FLEXIBILITY DETERMINATION OF DISTRIBUTED ENERGY RESOURCES, STORAGE SYSTEMS AND HEATING UNITS CONSIDERING LOAD AND FEED-IN UNCERTAINTY

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ABSTRACT

With the transition from a load driven energy system towards an energy system based on renewable energy sources (RES) flexibility of distributed energy systems becomes an important issue. Since a high simultaneity of devices such as PV plants, heat pumps or electric vehicles can cause local grid congestions a flexible and grid-friendly operation of these assets can be an option to avoid expansion measures. This contribution aims at a determination of available flexibility provided by distributed energy systems taking into account load and feed-in uncertainty in a Monte-Carlo Simulation.

INTRODUCTION

Operational flexibility of attached customers is supposed to be the silver bullet of distribution system operators (DSOs) to avoid grid expansion measures. In the recent years many contributions addressed the topic of flexible operation of various energy systems such as battery storage systems (BSSs), Combined Heat and Power Plants (CHPs) or heat pumps with attached Thermal Energy Storage (TES). Nonetheless, in cases where the assets are not owned by the DSO, the uncertainties of customer behaviour (load) and weather conditions (feed-in) influences the available flexible capacity significantly. One type of such a flexibility provider can be an energy system consisting of a household hold, solar generator and BSS (PV-BSS-System).

MODELLING UNCERTAINTY

In the following section the modelling of load and feed-in uncertainty is described. In general uncertainty can be described by probabilistic methods, non-probabilistic methods or stochastic processes such as Markov chains.

Uncertainty of Renewable Generation

The power generation of renewable energy sources (RES) is strongly depended on weather conditions such as cloudiness or wind speeds. Therefore the generated power can only be forecasted with an uncertainty that cannot be neglected.

Photovoltaic Generation

For characterizing the uncertainty of the PV profile a non-probabilistic interval uncertainty method based on a method called Historical Error Method (HEM) is used. The interval uncertainty is a simple method for uncertainty characterization. The basis of this interval uncertainty method is an analysis of historical data and forecasts for the year of 2014. An exemplary comparison of forecasted and measured solar infeed data is depicted in Fig. 1.

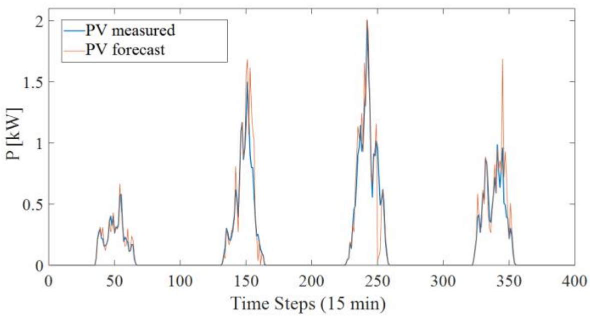

Fig. 1: Interval Uncertainty

The HEM is implemented according to equations (1), (2) and Table I, in which the symbol α, β and γ are representations of real numbers.

$$D = (P_{FC} - P)/P \quad (1)$$

$$\overline{P_{FC}} = P(1 + \overline{D}) \quad (2)$$

In a first step the relative deviation D of the forecasted infeed power is calculated. Since this calculation can result in being not a number (NaN) or infinity (Inf) the calculated value might need to be modified according to

Table I. In the final step a random deviation $\overline{D}$ following normal distribution is added to the measured reference profile to create a large number of forecast profiles that can be used in a Monte-Carlo Simulation.

Table 1: Historical Error Method

Measured data P	Forecast data P_{FC}	Original deviation D	Applied deviation $\overline{D}$
0	0	NaN	0
0	β	Inf	0
α	β	γ	$0 \leq \overline{D} \leq \gamma$

Uncertainty of Demand

The prediction of residential load profiles for single households is a hard task. Since standard load profiles only apply for the sum of many households they cannot be applied. For characterizing the uncertainty of the demand profile, a Load Profile Generator is used which has been created by the author of [4]. It is based on the Markov chain stochastic method. The input is a standard load profile normalized to an energy demand of 1000 kWh and at least 1000 profiles of individual households are generated in a time resolution base of 15 min for a whole year, which, taking into account a permissible tolerance, has a likewise standardized energy requirement of 1000 kWh. By appropriate scaling, the actual energy demand of the respective household can be taken into account.

OPTIMIZATION OF DISTRIBUTED ENERGY SYSTEMS

In the following section the optimization models for an optimal operation of distributed energy systems are presented. In general characterization of a distributed energy system can be found in Fig. 2. It consists of a combination of generation, demand and storage system that are connected by a central control unit. It is to be mentioned that not all of the elements need to be included so that i.e. a PV plant can be defined as distributed energy system as well.

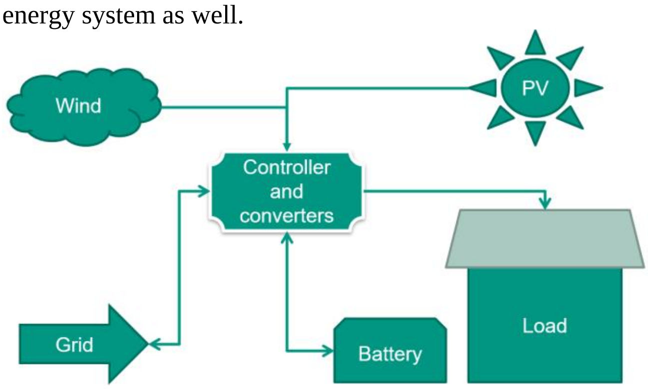

Fig. 2: Distributed Energy System

The resulting optimization problem is formulated in MATLAB and solved using OPT-Toolbox [5].

Constraints

In the following sections the equations for the characterization of the components are described. These equations build the constraints of the resulting optimization problem.

Power Balance

In each time step the required power and heating demand need to be met. This results in the following two power balance equations:

$$P_g^t + P_b^t + P_{PV}^t - P_{HP,el}^t = P_e^t \tag{3}$$

In every time step the thermal demand P_{th}^t needs to be covered by the heat pump and the storage system:

$$P_{HP,th}^t - P_{sto,th}^t = P_{th}^t \tag{4}$$

Battery Storage System

The technical boundaries of the battery storage system result in (5) to (7). The simplified model is characterized by a maximum (dis-)charging power and a limitation of the used capacity.

$$-P_{b,max} \leq P_b^t \leq P_{b,max} \tag{5}$$

$$E_{b,min} \leq E_b^t \leq E_{b,max} \tag{6}$$

The energy stored in the battery E_b^t depends on the energy that is already stored in the system E_b^{t-1}, the charging power P_b^t, the (dis-)charging efficiency η_b, and the self-discharge rate η_{SD}.

$$E_b^t = E_b^{t-1} + \eta_b P_b^t \Delta t - \eta_{SD} E_b^{t-1} \tag{7}$$

Heat Pump System

The simplified modelling of a heat pump can be formulated using a temperature dependent coefficient of performance (COP) as their efficiency.

$$P_{HP,th}^t = COP \cdot P_{HP,el}^t \tag{8}$$

Thermal Energy Storage (TES)

To provide flexibility using heat pumps plants thermal storage systems are needed. The technical boundaries of the thermal storage system result in (8) to (11). The TES is assumed to be ideal. This results in neglecting the losses since this would lead to a way more complex model.

$$-P_{Sto,th,max} \leq P_{sto,th}^t \leq P_{Sto,th,max} \tag{9}$$

$$E_{Sto,th,min} \leq E_{sto,th}^t \leq E_{Sto,th,max} \tag{10}$$

Objective Function

In every applied case the objective function value is time independent. Therefore the overall objective function is the sum over all time steps. The applied objective minimizes the operating cost. The cost vector C contains the cost of purchasing electricity from the retailer (0.3 €)

as well as the feed in remuneration which is included as negative cost (-0.12 €).

$$F_1(x) = \sum_{t=1}^{\tau} C \cdot x^t \cdot \Delta t \qquad (11)$$

MONTE-CARLO SIMULATION

The Monte-Carlo Simulation (MCS) is a simulation process that takes into account the variability of the inputs which enables a statistical description of the phenomenon under consideration. It is predominantly used in investment decisions and risk management, often to aid decision making in various business domains that involve long term planning under uncertainty. Its adaptability allows it to be applied in energy system modelling, especially when the input parameters of the models are subjected to uncertainty. The MCS works by iterating through the inputs that have inherited uncertainty, calculating the results repeatedly, each time using a random set of values and produces a range of possible outcomes that underline the probabilities of occurrence.

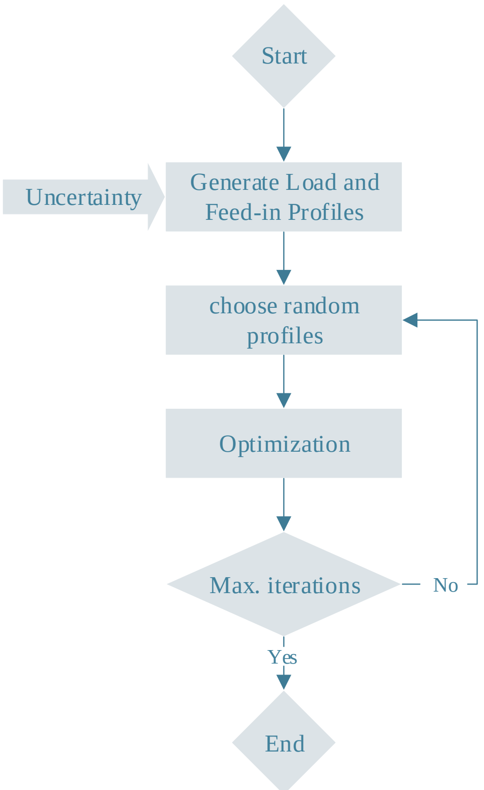

Fig. 3: MCS overview

The more repetitions are carried, the more accurate results are obtained. The results can then be visualized and analysed using different graphical representations, for example histograms, and through probability distribution techniques, the likelihood of occurrence of a result within a given interval can be estimated. The representation of a typical MCS process is shown in Fig. 3. In the following simulations the number of iterations of the MCS has been set to 10.000.

RESULTS

In the following section the results of the performed MCS are analysed. In the first section the optimization is performed for as system consisting of photovoltaic generator, battery storage system and a residential load.
In the second section a heat pump including thermal storage system is added. The parameters of the system can be found in the following table.

Table 2: Model Parameter [6, 7]

Parameter	Value
Battery Capacity [kWh]	3.5
max. Charging Power [kW]	3
BSS Charging Efficiency	0.98
BSS self-discharge [%/month]	1
min. State of Charge	0.1
max. PV Power [kW]	10
Annual power demand [kWh]	2000
Heat pump: max. el. Power [kW]	6
COP	3.5
TES Capacity [l]	500
Annual heating demand [kWh]	10000

PV-BSS-System

In this section the optimization results for a PV-BSS-System are described. Important parameters to characterize the available flexibility of the BSS are the unused storage capacity and the available (dis-)charging power.
In Fig. 4 the results of the used BSS capacity during a day in summer is shown. Since the results were obtained in a MCS with 10000 repetitions considering only the maximum values of all the results is not sensible. A good idea of the distribution of the results can be gained looking at certain quantiles or the mean values. Taking the mean value it can be stated that the BSS system is charged as late as possible during times with PV infeed to avoid self-discharge. The discharge takes place from 18:00 to 21:00. Taking into account the quantilee it is clear that the BSS will be charged less than 84% at around 18:00 in 75% of the cases. In Fig. 5 the distribution of the (dis-)charging power is shown.
Regarding the available flexibility of the BSS the shown quantiles are of interest as well. Taking 12:00 as an example the results show that in 90 % of the optimization results the SoC of the BSS is below 57 % while the charging power is below 51 % of the rated power.

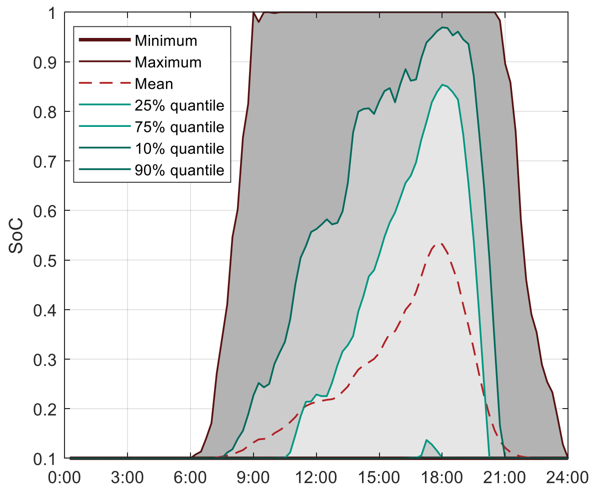

Fig. 4: State of Charge (SoC) of PV-BSS (summer)

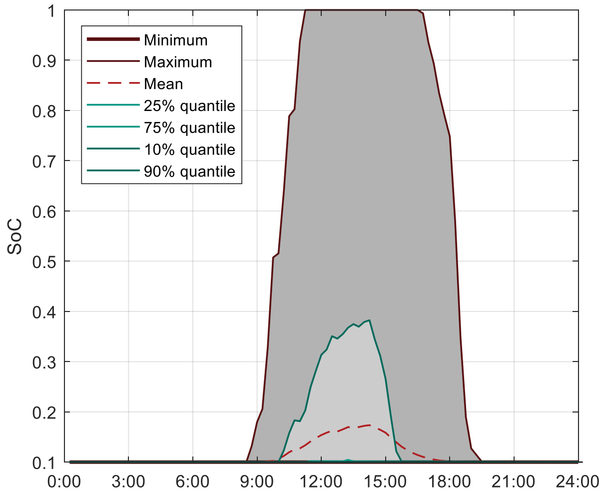

Fig. 6: State of Charge (SoC) of PV-BSS (winter)

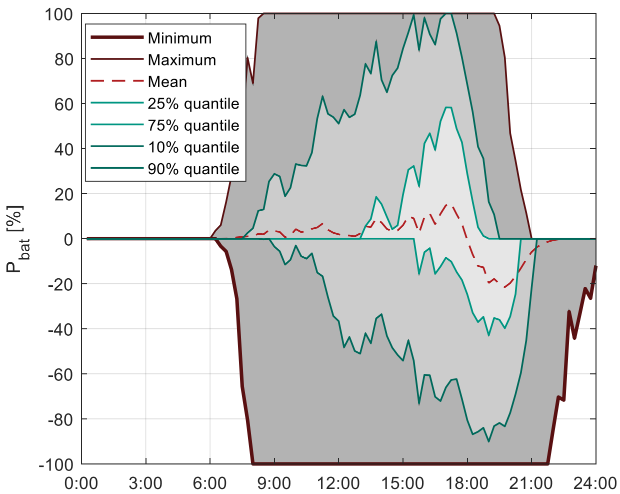

Fig. 5: Charging Power of PV-BSS (summer)

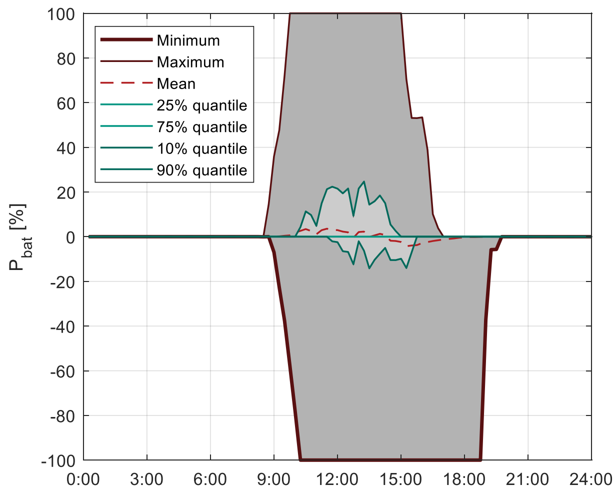

Fig. 7: Charging Power of PV-BSS (winter)

Therefore this asset could be used as a flexible asset during this time with a high probability. There is a lot of remaining capacity as well as the potential to increase the charging power. In at least 75 % of the MCS results the SoC is even below 20% at that time and the BSS is not charged at all.
The consideration of a winter scenario leads to a different result since due to the lower PV infeed. The mean usage of the BSS shows a maximum of 18 % of the installed capacity while. In accordance to the low usage of the installed capacity the (dis-)charging power is low as well. Therefore the available flexibility of the BSS is high in the winter scenario.

PV-BSS-HP-System

The PV-BSS-HP-System is an extension of the previously analysed PV-BSS-System. In this case a Heat Pump including TES is added.

The resulting distribution of the BSS usage in summer can be found in Fig. 8 and Fig. 9. The results for the PV-BSS-HP-System look similar compared to the results for the PV-BSS-System.
Since the heating demand in the summer season can be neglected and domestic water heating is not considered the heat pump is not used during this time of the year.
Considering the mean value it can be stated that the BSS system is charged as late as possible during times with PV infeed to avoid self-discharge. The discharge again takes place from 18:00 to 21:00. Taking into account the quantiles it is clear that the BSS will be charged less 95 % at around 17:30 in 90% of the cases.
In Fig. 9 the distribution of the (dis-)charging power is shown. In most cases the inverter does not reach its maximum power.
Regarding the available flexibility of the BSS the shown quantiles are of interest as well. Taking 12:00 as an example the results show that in 90 % of the optimization results the SoC of the BSS is below 51 % while the

charging power is below 58 % of the rated power. Therefore this asset could be used as a flexible asset during this time with a high probability. There is a lot of remaining capacity as well as the potential to increase the charging power. In 75 % of the MCS results the SoC is even below 16% at that time and the BSS is not charged at all.

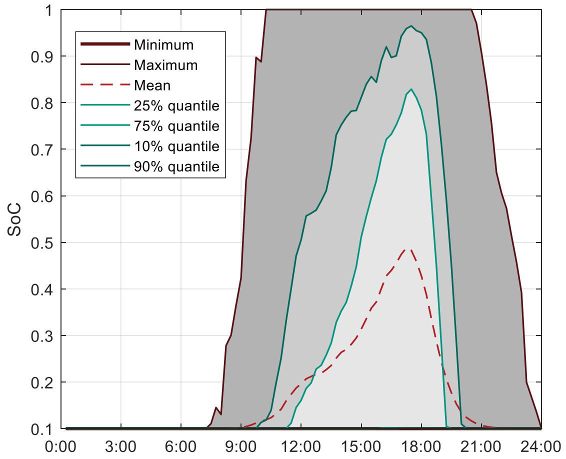

Fig. 8: State of Charge (SoC) of PV-BSS-HP (summer)

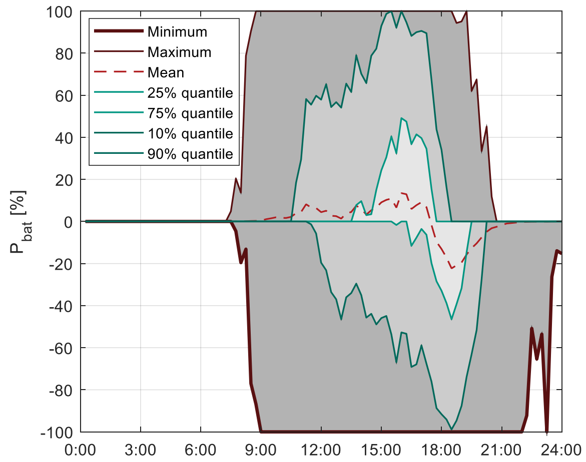

Fig. 9: Charging Power of PV-BSS-HP (summer)

During the winter season the heating demand leads to an operation of the heat pump. The results obtained in the MCS show that in the considered PV-BSS-HP-System the BSS is not used at all. The envelop curve of all the maximum values for the SoC and the (dis-)charging power equals zero. The produced energy of the PV plant is directly used by the heat pump. In theory, this results in a large available flexibility of the BSS during this season.

CONCLUSIONS

The investigations presented in this paper aim at a determination of available flexibility provided by BSS in PV-BSS and PV-BSS-HP-Systems taking into load and feed-in uncertainty. To include the uncertainty of the power demand of households different stochastic load profiles are used within a MCS with 10000 repetitions. To describe the uncertainty of the feed-in of a PV plant historical forecast and actual feed-in data are compared. The deviations are analyzed and random forecast errors based on the actual forecast error is added to the actual fee-in values.

As the results show the available flexibility of the BSS is high during the winter seasons. Therefore these systems could be used by the grid operator to buffer a high simultaneity of heat pump power demand if the needed communication infrastructure is available (e.g. CLS interface of smart meter gateway). During the summer seasons installed BSS tend to buffer peaks of PV infeed intrinsically while peaks in the demand are buffered as well.

Taking into account the uncertainty of the profiles quantiles of the used capacity and (dis-)charging power of the BSS can be derived. If the maximum of the values is considered to derive the flexibility the amount of flexibility becomes small. Therefore it is reasonable to consider flexibility areas. These areas are limited by the quantiles. The more flexibility is required, the larger is the probability that the users optimal scheduling is affected.

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