

Stochastic Optimization Model for Energy Management of a Hybrid Microgrid using Mixed Integer Linear Programming

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Abstract: In the context of increasing decentralization of the energy supply system, the concepts of microgrids are well suited to realise a reduction of CO₂-emissions and create opportunities for new business models. For this the operation of the microgrid has a significant impact. In real systems, however, the consideration of uncertainties in generation and consumption data is essential for the operating strategy. Therefore, in this paper we propose an optimization model based on mixed-integer linear programming for the hybrid microgrid of a residential building district and include stochastic optimization in a computationally efficient way. For this, a two-stage approach is used. In a first step, we do a day-ahead optimization to determine a schedule for the combined heat and power plant and the power exchanged with the grid. In a second step, based on the results of the day-ahead optimization and the observed values for the uncertain parameters the intraday optimization is carried out. Using a numerical example, we demonstrate the advantages of this stochastic optimization over conventional optimization based on point forecasts. The data used originates from a real project district in Darmstadt, Germany.

Keywords: Residential micro grid, battery energy storage system, optimal operating strategy, mixed-integer linear programming, stochastic optimization

1. INTRODUCTION

A concept to realise a CO₂-reduced energy supply are so-called microgrids, which for this reason are becoming increasingly widespread in electrical supply systems (Hirsch et al., 2018). Microgrids are local energy networks that connect energy generation units, energy storage units and loads. The energy generation units can be differentiated into controllable (mostly fossil) and uncontrollable (mostly renewable) units. The main difference between microgrids and macrogrids is especially the local proximity of producers and consumers as well as the resulting possibility to consider the microgrid as an overall system that can be controlled (Dulău and Bică, 2019; Gildenhuis et al., 2019). In addition to the ongoing technological development of microgrids and their components, these also represent an important part of novel business models in the energy sector. These are not only driven by the fundamental trends mentioned above, but also by changing legal regulations resulting from the political discourse on the transformation of the energy supply systems (Meena et al., 2019). For these reasons, microgrids are also intensively investigated in science and the number of published contributions is rising rapidly (Shah Danish et al., 2019). In addition to several publications dealing with economic and political evaluation as well as classification of the general microgrid concept (Burke and Stephens, 2018) (Farrelly and Tawfik, 2020) (Ajaz, 2019), the majority of publications on microgrids deal with mathematical and technological aspects. Here, especially the question of local energy management is especially important for real microgrids

for a number of different reasons (Hirsch et al., 2018), where the most important ones are summarised below:

- increased local production of renewable sources,
- rising energy prices due to additional charges,
- most energy systems consist of electric and thermal components that have to be considered simultaneously,
- incentives to use the locally produced energy for local customers/consumers,
- decreasing prices for energy storage systems (batteries) that allow for time shift of energy,
- inefficient and unwanted grid reinforcements leading to the situation that not all of the locally produced energy can be fed back to the grid.

For a majority of microgrids, the high number of control variables even in systems with only a few energy components makes it difficult to use a rule based approach for controlling the energy flows in the system. Hence, various optimization algorithms are used to solve the problem at hand. In this context, a basic distinction can be made between linear and non-linear approaches. Non-linear approaches for example are presented in (Bhattacharjee and Khan, 2018) and (Hossain et al., 2019). Compared to non-linear approaches, linear approaches have the advantage that efficient solution algorithms can be used. Since in addition to continuous variables also binary variables are needed to model microgrids, many of the linear approaches use mixed integer linear programming (MILP) formulations such as in (Cardoso et al., 2018), (Nemati et al., 2018) and (Mashayekh et al., 2017). The

MILP approach has the additional advantage that the quality of the optimisation results can be quantified. One main drawback of it is the inconvenient and time-consuming formulation of the problem, but still quite often MILPs are used for optimising microgrids and their operating strategies. Numerous scientific contributions optimize the operating strategies of microgrids with deterministic input data. In real systems, however, the consideration of uncertainties in generation and consumption data is essential for the operating strategy. Therefore, the consideration of uncertainties is increasingly considered in scientific discourse. Here, individual scientific contributions often deal with certain partial aspects of microgrids that are subject to uncertainties such as load forecasts (Alvarado-Barrios et al., 2020), but also with methods to deal with these uncertainties, e.g. the adapted operation of a combined heat and power plant (Zhang et al., 2019). For dealing with uncertainties in microgrids, various types of optimization algorithms are used in literature. Often, two-stage MILP approaches like (Balderrama et al., 2019), (Parisio et al., 2016) or (Silvente et al., 2018) are used because they can efficiently handle the commonly extensive problem formulations.

In this contribution, we focus on one main source of uncertainty (PV production in this case) in a residential district consisting of several multi apartment buildings. The supply system is modelled using a MILP approach where the main components are the mentioned PV system, a Combined Heat and Power plant (CHP) and a Li-ion battery. The model is unique in the way it includes the aging behaviour of the battery. This is necessary due to the high initial cost of the component and the strong dependency of its aging behaviour on the operation. The goal is to define a computationally efficient way of including stochastic optimization into the model and demonstrate the advantages over conventional optimization based on point forecasts. Before the stochastic

optimization process is described in detail (Chapter 3), we introduce the basic MILP model with focus on the battery model and the implementation (Chapter 2). The results that can be achieved using the stochastic optimization approach are presented for a numerical example (Chapter 4). The article concludes with a short summary and outlook.

2. MODEL DESCRIPTION

As mentioned, we focus on residential microgrids with several multi apartment buildings. These buildings are supplied by a mix of locally as well as centrally produced electricity. A local energy supplier (LES) is responsible for the operation of the energy supply system as well as the trading of electricity with the market and selling energy to the local residents. The goal of the LES is to operate the multi building district as cost efficient as possible while at the same time fulfilling all customer needs in terms of electricity and heat. The basic model is based on the approach described in (Weitzel et al., 2018).

2.1 Structure of the microgrid model

In order to be able to formulate a MILP problem and consecutively solve it, we need to define a microgrid model. The chosen modelling depth includes electric and thermal energy flows but does not include voltage, current, mass flow, temperature etc. That is why, both the thermal and the electrical system can be modelled using a single bus approach. Figure 1 demonstrates the coupling of the components and subsystems. The local residents' heat demand is solely met by local production that comes from a CHP and an auxiliary heater and can be buffered in a Thermal Energy Storage System (TESS). The heater is installed due to backup reasons and for times where no electric energy can be sold to either residents or the grid. The thermal subsystem is connected to a natural gas grid. The electrical output of the CHP is fed into

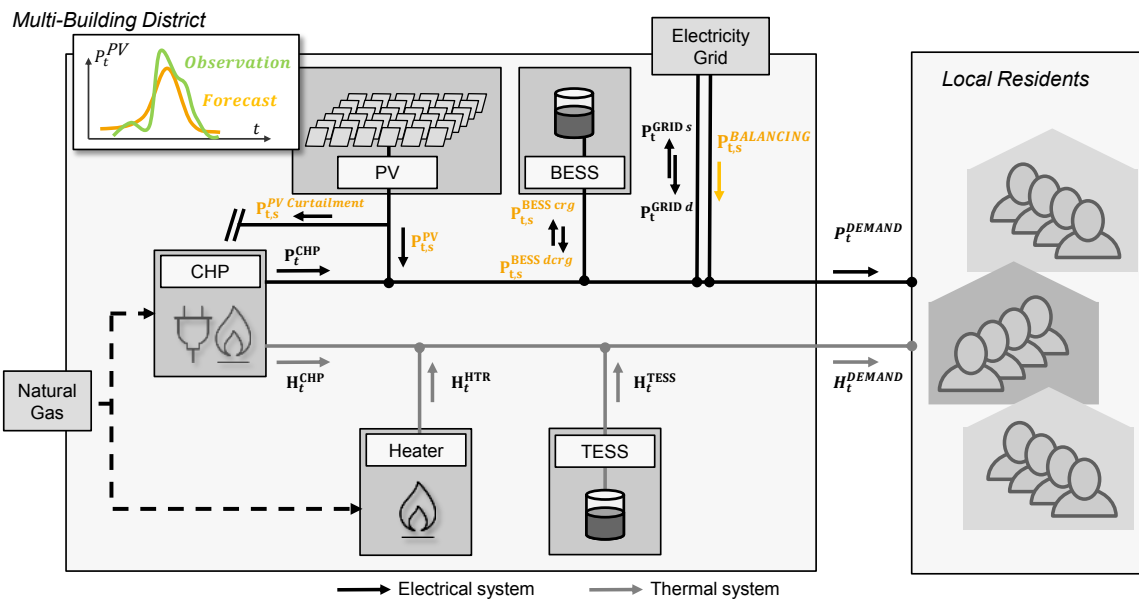


Fig. 1. Adapted structure of the micro grid model for day-ahead (black) and intraday optimization (orange) (modified graphic, based on (Weitzel et al., 2018))

the electrical subsystem together with the generation of PV modules. In order to increase the self-consumption of the microgrid, a Battery Energy Storage System (BESS) is also installed. All electrical components are connected to the electricity grid and supply the customers with electric energy. This microgrid configuration is already quite common in modern households, especially bigger apartment buildings and multi-building districts in cities.

2.2 Objective function

The objective of the LES is to maximize its operating profit over a planning horizon T that consists of seven components. On the revenue side lie the revenues Rev_t^{cust} that result from delivering heat and power to customers at a fixed price and the revenues Rev_t^{grid} that arise from sells of surplus electricity to the grid considering time variable prices. The five remaining components are cost components that reduce the LES's profit: the purchased electricity from the grid Pur_t^{grid} , the fuel cost of the CHP $Fuel_t^{\text{CHP}}$, the fuel cost of the auxiliary heater $Fuel_t^{\text{HTR}}$, the network charges NC_t and the battery aging cost BAC_t . Full network charges apply to electricity that is transferred using the public grid. Locally produced electricity that is also locally used is charged with a reduced amount of network charges. Battery aging cost are discussed in greater detail in section 2.3. Equation (1) shows the complete objective function that is maximized by the LES.

$$\max \mathcal{F} = \sum_{t=1}^T (Rev_t^{\text{cust}} + Rev_t^{\text{grid}} - Pur_t^{\text{grid}} - Fuel_t^{\text{CHP}} - Fuel_t^{\text{HTR}} - NC_t - BAC_t) \quad (1)$$

2.3 Battery Aging Costs

The battery is one of the most relevant components due to its high initial cost and the aging behaviour that is highly usage dependent. It provides flexibility in the electric subsystem for the LES. In order to be able to adequately integrate the BESS into the operating strategy, its aging behaviour must be modelled as realistically as possible. Weitzel et al., 2018 suggest an aging model that uses realistic calendric and cyclical aging behaviour and integrates it into a MILP model using a piece-wise linearization approach. The battery aging costs considered in the objective function consist of two components, as shown in equation (2): the cost due to calendric aging $BAC_{\text{cal},t}$ and the cost due to cyclical aging $BAC_{\text{cyc},t}$. Both are calculated by a multiplication of the factors $\varepsilon_{\text{cal},t}$ and ε_{cyc} , which depend on different parameters and the investment costs of the battery INV_{BESS} .

$$BAC_t = BAC_{\text{cal},t} + BAC_{\text{cyc},t} = [\varepsilon_{\text{cal},t} + \varepsilon_{\text{cyc}}] \cdot INV_{\text{BESS}} \quad (2)$$

The data for the battery model come from (Sarasketa-Zabala et al., 2015) and (Sarasketa-Zabala et al., 2014). In order to implement the non-linear behaviour in a MILP formulation, it has to be reformulated using a piecewise linear interpolation approach, for details see (Weitzel et al., 2018).

2.4 General constraints

In this paper, the most important constraints for understanding the model shall be presented in a simplified manner.

The model is based on the microgrid's power and energy balances. The balance of the electrical and thermal subsystems at any point in time t is ensured by the equations (3) and (4).

$$P_t^{\text{CHP}} + P_t^{\text{PV}} + P_t^{\text{BESS},d} + P_t^{\text{grid},d} = P_t^{\text{grid},s} + P_t^{\text{BESS},c} + P_t^{\text{demand}} \quad (3)$$

$$H_t^{\text{CHP}} + H_t^{\text{HTR}} + H_t^{\text{TESS}} = H_t^{\text{demand}} \quad (4)$$

P_t^{CHP} and H_t^{CHP} represent the electrical and thermal generation of the CHP, while P_t^{PV} describes the electric PV generation and H_t^{HTR} the thermal generation of the HTR. The PV modules and the HTR are modelled in a simplified manner, while the CHP is modelled with operating point dependent parameters and costs. H_t^{TESS} describes the discharge of the TESS, $P_t^{\text{BESS},d}$ and $P_t^{\text{BESS},c}$ the discharge and charge of the BESS. In comparison to the simplified modelled TESS, for which only standing losses are considered, a detailed model of the BESS is used as already described. In the electrical subsystem, $P_t^{\text{grid},d}$ and $P_t^{\text{grid},s}$ represent the additional possibility of exchanging energy with the public grid. P_t^{demand} and H_t^{demand} are the electrical and thermal demands of the microgrid that must be met at all times.

In addition to the objective function and the power balance equations described above, numerous other constraints are required. These include in particular the storage equations and the constraints for the generation units such as CHP or PV. Furthermore, additional equations are needed to linearize non-linear relationships. This is especially related to the battery-aging model and the operating point dependent modelling of the CHP. A comprehensive formulation of the constraints can be found in (Weitzel et al., 2018).

2.5 Implementation and solution

The presented problem formulation is implemented in the commercial numerical computing environment MATLAB. For this purpose, the primary normal form is used, which is common for the formulation of mixed integer linear problems (Zimmermann, 2008). Equations (5) and (6) show the formulation of the inequality and equality conditions in primary normal form. This form results in a strict separation between the endogenous and exogenous variables. The endogenous variables of the problem are summarized in vector \mathbf{x} , while the exogenous variables are summarized in the vectors of the right-hand side \mathbf{b}_{ineq} and \mathbf{b}_{eq} . The matrices \mathbf{A}_{ineq} and \mathbf{A}_{eq} each contain the left sides of the equality and inequality conditions.

$$\mathbf{A}_{\text{ineq}} \mathbf{x} \leq \mathbf{b}_{\text{ineq}} \quad (5)$$

$$\mathbf{A}_{\text{eq}} \mathbf{x} \leq \mathbf{b}_{\text{eq}} \quad (6)$$

For the implementation, the primary normal form is essential, because it allows for using standardised solvers. The pre and

post processing of the problem at hand is implemented in MATLAB. For solving the MILP, IBM CPLEX is used. It is based on a so-called branch-and-cut process, which uses various aspects of other solution methods and heuristics (IBM Corporation, 2014). A receding horizon technique is implemented for computing-efficiency. In this context, three different time horizons are considered, the planning horizon T , the optimization horizon T_O and the control horizon T_C . With these different horizons, the technique addresses two different problems. Firstly, the large size of the problems formulated for long planning horizons T . Therefore, the problem is not formulated for the entire horizon T but is composed of subproblems, where each has the optimization horizon T_O . This leads to the fact that at the end of each period T_O the end-value problem occurs, which means, that the algorithm assumes that no further energy demand occurs after the end of the optimization horizon. This usually leads to empty storages in the last time step. In order to counteract to this problem, only the part of the operating strategy for the shorter period T_C is included in the final result and the rest of the strategy for T_O is discarded. After this, T_O moves forward by the length of T_C and the optimization of the next subproblem starts. For this paper we set $T = 240 h$, $T_O = 48 h$ and $T_C = 24 h$. This results in problems with 3208 variables and 2391 equations for the optimization horizon T_O in case of a deterministic problem formulation.

3. STOCHASTIC OPTIMIZATION PROCESS

Real energy systems – especially those with a high share of renewable generation – are exposed to uncertainty in terms of variable production, e.g. due to changing weather. Also the exact demand of local residents is difficult to predict exactly as the user behaviour is subject to random decisions and change of plans. In order to include these aspects in the discussed LES concept based on a MILP formulation the technique of scenario optimization has proven to be suitable (Silvente et al., 2018), (Balderrama et al., 2019). The goal of the following sections is to show for a real-life problem what advantages can be achieved with scenario optimization based on a MILP formulation.

3.1 Challenges for Local Energy Suppliers

Two aspects lead to challenges for the LES that are used to motivate the scenario approach introduced in this contribution. First, subsidiaries for decentralised renewable energy production are in rapid decline in most countries. This leads to the situation that renewable energy has to be traded on energy exchanges instead. Here two basic products exist, namely day-ahead (DA) and intraday (ID) trading. DA prices are low and easy to predict. ID is often more expensive and volatile and much harder to predict. Secondly, energy prices consist of several components that also include network charges for using the public electricity grid and other cost apportionments for subsidising renewable energies. A certain share of these cost components can be reduced when energy is produced and consumed locally. This leads to an interesting possibility to increase the profit for a LES.

These two aspects together strongly increase the motivation for the LES to store and sell locally produced electricity to the

local residents. In order to optimise the microgrid's operational strategy, forecasts for production and demand are necessary. Especially for PV production point forecasts (only one value per time step) are commercially available and are often used by energy companies.

3.2 Scenario generation

In the introduced use case with the scheme shown in Fig. 1 the main source of uncertainty is the PV power production. The electricity and heat demand of the local residents can be predicted with much better accuracy using e.g. adapted persistence forecast methods (Yan et al., 2017). Therefore, the following chapters consider the PV production as only uncertain parameter, for which scenarios have to be generated. The scenario generation method is based on (Ma et al., 2013) and is often used in wind power scenario generation. It uses the power curve point forecasts combined with historical forecast errors. The main advantage of this approach is that the data is often available. Another advantage of the approach is that it is not only based on historical data, but includes point forecasts calculated with the help of Numerical Weather Prediction models (Biel et al., 2018). Therefore, they include available external information about the future PV production. For the approach, a calibration period is needed to generate useful predictions. During that period the power forecasts, the observed power curves are needed. For the planning horizon only the point forecast is necessary. (Ma et al., 2013) suggest to create at least 500 scenarios leading to a large problem size as it increases roughly by the square of the number of used scenarios. In order to reduce the computational burden, (Biel et al., 2018) suggest a combination of scenario generation and reduction using the method of (Li et al., 2016). This approach aims at finding a limited set of scenarios that resemble the stochastic process described by the large number of scenarios as accurately as possible. For the following numerical example, the scenarios have been reduced to five representative scenarios sampled hourly. Figure 2 shows the PV forecast of one day and five scenarios as well as the observed PV power curve.

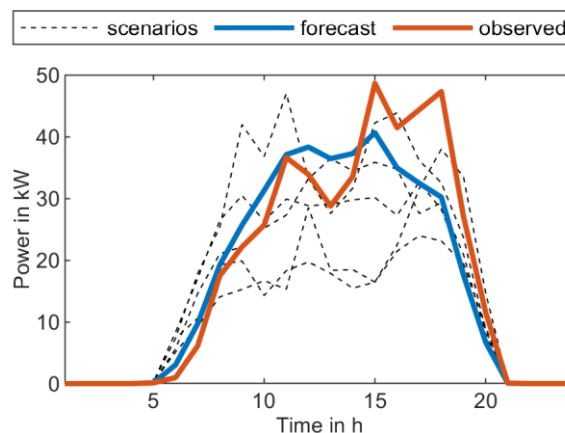


Fig. 2. PV scenarios, forecast and observed power curve

3.3 Coupling of day-ahead and intraday optimization

The optimization process consists of two main steps: day-ahead (DA) and intraday (ID) trading of electricity.

On the DA market, trading deals have to be closed until noon on the previous day for the following day. Therefore, the first step consists of a day-ahead optimization using scenario optimization. It is the goal of the LES to determine a schedule for the CHP and power exchanged with the grid (positive and negative) for the next day. The CHP schedule is assumed to be fixed during the intraday optimization because a high number of startups drastically increases the maintenance cost (Kopanos et al., 2013). That is why it is not considered as intraday flexibility.

In the second step, the LES takes the previously determined schedules for CHP and grid exchange as fixed inputs and performs an intraday optimization with the observed PV time series. Since the ID market is much more difficult to model, we use a simplified approach. The additional degrees of freedom that the LES needs to ensure the solvability of the problem are introduced to the model in the form of balancing power and PV curtailment. Balancing power can only be drawn from the grid to ensure the fulfilment of the customer electricity demand in phases of lower local supply than predicted. In case of a surplus of local supply that cannot be stored cost efficiently, PV curtailment is possible. Figure 3 shows the connection of DA and ID optimization.

4. NUMERICAL EXAMPLE

In order to demonstrate the potential of the scenario method and quantify the advantage for a realistic example, data from a practical research project is used and an exemplary period of ten days is optimized.

4.1 Input data and data sources

The data used in the numerical example originate from a project that is investigating different energetic aspects of an existing residential area, as described in (Conci and Schneider,

2017). Aside from the renovation strategy of existing multi-apartment buildings in the city centre of a German city, the energy supply system of the complex is designed. The resulting system represents a typical microgrid with decentralised renewable and conventional production, heat and electricity demand, energy storage systems and a connection to the power grid. Due to the high number of system components with partly multi-modal character (CHP), simple control strategies do not leverage the potential of the system. Hence, the described LES approach is applied to the energy supply system. The real system is characterised by the parameters shown in Table 1.

Table 1. Overview of the most important input parameters

	Parameter	Value
Demand	Yearly power demand of residents	223 MWh
	Electricity price of residents	0.25 €/kWh
	Yearly heat demand of residents	585 MWh
	Heat price of residents	0.065 €/kWh
Supply	Max. electric power of CHP	20 kW
	Max. thermal power of CHP	39 kW
	Power of heater	350 kW
	Peak power of PV system	100 kW
	Average DA price	0.03 €/kWh
	Add-on for grid exchange (network charges etc.)	0.18 €/kWh
	Add-on for local consumption (reduced network charges etc.)	0.08 €/kWh
	Price for balancing power	0.20 – 0.60 €/kWh
Gas price	0.04 €/kWh	
Storage	Size of BESS	100 – 400 kWh
	Power of BESS	100 – 400 kW
	Price of BESS	150 €/kWh
	Size of TESS	70 kWh
	Power of TESS	140 kW

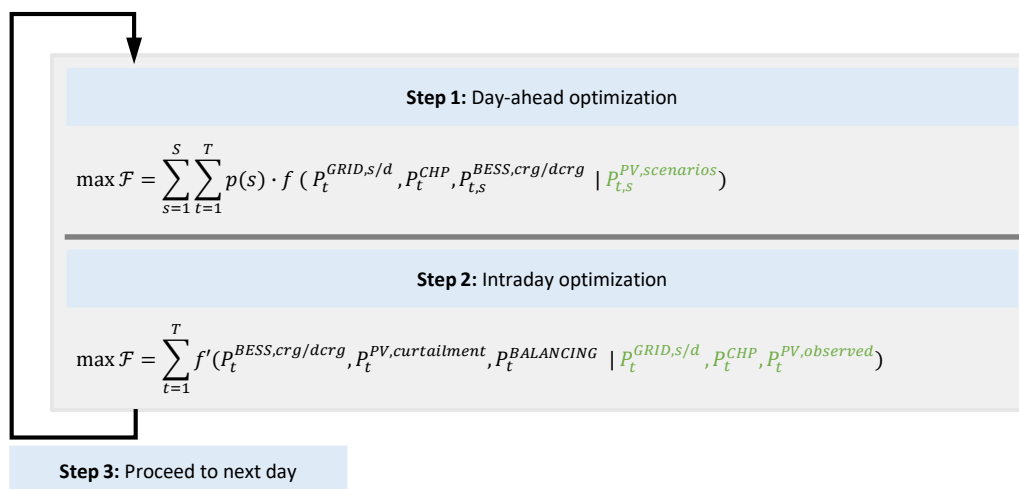


Fig. 3. Process of stochastic optimization

For the numerical example the German energy market is modelled in the simplified manner, as described in chapter 3.1. For the DA market variable hourly historical prices from 2015 are used, whereas the ID market is simplified using a fixed

price for energy demand. This fixed price is varied within the parameter study between 200 and 600 €/MWh. Also the battery capacity is variable in three steps between 100 and 400 kWh.

4.2 Results

In order to show the influence of the optimization approach and the parameter selection on the results, a limited parameter study is carried out. We calculate results for a model without uncertainty (DOpt) where the observed PV production is known a priori. This case serves as the benchmark for the other alternatives with uncertainty. In order to evaluate the advantage of the scenario approach, the optimizations are also carried out using only the point forecast during DA optimization (POpt). In contrast to that, the scenario optimization (ScenOpt) uses five PV scenarios that are created with the approach introduced in Chapter 3.2. ID optimization is the same for the two cases. In addition to the optimization approach, the parameters battery capacity and price of balancing energy are varied. Table 2 gives an overview of the parameters. In total 27 variants with a length of ten days (01.06.2015-09.06.2015) were calculated. The variants were optimized using Matlab and the IBM CPLEX solver on a computer with an Intel Xeon Gold 6144 CPU clocking with 3.50GHz and 64GB of RAM and the Windows Professional (64 bits) operating system.

Table 2. Parameter subject to variation

Parameter	Value 1	Value 2	Value 3
Optimization approach	No uncertainty (DOpt)	Point prognosis (POpt)	Scenario technique (ScenOpt)
Battery (BESS) capacity	100 kWh	200 kWh	400 kWh
Price of balancing energy (BE)	200 €/MWh	400 €/MWh	600 €/MWh

Figure 4 shows an overview of the profits of all 27 variants relative to the base case with a BESS capacity of 100 kWh, BE price of 200 €/kWh and DOpt. What we can see is that a bigger BESS in all variants lead to an increase in operating profit for all BE prices. The additional flexibility available thus has a positive effect. Regardless of the size of the BESS, it becomes clear that the best possible result is always achieved with the optimization under certainty.

For all fixed combinations of BE prices and BESS capacities, ScenOpt always achieves better results compared to POpt. This is due to the fact that the ScenOpt approach has additional information regarding the PV production that may occur and therefore adapts the optimal operating strategy. In the case of the lower BE price of 200 €/kWh, however, this is realised in a different manner than for the two cases with higher prices. The price of 200 €/kWh for BE is competitive to the DA market. The operation strategy resulting from the DA optimization is therefore adapted in the ScenOpt approach during the ID optimization by a higher use of BE compared to the POpt approach. The ScenOpt approach can take more advantage of the low-cost BE during ID optimization because of the less risky strategy it chooses during DA optimization.

This is the case due to the additional PV production information included in the scenarios. For the cases of BE costs of 400 €/kWh and 600 €/kWh, the reasons for the advantages of ScenOpt over POpt are the same.

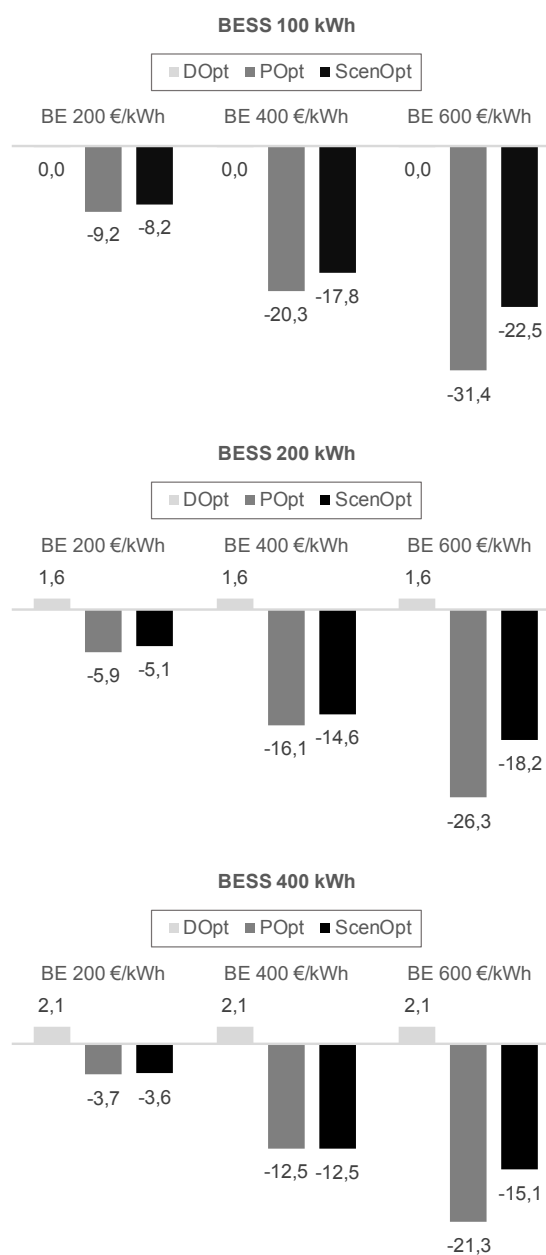


Fig. 4. Results of the parameter variation clustered in size of BESS (top: 100 kWh, centre: 200 kWh, bottom: 400 kWh) and price for BE (left: 200 €/kWh, centre: 400 €/kWh, right: 600 €/kWh). Displayed is the difference in percent to the base case (BESS 100 kWh, BE 200 €/kWh with an absolute profit of 1035 €)

When cross analysing the results regarding the factors BESS and BE, the positive effect of the ScenOpt method becomes obvious. It is noticeable that with increasing BE the influence of the storage size on the results decreases relative to the influence of the optimization approach. For instance, at a BE price of 200 €/kWh the ScenOpt approach with a BESS of 100 kWh achieves a worse result than the POpt approach with a 200 kWh BESS. This is no longer the case with high BE prices. If the price for BE rises to 600 €/kWh it is required to use a BESS of 400 kWh to perform better with the POpt approach than with the ScenOpt approach and a BESS of 100 kWh. So the more expensive BE, the more valuable it is for the LES to use the ScenOpt approach compared to increasing the storage size.

As the differences between POpt and ScenOpt is most significant at higher BE prices, the following in-depth analysis focuses on BE prices of 600 €/MWh. Table 3 shows average performance indicators that demonstrate the LES's behaviour during DA and ID optimization.

Table 3. Different average performance indicators for all BE 600 €/MWh cases during DA and ID operation

performance indicators	POpt	ScenOpt
ID optimization		
Average sum of balancing energy	519 kWh	321 kWh
Average state of charge of BESS	32%	37%
Average energy throughput of BESS	1098 kWh	945 kWh
Average sum of PV curtailment	67 kWh	302 kWh
DA optimization		
Average energy bought from grid	161 kWh	127 kWh
Average energy sold to grid	2939 kWh	2422 kWh

From the data it becomes evident that the advantages of the ScenOpt for high BE costs are mainly due to a lower grid interaction during DA optimization in combination with lower battery aging costs and BE costs during ID optimization. The scenario approach is an effective measure to reduce BE demand during ID optimization. A higher state of charge (SoC) of BESS is used to generate additional flexibility and at the same time, the total energy that is sold to the grid is reduced. A high feed-in obligation to the grid can lead to problems during ID optimization if the produced PV energy is significantly lower during the day than forecasted. Due to the additional scenario information, the ScenOpt approach reduces this risk. Also, the battery aging is significantly lower for ScenOpt, which can be explained by the higher safety margin in the battery. This margin leads to a smoother operation of the battery because it is not necessary to fulfil extreme grid obligations with high power outputs. Due to the higher average SoC of the BESS and thus lower available capacity for charging, it is more often the case that PV power has to be curtailed, especially for smaller BESS capacities.

5. CONCLUSIONS

The presented approach shows that the use of the scenario technique can bring advantages for the operation of a real microgrid under uncertainties without the need for additional information compared to point forecast approaches. The advantage compared to the usage of a point forecast mainly

depends on two factors, the possibility of encountering uncertainties internally (e.g. with BESS) and the costs of encountering them externally on the ID market. With the ScenOpt approach, both factors are optimally utilized during the ID optimization. In the previous DA optimization risky operating states are avoided or mitigated due to additional information of possible scenarios of uncertain parameters. This is especially the case for restricted state variables such as storage capacities that trigger an alternative mechanism when reaching their limit.

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