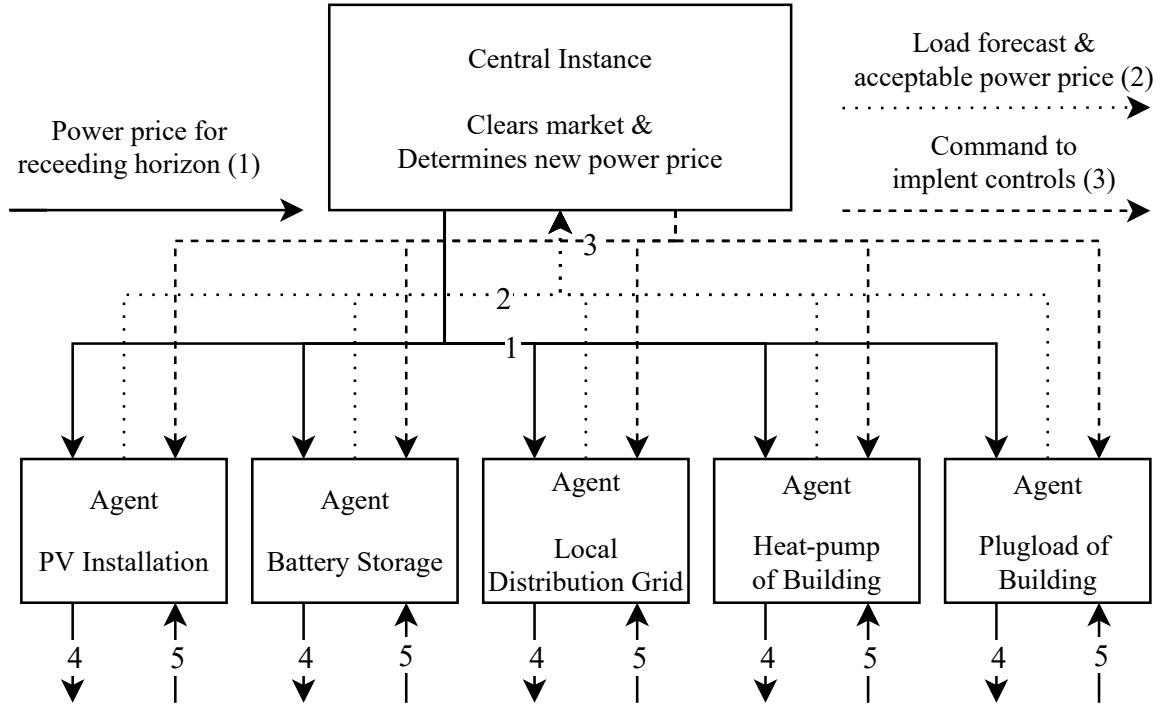


Figure 1: Communication between agents and the coordinating “Central Instance”. The Central Instance sends a forecast of the power price in the upcoming horizon to the agents (1) and receives their planned power consumption/supply and the corresponding prices (2). Those bids are combined and the resulting plan is distributed again (3). The reading and setting of local sensors and actuators is done by the agent (4 & 5) and no other party receives details about those measurements/commands.

The communication between the agents and the central instance is done in three steps. All agents receive a forecast of the power price in the upcoming time-steps (1). This forecast is used to determine how much power each agent is able and willing to consume or provide and at which price. This is determined by each agent individually and without knowledge about the other agents. The results are communicated back to the central instance (2), which conducts a market clearing with these replies. The result of the market clearing determines how much power each agent is allowed to consume/provide to achieve a maximal social welfare. This control request is then sent to the agents, so that they can implement the behaviour for the upcoming time-step (3). One time-step later, the whole procedure starts over again, forming a rolling horizon.

To perform the forecasts, agents often rely on measured values from local sensors (5). To implement the requested controls, they use actuators (4). The communication to sensors and actuators is done by the agents themselves. Therefore, the connection is easier to establish and no other parties are involved in this communication. This increases security and offers more flexibility with regard to the types of sensors and locally used protocols, as they do not interfere with the communication between agent and central instance.

The trading price for each time-step is determined by the market and is equal to the highest price at which an agent is still able to sell power at that time-step. Therefore, it is a supply-based pricing. All buying-agents with a price at or above the trading price are allowed to buy power. A more detailed explanation of the whole scheduling approach can be found in [13].

One central aspect with regard to privacy concerns is that the agents do not communicate with each other, but only with

the central instance. Therefore, the agents do not obtain any information from others but only aggregated information from the central instance. Furthermore, each agent only communicates the result of the process of forecast-determination (price and power), but no information on how this forecast was determined. By this, the model that is used internally stays secret. This increases security as transferred knowledge is minimized. A study in 2013 [14] showed, that data privacy is more important than any other examined factor for the willingness to pay for new smart meters. This suggests, that the acceptance increases when a district energy system works fine while still preserving privacy by sharing very little information.

2.2. Types of Used Agents

In the present work, each agent represents a certain part at the local energy market. The represented aspects are the heating of a building, plugloads for electrical demand, a photovoltaic installation, the connection of the local distribution grid and the district energy system, and the battery storage that is the main focus of this work. Although the heating of a building and the electrical demand belong together, they are split into two agents in order to differentiate between the behaviour of the static demand (plugloads) and the shiftable load (heat-pump) more clearly.

The advantage of the agent-based structure is that each agent can be developed individually and as it best fits for the specific purpose. The individual agents used in this publication are characterized in two ways. First, by how the forecast is determined, and second by the values of the forecast. In terms of the value-based characterization the agents can be divided into three categories: supply-only (producers), demand-only (consumers) or supply for some, demand for other time-steps (prosumers). In terms of how the forecast is determined, there are also three categories present in this publication. The forecast of the power can either be static, calculated by simple algebra (using a simulation) or determined by solving a mathematical optimization problem. For each of the optimization based agents, the type of model (e.g. linear or quadratic; with or without integers) can be chosen separately and as needed.

Static agents

The first approach is done for agents characterized by static load profile to represent consumers with a need to run at certain times regardless of the power price. The used profile represents measured load-data from an office building. Also a static approach is used for an agent representing the connection between the district energy system and the local distribution grid, as it is assumed that the grid is always capable of supplying power to the district system. These agents are not able to react to changes in the power price and will abide with their behaviour.

Simulation agents

Examples for the second approach (algebraic calculations) are photovoltaic systems, where the power output is determined from parameters of the installed PV-modules and a weather forecast. This type of agent is also not able to adapt to changes in power prices but adapts to changes in conditions, such as e.g. weather forecasts. This reaction is done in an algebraic way that does not require solving of an optimization problem.

Optimization agents

The third approach (optimization) is pursued by using Model Predictive Control (MPC). Examples of this approach are the agent representing the thermal behaviour of buildings heated with a heat-pump, and the agent representing a storage system such as battery storages.

2.3. Battery model

The battery model is designed to be used in an agent as part of model predictive control. The central instance imposes a receding horizon by requesting updates on the operation strategy every 15 minutes with a forecast horizon of 24 hours. This parametrization is used in this publication, but can be chosen otherwise if needed. As the battery storages aim to supply power over night and during times of little energy supply (e.g. when it is cloudy), a forecast horizon of 24 hours suffices. An extension of the horizon length would also lead to strongly increased computational loads.

The optimization problem includes ageing mechanisms for each cycle as well as calendar ageing. The aspects and specific values for the parameters are derived from [15–18]. The model includes non-linear ageing mechanisms, that are linearized (see below), leading to a Mixed Integer Linear Programming (MILP)-Problem that needs to be solved. This optimization problem is solved using a commercial solver named “Gurobi” in version 9.0.2 [19].

The model used by the battery agent is characterized by parameters that are fixed over time. Examples are the time-steps (t) of the whole horizon (T), prices ($P(t)$) for electrical power for each time-step and the duration of a single time-step (Δt). Also the maximal energy ($E_{\max}$) that can be stored and the maximal power allowed for charging ($P_{\text{charge}_{\max}}$) and discharging ($P_{\text{discharge}_{\max}}$) are parameters, that are kept constant (e.g. degradation does not directly reduce the available storage capacity). The maximal energy as well as the maximal power are not time dependent but stay constant for all time-steps. For this examination the maximal energy / storage capacity is set to 3.6 kWh. The maximal power is calculated from the C-rate. The C-rate is defined by the rate of time (usually hours) it takes to charge or discharge a battery. As the C-rate is applied for charging ($P_{\text{charge}_{\max}}$) and discharging ($P_{\text{discharge}_{\max}}$), the maximal power is also identical.

Apart from the parameters, the model exhibits variables, that are optimized by the solver. The most important variables are the charging and discharging power ($P_{\text{charge}}(t)$ & $P_{\text{discharge}}(t)$) that are determined for each time-step. Furthermore, a

binary variable ($B_{\text{charge}}(t)$) is introduced to prevent parallel charging and discharging in each time-step.

$$P_{\text{charge}}(t) \in \mathbb{R}^{0+} \quad (1)$$

$$P_{\text{discharge}}(t) \in \mathbb{R}^{0+} \quad (2)$$

$$B_{\text{charge}}(t) \in \{0, 1\} \quad (3)$$

Some expressions are introduced to shorten the equations and increase readability:

$$P_{\text{net}}(t) = P_{\text{charge}}(t) - P_{\text{discharge}}(t) \quad (4)$$

$$\begin{aligned} \text{SOC}(t) = & \text{SOC}(t-1) \cdot \eta_{\text{selfdischarge}} \\ & + (P_{\text{charge}}(t) \cdot \eta_{\text{charge}} - P_{\text{discharge}}(t)/\eta_{\text{discharge}}) \cdot \Delta t / E_{\text{max}} \end{aligned} \quad (5)$$

$$\text{SOC}(0) = \text{SOC}_{\text{init}} + (P_{\text{charge}}(0) \cdot \eta_{\text{charge}} - P_{\text{discharge}}(0)/\eta_{\text{discharge}}) \cdot \Delta t / E_{\text{max}} \quad (6)$$

The resulting power (P_{net}) is positive for time-steps in which the battery is charged and negative while discharging. The SOC (state of charge) of each time-step is computed from the SOC of the previous time-step and current charging or discharging power. The self-discharge is assumed to be around $2.08 \cdot 10^{-5} \text{ h}^{-1}$ (totalling around 1.5 % per month). For the first time-step, $\text{SOC}(t-1) \cdot \eta_{\text{selfdischarge}}$ is replaced by a predefined initial SOC value of 0 (cf. equation 6).

The following constraints restrict the behaviour of the battery-model. By multiplying the maximal power with a binary variable (in equation 7 & 8), parallel charging and discharging is prevented.

$$P_{\text{charge}}(t) \leq B_{\text{charge}}(t) \cdot P_{\text{charge}_{\text{max}}} \quad \forall t \in T \quad (7)$$

$$P_{\text{discharge}}(t) \leq (1 - B_{\text{charge}}(t)) \cdot P_{\text{discharge}_{\text{max}}} \quad \forall t \in T \quad (8)$$

$$0 \leq \text{SOC}(t) \leq 1 \quad \forall t \in T \quad (9)$$

To determine the optimal operational behaviour of a battery, the costs for replacing or refurbishing the battery need to be taken into account. The costs for replacing the battery are denoted by $\mathcal{C}$. An additional index specifies an origin for this replacement cost. For example, $\mathcal{C}_{\text{cycles}}(t)$ are costs for replacement of a battery occurring from the charging or discharging of time-step t . This means, that the replacement costs are divided by the maximal number of cycles ($N_{\text{max}}^{\text{Cycles}}$) that a battery can be charged and discharged before replacement is needed. This cost is added to total energy charged and discharged leading to a penalty, as each charging and discharging degrades the battery, resulting in an earlier replacement. Although this approach does not include interest rates for spent or saved money, it gives a rough estimate of the cost due to cyclic degradation. For the current approach this estimate suffices. To determine the appropriate penalty for each time-step, the fraction of full cycle-equivalents that come from the power of this single time-step is determined and denoted as $N^{\text{Cycles}}(t)$.

$$N^{\text{Cycles}}(t) = \frac{\Delta t}{2 \cdot E_{\text{max}}} \cdot (P_{\text{charge}}(t) \cdot \eta_{\text{charge}} + P_{\text{discharge}}(t)/\eta_{\text{discharge}}) \quad (10)$$

$$\mathcal{C}_{\text{cycles}}(t) = \frac{\mathcal{C}}{N_{\text{max}}^{\text{Cycles}}} \cdot N^{\text{Cycles}}(t) \quad (11)$$

As calendar degradation strongly depends on the internal voltage of the battery-cells, the relation between SOC and voltage ($U(t)$) is given in equation 12 (taken from [20]). The values for the parameters are deployed for a temperature of 25 °C and averaged between the values for charging and discharging processes to remove hysteresis in order to simplify the model to be used for optimization. The relation between the voltage and the ageing process is derived from [16]. We chose a factor of 0.2 in equation 13 since a capacity degradation of 20 % is considered as acceptable before a battery needs to be replaced.

A simplification for the connection between SOC and degradation is applied. The non-linear correlation between SOC and calendar ageing (cf. equation 13) is replaced by a piecewise linear formulation with 9 segments (cf. equation 14). This formulation matches the original curve quite well ($R^2 > 0.9999$) for the whole range of SOC. The main reasons for this simplification are the strongly reduced computation time and the larger variety of suitable solvers, as the problem is no longer a MINLP but a MILP.

$$\begin{aligned}
p_0 &= 3.621 \\
p_1 &= -0.2947 \\
p_2 &= 6.952 \cdot 10^{-5} \\
a_1 &= 5.135 \cdot 10^{-4} \\
a_2 &= -0.1354 \\
U(t) &= p_0 \cdot \exp(a_1 \cdot \text{SOC}(t) \cdot 100) \\
&\quad + p_1 \cdot \exp(a_2 \cdot \text{SOC}(t) \cdot 100) \\
&\quad + p_2 \cdot (\text{SOC}(t) \cdot 100)^2 \\
\alpha &= (7.543 \cdot U(t) - 23.75) \\
&\quad \cdot \exp\left(\frac{-6976}{298.15}\right) \cdot 10^6
\end{aligned} \tag{12}$$

$$C_{\text{calendar}} = \frac{C \cdot \Delta t}{0.75 \sqrt{\frac{0.2}{\alpha}} \cdot 24} \tag{13}$$

$$C_{\text{calendar, simple}} = \frac{C \cdot \Delta t}{\text{PWL}(\text{SOC}(t)) \cdot 24} \tag{14}$$

As both types of degradation can occur independently, the penalties for both types of degradation are added up as it is also done e.g. in [16]. Therefore, they are simply subtracted from the achieved profit. The objective of the optimization is to maximize the own profit, as shown in 15.

$$\max \left(\sum_{t \in T} (-\mathcal{P}(t) \cdot 10^{-6} \cdot P_{\text{net}}(t) \cdot \Delta t) - C_{\text{calendar}} - C_{\text{cycles}} \right) \tag{15}$$

Further information on the modelling of the battery can be found in [21].

2.4. Values of Parameters & Sensitivity Analysis

To determine the most relevant parameters, multiple parameters are varied and the behaviour of the whole system after variation of the parameters is examined. The parameters are varied according to Table 1. The specific cost of the battery is derived from [22] for the year 2030.

Table 1: Values for parameters of battery storage & range of variation for sensitivity analysis.

Parameter	Symbol	nominal value	Range	Unit
Storage capacity	E_{max}	3.6	2.88 – 4.32	kWh
Charging efficiency	η_{charge}	0.95	0.94 – 0.96	-
Discharging efficiency	$\eta_{\text{discharge}}$	0.95	0.94 – 0.96	-
C-Rate		1/3	0.267 – 0.4	-
Specific cost of battery	C/E_{max}	0.17	0.14 – 0.20	EUR/kWh

The other agents are dimensioned as follows. For the agent representing the plug-loads, measured data from an office-building was used in a scaled form to match the overall dimensions of the system at hand. The peak-load of this profile is scaled to be 4 kW. The heat-pump can consume only 2 kW at maximum. The PV provides a maximal power of 10 kW on that day, to be able to provide all agents and leave some headroom to see changes when the parameters of the battery are altered (e.g. an increased charging power). The connected grid is large enough to provide all power needed for times, when no power from the photovoltaic installation and no power from the battery can be supplied.

However, the dimensioning of the individual agents can be adapted as needed. The main focus of this publication is to illustrate how the system works and on how the battery affects the systems' behaviour and is not meant to be a showcase of a specific system.

The prices at which the different agents buy and sell energy are constant over time and specific to each type of agent. The power supplied by the grid is set to the average power price for industry (with a yearly consumption of 24 GWh) of 2020 in Germany which is 165.4 EUR/MWh [23]. In many cases the real power price will be higher. Therefore, this assumption exhibits a case, where the difference in power price between renewable power and grid power is small. The price of the PV-power is set to 58 EUR/MWh. Depending on the type of PV-Installation even smaller prices can be achieved as of 2018 [24]. This difference in price between grid and PV makes it attractive to other agents to shift power to the times with a high supply of power by PV. The battery offers its power at a price of 90 % of the price of the power-grid in order to be

preferred compared to the grid, while still maximizing the own profit. Although the determination of the price at which the energy is offered by the battery could also be handled dynamic, this static approach already provides good results. Hence, the static approach is chosen to better pinpoint the source of changes in the upcoming sensitivity analysis.

3. Results & Discussion

In this section, the general behaviour of the energy system is described and discussed, followed by an overview of the sensitivity of the whole system to a variation of parameters of the battery storage as introduced in Section 2.4..

3.1. Behaviour of district energy system

For the following analysis an arbitrary time in fall is chosen. The decision which day to chose affects the amount of power provided by photovoltaic as well as the power required for heating of the building. The chosen time in fall shall give a glimpse on how this system can work for average days and not the behaviour on winter or summer days, when either very little PV power is supplied or very little heating is needed. As the system stores excess energy during the day to provide in the afternoon and night, the examined time starts in the morning (six o'clock) and ends one day later at six o'clock, so that the storage-effect can be seen and is not limited by fixed values of SOC for specific times (e.g. 50 % at midnight). To make the results easier to compare, differences between the initial SOC and the final SOC are sold (or bought) after the last time-step (at price determined in the last time-step). By this, the profit is not affected if the storage keeps some energy until the end of the examined period.

In the district energy system, the flexibility of demand side management is provided by the battery storage and by the heating of a house. This can be seen in Figure 2. There, the consumption (or supply) of the agents is shown together with the power price for all time-steps.

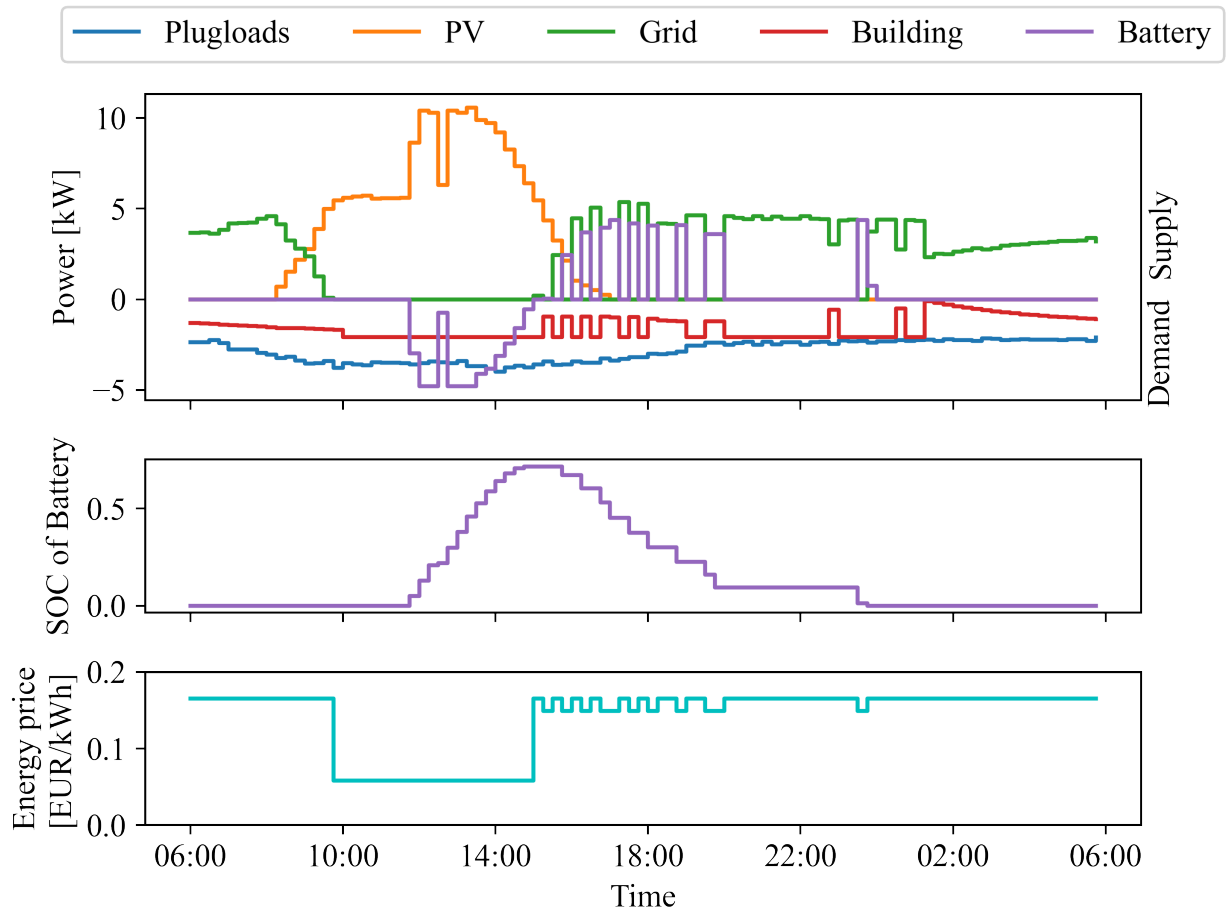


Figure 2: Overview of the power provided and consumed by the different agents over all time-steps for the nominal values of the battery storage. The upper graph presents the power that each agent consumes or provides for each time-step. Values above zero indicate a supply, whereas values below zero show a demand for those time-steps. The graph in the middle exhibits the State of Charge of the battery over time. The lower graph shows the price at which the power is traded for each time-step.

The building-agent with a heat-pump (shown in red) exhibits a larger demand during the daytime, when cheaper power

is available and a partly reduced demand after sunset, when power prices rise again. There is another period of increased demand during evening and around midnight. This peak is not connected to cheaper power, as during the day. Instead it is the result of the temperature dependent coefficient of performance (COP) of air heat pumps. This COP increases when temperature difference decreases [25]. The ambient temperature is higher around midnight than in the following hours later that night. Therefore, the heat pump can operate more efficiently during this period of time. To fully use this advantage, the heat pump runs at maximal power for some hours to reduce its consumption later that night. As this increased demand around midnight occurs in all examined scenarios and does not originate from the battery storage, it is not regarded and discussed further in the following sections.

The battery agent (in purple) also shows the most activity around the time of sunset. These peaks illustrate, that the battery agent charges before the sun sets and provides the power, once not enough electricity can be provided by the photovoltaic. This is already the case before the sun fully sets. So for some time-steps the power to the system is provided by the photovoltaic and the battery storage together without needing the grid. As can also be seen in the figure, the battery is not fully charged. The agent is not able to charge the battery storage above a SOC of 0.7. This is due to the fact that the battery is not able to charge as much as it would according to the MPC results in all time-steps (e.g. around 13:00, it charges less). As the battery-agent plans to charge as late as possible (leading to a minimization of self-discharge), those time-steps, where less is charged than planned, cannot be compensated. Therefore, the battery is not fully charged at sunset.

It can also be observed, that the price of power changes at some specific points in time. It decreases as soon as sufficient power is offered by photovoltaic so that no power is needed from the local power-grid. As soon as power from the battery is used (but not yet power from the grid), the price jumps to a higher plateau. Once additional power from the grid is used, the price is again at the highest value. After sunset, the price fluctuates for a little while. This is because the market mechanism tries to avoid the parallel use of power from the grid and the battery storage. This leads to frequent changes of the price.

The curve of power price appears simple, as only three agents offer power and because they do so at certain, fixed price levels. Although the market mechanism supports time-dependent prices provided by the agents, the prices are actively fixed in this example to easier show the effects of parameter-variation.

It is important to stress, that in Figure 2 only the traded power is shown, not the power offered by systems. The photovoltaic offers higher amounts of power than are traded before 14:00, when the battery starts to charge. Since only limited amounts of power are demanded in those first time-steps, it cannot be traded and is therefore not shown in the figure.

3.2. Sensitivity of battery parameters

To discuss the sensitivity of the battery model, it is helpful to focus on a few indicators describing the behaviour of the system. The two indicators chosen here are the profit earned by the battery over the course of a day and the fraction of used power provided by the photovoltaic. Both are compared for different values of the parameters as mentioned in section 2.4..

In Figure 3 the outcome of the parameter variation is shown.

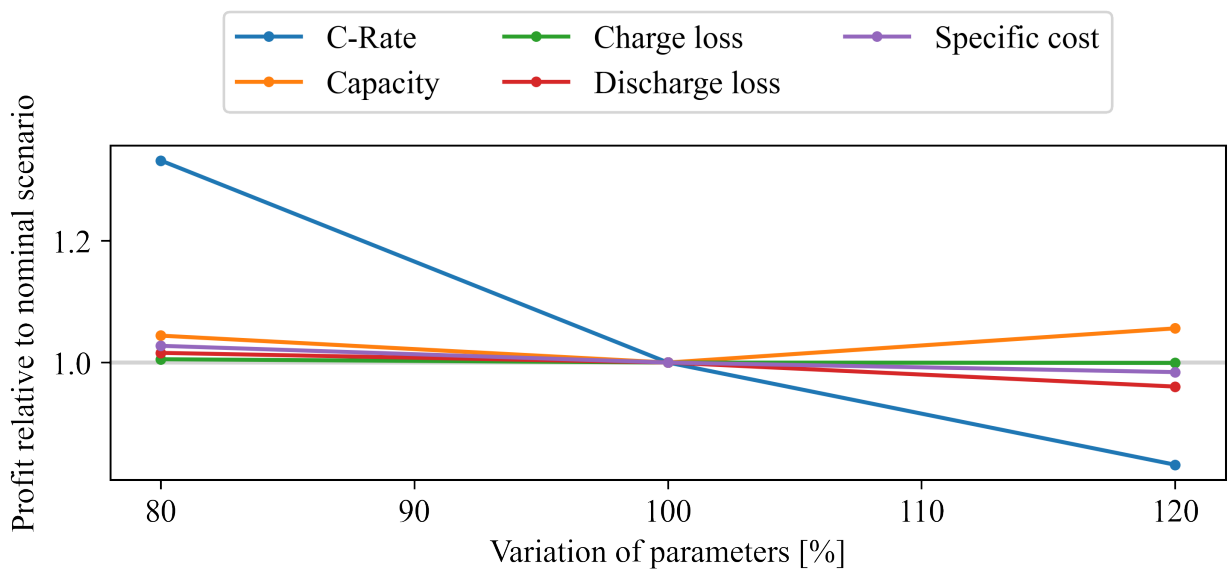


Figure 3: Overview of the profit of the battery agent. The x-axis shows the variation of the parameter described in the legend, whereas the y-axis exhibits the normalized amount of money earned. The simulation result for the nominal values is scaled to be 100 %.

There, the profit of the battery agent is plotted against the different parameters increased or decreased by 20 %. The 100 % mark is used for the nominal values and the y-axis indicating the profit is also normalized to the result of this scenario. The profit includes the revenue from trading the energy and also the cost of degradation (both calendar and cyclic degradation). As can be seen in the figure, the variation of charging and discharging power (C-rate) has the highest influence.

Additionally to comparing the profit of the battery, also the fraction of used power from photovoltaic is examined. It is shown in Figure 4. By also taking this chart into account it can be determined if the change in profit is due to internal losses or costs or if the behaviour of the battery changed leading to a different value for the profit.

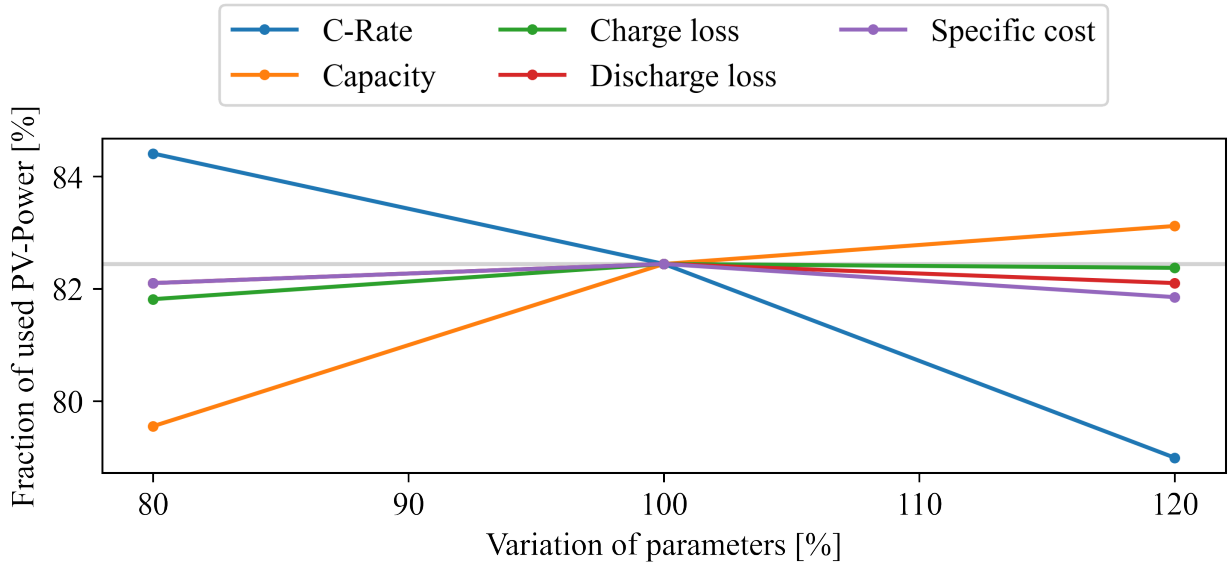


Figure 4: Overview of the fraction of used PV-power on the total offered PV-power. The value for the nominal case is also highlighted with a horizontal gray line. The values for 80 % of discharge loss and 80 % of specific cost are very similar, which is why the marker for discharge loss (red) is covered by the purple marker for specific cost. For an energy-system with identical agents but without the battery agent, the fraction of used PV-power is at 64 %. This means that for nearly all parameters, the fraction of PV-power that remains unused is decreased by around 18 percentage points.

The result of the variation of each of the individual parameters is discussed in the following.

3.2.1. C-Rate of battery

The C-rate of the battery has by far the largest influence on both the achieved profit and the used power provided by the photovoltaic. Increasing the maximal charging/discharging power by 20 % decreases the profit. This is most likely due to combination of how the agent and the market work. The agent plans to charge as late as possible to reduce self-discharge and penalties (cf. 3.1.). As the maximal power is higher with an increased C-rate, the battery can be charged in fewer time-steps. If in some of those time-steps less power is provided than planned, the issues are larger compared to a situation where charging is distributed over more time-steps. Therefore, the profit and usage of PV-power is reduced with an increased C-rate. This could be compensated if the optimization-model would include some margin for unforeseen issues (e.g. less power than planned).

3.2.2. Capacity

The change of capacity is an asymmetric variation. For increased capacities, the profit and photovoltaic usage increase. For decreased capacities this looks different. The profit slightly increases but the fraction of used photovoltaic power drops. It can be seen that decreased capacities lead to a slight change in behaviour of the battery in combination with this agent-based coordination.

The reason for the increased profit while decreasing capacity lies in the determination of cost. In this model, a specific cost is assumed. This cost scales linearly with storage capacity. As the cost scales with the capacity, so do penalties for degradation, as they depend on the cost. This is why a reduced capacity can lead to a higher profit.

3.2.3. Specific cost of battery

The variation of the specific cost exhibits the effect of penalties on the behaviour and the profit. It can be seen, that with increased specific cost, the battery gets more expensive and therefore, the penalties for degradation also increase. The inverse can be seen for decreased specific cost. However, this is only valid for the profit of the battery. The usage of

PV-power shows, that the behaviour of the battery-agent is only slightly affected. So the main reason for the change in profit is to be found in the cost of degradation.

3.2.4. Charging and discharging losses

The charging and discharging losses are varied around a value of 5 %. This has a slight impact on the achieved profit but also on the used renewable power provided by photovoltaic. The increase of discharging loss to 6 % (leading to a discharging efficiency of 94 %) yields the highest deviation from the nominal case (with regard to profit). However, this decrease of 4 % against the nominal case is also partly due to a late discharge of the battery-storage (not shown). This leads to higher penalties (due to stronger calendar degradation) as the SOC is higher for more time-steps. Without those increased penalties, a more symmetrical behaviour would be observed.

4. Conclusion & Outlook

This publication examines the behaviour of a battery storage to different variations of parameters. The battery storage is controlled in an agent-based approach in the context of a district energy system. It has to be noted, that the exhibited behaviour is the result of the combination of how multiple agents and the central market mechanism interact and how they influence each other. It does not reflect the behaviour of isolated batteries.

This behaviour is discussed for a variation of different parameters of a battery storage. It focuses on how those variations affect the overall profit obtained by that storage in a multi-agent system and on how much of the available power provided by PV is used. The sensitivity analysis shows that the charging and discharging power of the storage influence the result the most. Both for the obtained profit and also for the ability to use power provided by sources of renewable energy. The other examined parameters such as charging and discharging losses as well as specific cost had smaller influence than the parameters directly affecting the power of the battery storage (e.g. C-Rate and Capacity).

Apart from the behaviour of the battery storage and the battery agent themselves it will also be important how the forecasts from multiple storages in the same system will look like and will influence each other. This may impose new challenges but also may lead to higher rates of used renewable energy, as multiple storages can complement each other. It especially holds true for storage systems with strongly different characteristics (e.g. short-term storages coupled with long-term storages). A consequence of this combination could be a reduced power consumption from the local distribution grid and increased self-sufficiency of the district energy system. This may be reviewed in an upcoming publication.

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