Impacts of a forecast-based operation strategy for grid-connected PV storage systems on profitability and the energy system

Lukas Teichtmann
Fraunhofer Institute for Systems and Innovation Research ISI
Breslauer Strasse 48
DE-76139 Karlsruhe
Germany
lukas.teichtmann@online.de

Anna-Lena Klingler
Fraunhofer Institute for Systems and Innovation Research ISI
Breslauer Strasse 48
DE-76139 Karlsruhe
Germany
anna-lena.klingler@isi.fraunhofer.de

Keywords

batteries, photovoltaics, optimisation, load management, neural network, forecast

Abstract

Integrating photovoltaic (PV) electricity generation into the German energy system is proving to be a growing challenge due to its fluctuating nature. The combination of more rigid regulation for feeding PV power into the grid and steadily rising electricity prices means that energy storage devices are becoming more attractive to private households as a way of upping their energy self-sufficiency. At the same time, storage systems make the household's power purchasing strategy more complex. For these reasons, control concepts are required for PV and storage systems that ensure system-friendly operation as well as considering the household's primary objectives. This paper presents a three-part model for the forecast-based load management of a battery storage system in combination with a PV system. In the first modelling step, forecasts of hourly electricity demand and solar generation are created using artificial neural networks. In a second step, the model optimizes the energy flows considering a real-time price tariff based on EPEX Spot in addition to its main task of using the forecasts to maximize on-site self-consumption. In the third step, a control algorithm adjusts the actual energy flows if forecast deviations occur. The study shows that the model enables system-friendly operation of the battery storage as well as intensified usage. As an added value, the forecasting approach presented is closer to reality than the otherwise frequently used optimization algorithms that assume perfect foresight of electricity load and generation. It therefore provides a real-world basis for planning, but also shows that the inevitable forecasting errors are reflected in higher electricity bills. Considering the inaccuracy of forecasting and the related higher cost for falling short on the provision of electricity for the individual household, we conclude that households should be paid higher rewards (e.g. by higher price top-up payments at peak demand or supply) if they supply electric energy in times of higher demand and store energy if there is abundant supply.

Introduction

PV power is an increasingly important component in the renewable energy mix. In 2015, roughly 7.5 % of German electricity consumption was supplied by PV power (Wirth, 2016, p. 5). Until 2020 it is estimated that a minimum share of 10 % of total electricity consumption can be supplied by PV power (Bundesverband Solarwirtschaft, 2012, p. 1). However, the integration of PV power into the grid poses major challenges to grid operators and energy suppliers. As PV power is highly dependent on the weather, its contribution to the energy supply fluctuates. The increased integration of PV systems in recent years brings with it the risk that parts of the infrastructure may be temporarily overloaded. Secondly, circa 80 % of all German PV systems are integrated into low-voltage networks, which were originally only intended to distribute energy in one way, from the energy provider to the customer. Consequently, these parts of the grid are not designed to deal with reverse loads coming from the distribution grids if PV generation peaks during midday hours (Kairies et al., 2016, p. 12). The legislator already reacted in 2012 to counter grid overloads caused by solar power systems by amending the German Renewable Energy Act (EEG). The amendment requires even small-scale PV systems to comply with power delivery limits of 70 % of the rated installed power (German Renewable Energy Act 2012).

One way to reduce such problems is to operate PV systems in combination with decentralised storage systems, such as stationary lithium-ion batteries or the batteries of electrically powered cars. The decentralised storage of electricity has twin benefits: First, the operator of a combined PV storage system can increase his/her self-sufficiency, thereby reducing the need to procure electricity from the energy provider and making the operator less susceptible to rising electricity prices (Kairies et al., 2016, p. 15). Second, PV storage systems can significantly reduce the pressure on the low-voltage grid by smoothing peaks in supply and demand. If electricity is stored during times of high irradiation, maximum feed-in can be significantly reduced (Moshövel et al., 2015, p. 574).

Kairies et al. (2016, p. 8) estimate that between May 2013 and January 2016, roughly 34,000 decentralised storage systems were installed in German households. The number of newly installed storage systems nearly doubled in the years 2014 and 2015, amounting to a total capacity of 0.2 GWh installed in low-voltage grids. This is particularly surprising, because most of the operators of such systems do not expect their investment to be economically efficient. The majority of operators install such systems to hedge against future expected increases in electricity prices (Kairies et al., 2016, p. 58). Due to expected declines in installation and system prices and a growing interest in the self-sufficient use of the generated electricity, various studies anticipate an increasing usage of storage systems, e.g. (Navigant Research (2015)).

The mode of operation determines to which degree PV battery systems are operated in a system-friendly way (Weniger et al., 2016, p. 25). Important operating strategies from literature are summarized in Table 1.

Struth and Kairies (2013) compare different operating strategies for PV storage systems and conclude that the largest grid relief is achieved with a strategy using persistence forecasts. Resch et al. (2015) model and evaluate seven different operating strategies for residential storage systems in combination with grid-connected PV systems. To facilitate simulation, Resch et al. (2015) assume perfect foresight for all strategies that regularly require forecast data for load and PV generation. The authors show that the use of a more complex control strategy improves the ability to limit peak voltage at the point of common coupling as well as reducing overall curtailment losses. They add that the ability to achieve a high self-consumption ratio and the ability to reduce peak voltage are not mutually exclusive. Moshövel et al. (2015) show that an operating strategy using persistence forecasts has a significantly higher potential to relieve the grid than a simple self-consumption strategy or a strategy with a fixed feed-in limitation of 70 %. Also, the self-consumption rate can be kept at similar levels to the standard self-consumption strategy. These results suggest that forecasting PV generation and load is useful to achieve system-friendly operation. Various forecasting algorithms have been studied for operating PV battery systems: Forecasts of PV generation are often calculated based on irradiation forecasts using Numerical Weather Models. Irradiation forecasts from these models are later converted into actual energy production using physical models (Mathiesen and Kleissl, 2011; Lorenz et al., 2009; Shi et al., 2012). Statistical models can also be applied which can be further subdivided into time series analysis (Martín et al., 2010), autoregressive models (Bacher et al., 2009), ARIMA models (Safi et al., 2002), fuzzy-based models (Boata and Gravila, 2012) and artificial neural networks (Yona et al., 2007; Mellit and Shaari, 2009). Martín et al. (2010) compare the forecasting results of persistence, autoregressive, fuzzy-logical and neural

Table 1. Overview over important operating strategies for PV storage systems.

Operating strategy	Features	Reference
Maximizing self-consumption	– controller-based; all power exceeding local demand is stored – charges the battery fully before noon, leaving the feed-in peaks at midday and during the afternoon unchanged	Struth and Kairies (2013), Resch et al. (2015)
Static/ fixed feed-in power limitation	– power is curtailed at defined thresholds – a simple feed-in limitation of 70% only leads to marginal improvements in limiting grid voltage fluctuations	Struth and Kairies (2013), Resch et al. (2015)
Charging interval periods	– energy is only fed into the battery at defined times – reduces the feed-in to some extent, but still leaves high feed-in before and after the interval	Struth and Kairies (2013), Resch et al. (2015)
Persistence forecasting strategy	– energy is stored and supplied based on persistence forecasts – promises the largest grid relieving potential (acc. to Struth and Kairies)	Struth and Kairies (2013)
Scheduled time interval with constant charging power	– sets a time interval – additional fixed constant charging power per interval	Resch et al. (2015)
Dynamic feed-in strategy	– based on PV and load forecasts; aims to fully charge the battery once at the end of the day – the charging power and feed-in power are constantly altered during the day in order to fully load the battery and feed back power to the grid as little as possible.	Resch et al. (2015), Weniger et al. (2014)
Dynamic feed-in with balancing	– similar process as “dynamic feed-in” – Charging power is simply increased during periods with expected high feed-in of other grid-connected PV-systems without batteries	Resch et al. (2015)
Feed-in damping strategy	– similar to the schedule strategy with constant charging power – simple predictions of irradiance are used to set the time interval instead of a static setting	Resch et al. (2015)

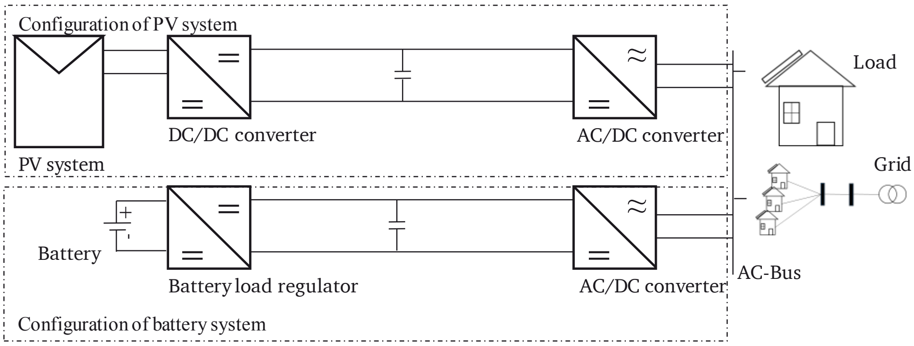

Figure 1. AC-coupled PV battery-system topology.

networks when predicting local half daily solar irradiance with a maximum horizon of three days. They conclude that the most accurate results are obtained with neural networks. This result is confirmed by Pedro and Coimbra (2012), who compare forecasting results for a local PV power plant with a time horizon of one and two hours. They demonstrated that an approach with neural networks performed better than an ARIMA model, and a k-Nearest-Neighbours approach. In the field of neural networks, Fernandez-Jimenez et al. (2012, p. 315–316) and Paoli et al. (2010) have implemented and evaluated up to five different types of neural network to locally predict the PV generation of PV systems. Their results show that neural networks are able to serve the purposes of irradiation and PV generation prediction with the lowest forecast deviations compared to other methods.

This paper presents a new forecast-based model, which is suitable for the control of PV-battery systems with a time horizon of 24 hours. The model comprises three modules. The first creates forecast data for load and PV generation, which are used as input to the second module, a linear optimization module. This optimization module allocates the energy flows on an hourly basis considering the price function of the European Energy Exchange (EEX). Finally, the third module, a controller, adjusts for forecast deviations. If required, the model can be adapted to any system size with regard to rated PV power, battery capacity or electricity demand of the household. The output of the model is a household-specific schedule for energy flows in the PV storage system over the next 24 hours. To obtain the simulation results presented in this paper, the model is trained and applied to an exemplary load and generation profile over the course of one year. In order to show the impact of forecast errors, the presented forecast- and price-based model is evaluated against a controller-based model. The controller-based model seeks to maximize self-sufficiency. Specifically, the results compare the system operation of the two models and reveal differences in the achieved profitability.

The "Methodology" section describes how the three modules function. The "Results" section reports the simulation results of the developed model and compares them with the controller-based model. The final section "Conclusion and Outlook" summarizes the findings and presents an outlook.

Methodology

The model is intended to operate a grid-connected PV storage system based on irradiation and load forecasts. This paper focuses on a single household and does not consider communities of households or large electricity consumers. Technically, the model represents a grid-connected battery storage, a PV system and converters. The system topology is AC-coupled, implying that the battery is connected to an AC-Bus via an AC/DC converter and a load regulator (see Figure 1). The advantage of the specified topology is that the complete system can be easily extended with additional PV modules and the battery system configuration can be modified independently of the PV system.

The model is implemented in JAVA and the frameworks "Encog Machine Learning" and "Gurobi Optimizer" are used. The modules are illustrated in Figure 2. First, the forecast module provides the system with 24-hour predictions of household load and PV generation. The forecasts algorithms are based on artificial neural networks; their output is then fed into module 2. This module creates optimized schedules for the energy flows between PV system, battery, household consumer and the grid based on a quadratic optimization approach. Naturally, the use of forecast algorithms means there are deviations between forecast values and actual values. A controller is then used to observe and compare the forecast values to the measured values of the current hour. The whole forecast and optimization process is repeated on an hourly basis and the energy flows are adjusted accordingly should forecast errors occur. Since changes in the energy flow schedule also cause the state of charge (SOC) of the battery to deviate from its originally calculated state, a new – controller-adjusted – SOC is fed back into the optimization module at the end of every hour. In the following section, all three modules are described in more detail.

FORECASTING WITH ARTIFICIAL NEURAL NETWORKS (MODULE 1)

The forecast module predicts future PV generation of the household's PV systems as well as its future load on an hourly basis. For this purpose, artificial neural networks (ANN) are used. As explained above, ANN are particularly suitable for forecasting in the renewable energy field as they are capable of learning and provide non-linear parametric models. They have the capacity to recognize patterns in data sets, memorize the structure and use the acquired knowledge at a later point in time (Paoli et al., 2010, p. 2149).

There are different types of ANN, for example, Multilayer Perceptron Networks (MLP, also called feed-forward networks), Radial Basis Function neural networks or Recurrent Neural Networks and many more (Dreyfus, 2005). To implement the ANN in this study, the open-source library "Encog Machine Learning" was used and adapted to the model's needs.

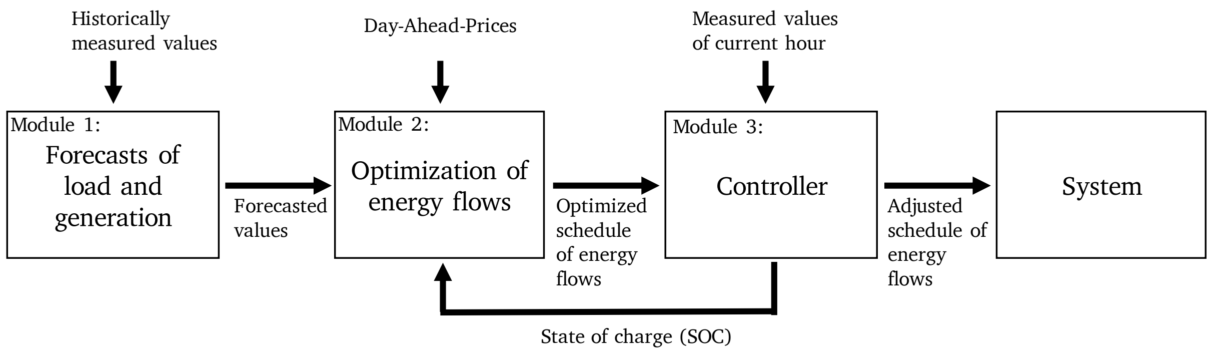

Figure 2. Schematic illustration of the forecast-based model.

Historical training data sets were fed into the ANNs in the form of time series, including historical weather conditions, measured historical PV generation and historical load data. In the subsequent training phase, all the data were presented to an internal pattern recognition algorithm, which follows the rules of a predefined learning algorithm. At the end of the training phase, the acquired knowledge of the pattern recognition process was saved and the networks were ready to predict future time series.

As the example in Figure 3 shows, an ANN is comprised of so-called neurons and organised in layers. These neurons are connected with each other and the information that passes between them is multiplied by a specific weight according to its importance for the results. These weights are adjusted during the training phase and store the learned "knowledge". Accordingly, an input a_j is passed from one neuron *j* to the next neuron *i* and is multiplied by the weight w_{ij} The resulting $a_j w_{ij}$ is one argument of a transfer function:

$$y_i = f(\sum_{j=1}^{n} a_j w_{ij})$$

which provides the input for the next neuron *i*. The transfer function defines the distribution of information between neurons and may be exponential, linear or sigmoid. During the training process, the weights are continuously modified based on the presented training data, the chosen transfer function and the rule of learning. Depending on the kind of neuron, information is received from outside the system or from other neurons. In a feed-forward network, layers are categorised by input layer, output layer and hidden layer and information is processed in only one direction, from input layer to output layer. Each of the neurons is assigned to one of these layers and each layer can include any desired number of neurons. The input layer receives data from outside the network, the output layer represents the interface to the outside world (Mubiru, 2008, p.2329; Paoli et al., 2010, p. 2149).

The best network configuration (number of neurons in each layer, number of hidden layers, learning rule and transfer function) is determined more or less by a "trial-and-error" process. Possible useful set-ups have been examined by Tymvios et al. (2005), Sözen et al. (2004) and Kern (2013). In this paper, the selected network is a feed-forward network and most of the other parameters are determined based on the promising results of Kern (2013). Three layers were chosen (1 input layer, 1 hidden layer and 1 output layer) for both load and PV forecast models. Three input neurons are created for the PV generation forecasting model to receive the underlying meteorological data. One input neuron is set for the ANN of the load forecast, which receives load data of the previous weekday. The hidden layer contains 3 neurons and uses a sigmoid transfer function. As learning rule, backpropagation was selected, meaning that during the training process, the calculated output values were constantly compared with the true (measured) vector of PV generation values. Subsequently, the error was fed back into the network and the process repeated until the smallest possible overall error occurred.

The training period covered two months (59 days) and was run with 6,000 iterations. The simulation and prediction timeframe is 1 year (365 days). Finally, the input values had to be normalized on an interval of 0.0 to 1.0 due to the chosen sigmoid function. The ANN were run on an hourly basis and retrained with updated data.

Input & Output data

The input data for training the ANN include location-based measured historical data of load and PV generation as well as archived meteorological data. In more detail, the training data for the network to predict short-term PV generation include archived data for global irradiance, the ambient temperature and relative humidity of a measuring station of the German Meteorological Service located 18 km from the considered location Meteorological Service, 2016). The PV generation data were taken from the "SonnJa!" project in Berlin. The project's PV module has an orientation of 35.0° south-west and an inclination of 14.6 ° (einleuchtend e.V., 2016). The measured PV generation profile was scaled to match the installed rated capacity of a PV module with a maximum of 5.0 kWp and annual full load hours of 1,134.3 hours (based on our own calculation). A data set with load values from the preceding weekday was handed over to the network as training input for the load ANN. The exemplary load profile is taken from the Intelliekon study and comprises hourly recordings for one household with an annual consumption of 3,300 kWh and no installed PV (Publikationen – Intelliekon, 2016). Please note that this exemplary household is not representative.

During the prediction phase of the next 24 hours, normally meteorological forecast data has to be used in the PV ANN. Such data is based on more complex numerical weather predictions and can be obtained free of charge from various weather forecasting services such as the Global Forecasting System (National Centers for Environmental Prediction., 2016), Open Weather Maps (OpenWeatherMap, 2016) or the German Meteorological Service (German Meteorological Service, 2016). See Fernandez-Jimenez et al. (2012, p. 312) for a more detailed description of using and refining meteorological data from metrological services. However, as forecasted meteorological data are hard to obtain in retrospect for the specified location, archived meteorological data have been used for the prediction step in this paper (German Meteorological Service, 2016). This makes the output of the forecast module more accurate than it would be in reality (see Result chapter).

The battery's usable capacity amounts to 5.0 kWh, the charging and discharging efficiency factor is 95.2 % and the battery can be completely charged and discharged during the time frame of one hour.

The ANN predict load and PV generation data on an hourly basis for the next 24 hours. Before being transferred to the second (optimization) module, the data is further processed into "deficit generation" and "excess generation". The optimization module only needs to know whether there is a surplus or deficit of electricity in any specific hour. If the current electricity generation of the PV system is larger than the current consumption of the household, the residual generation is called "excess generation". If the current PV generation is lower than the household's current demand, the power is defined as "deficit generation". These are the output values of the first module and are subsequently used as input into the second module.

OPTIMAL STORAGE OPERATION (MODULE 2)

The second module creates a schedule containing the energy flows between PV module, battery, household and grid. If the sun is shining and the PV module is able to provide power, the possible energy flows are: direct consumption of the household supplied by the PV module, charging the battery, direct grid feed-in or curtailment (if feed-in limits are exceeded). If the PV module produces no or too little electricity in comparison to the household's demand, the possible energy flows are: discharging the battery to the household or drawing electricity from the grid to supply the household's demand. Independently of the actual PV generation, the optimization algorithm can decide to discharge electricity from the battery into the grid.

The "Gurobi Optimizer" framework is used for implementation. The model represents an optimization problem defined by an objective function and multiple constraints. As the constraints include real numbers as well as quadratic terms, the optimization is classified as a mixed integer quadratically constrained programming problem.

The objective function is:

Maximize Inc:

$$\sum_{T=1}^{365}\sum_{t=1}^{24}(P_{DirGrid}(t) + P_{BatDis}(t)) \cdot \Delta t \cdot p_{DayAhead}(t)$$

$$+ P_{Cover}(t) \cdot \Delta t \cdot 29.14 + P_{Curt}(t) \cdot \Delta t \cdot 0{,}0,$$

where *Inc* is the annual income in €Cent, Δt is the time step of one hour, $P_{DirGrid}(t)$ is the hourly direct grid feed-in of the PV module, $P_{BatDis}(t)$ represents the discharge and grid feed-in of the battery, $p_{DayAhead}(t)$ is the hourly electricity price from the European Energy Exchange (EEX), $P_{Cover}(t)$ depicts the battery supply of the household's demand, €29.14Cent/kWh is the opportunity price according to 2014 average household tariff prices and $P_{Curt}(t)$ is the curtailment of generation if feed-in limits are exceeded. Curtailment is neutrally rated with €0 Cent/kWh and is only allocated by the optimization if no other solution is possible. According to the objective function, the optimization problem is structured so that the hourly energy flows are weighted by the electricity price (day-ahead price) of the respective hour or a flat tariff price. These weighted energy flows are maximized over a time period of 24 hours with the objective to defer the energy flows from hours with low prices to hours with high prices. Finally, the daily revenues are summarized over the full period of one year. The time frame of the optimization starts on 01.03.2014 and ends on 28.02.2015. The constraints are divided into technical, economic and regulatory. The technical constraints consider the 5.0 kWh maximum usable capacity of the battery, its charging and discharging capacities (the battery can be completely charged and discharged within one hour) and the efficiencies of battery and converters (which are a combined 95.2 % for each cycle). Furthermore, the battery cannot be used for charging and discharging at the same time. Finally, all the generated electricity must either be used or curtailed within one time step. The regulatory constraints are: The battery may not be charged from the grid and the feed-in limitation of 70 % of the maximum rated power of the PV module must be respected. The two economic constraints are:

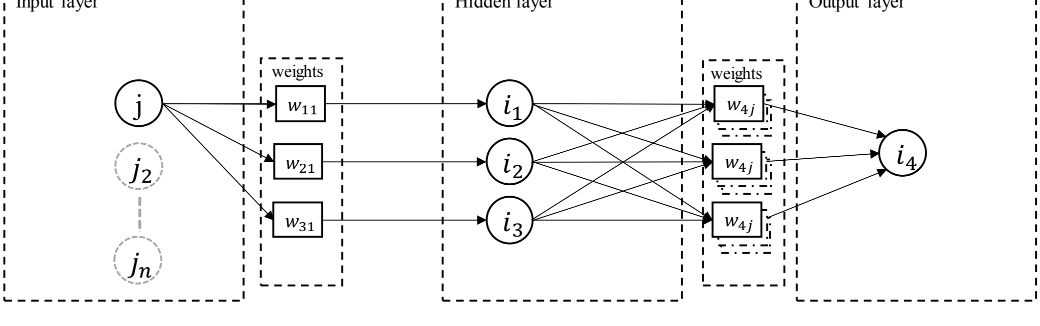

Figure 3. Structure of a feed-forward network.

Supplying the household's demand is always prioritized and the household's demand must always be supplied by either the battery or the grid.

Input & Output data

The input data for the optimization module are "deficit generation", "excess generation", state-of-charge of the previous simulation steps and day-ahead electricity price. The day-ahead prices can be obtained from the European Energy Exchange (EEX). These prices are calculated by EEX one day ahead by an auction procedure. These prices are published by 13:00 of the present day at the latest and cover hourly electricity prices for the whole of the subsequent day. The output of the second module is an exact schedule for every hour of the following day containing the energy flows by scale and form.

CONTROL ALGORITHM (MODULE 3)

Naturally, deviations occur during the forecast in comparison to the actual (measured) values. This is why the scheduled energy flows have to be constantly adjusted. The control algorithm only works during the present hour and makes adjustments for differences between values occurring in real time and the previously calculated energy flows. The controller adopts the decision of the optimization module in a first step and only tries to change the quantification of the energy flow. However, if any constraint is violated, a detailed, but static ranking list is followed. This list is stored in the controller and includes the economically next best solutions. Finally, the controller outputs a corrected timetable of the energy flows.

OPERATION OF THE MODEL

The annual simulation is subdivided into 24 hour steps which are executed repeatedly on an hourly basis. The process of continuously shifting the calculation period into the future in small time steps is called a "Rolling Horizon". Figure 4 exemplarily describes one simulation step. Every full simulation step comprises one forecast & optimization phase and one execution phase. During the forecast & optimization phase, the ANN is trained with newly measured data of the last hour; forecasts of load and PV generation for the next 24 hours are calculated and the optimization module schedules an operation plan for the energy flows. The execution phase covers one hour and includes the execution of the control algorithm, which adjusts the optimized energy flows to account for forecast errors. After completion of the execution phase, the forecast & optimization phase is repeated and the whole time frame is shifted one hour into the future. Furthermore, for the new simulation step, the (adjusted) SOC from the previous calculation is required, which is also passed on by the controller algorithm.

ALTERNATIVE OPERATION STRATEGIES

The operation strategy developed above is defined as a forecast- and price-based operation strategy. In order to compare the operation results of this strategy with another alternative operation strategy, a controller-based operation strategy is also considered. The controller-based operation strategy is a simple one, currently regularly used in private households. As soon as the PV system generates electricity, this is first used to meet the household's demand. The share of generation which exceeds demand is stored in the battery if capacity is available. As soon as PV generation falls below the household's demand, the battery supplies electricity to the household. This strategy is considered disadvantageous since full capacity is often reached during morning hours before PV generation reaches its peak at noon and in the afternoon. Furthermore, if a feed-in limitation has to be obeyed, curtailment losses will frequently occur.

ECONOMIC EVALUATION MEASURES

The savings and revenues resulting from the operation of a PV storage system are both considered for the economic analysis. Savings occur if the household's power demand can be self-supplied either by the battery or by the PV system directly and power does not have to be purchased from the electricity supplier. The opportunity price for savings is estimated with a constant value of €29.14 Cent/kWh (=the households electricity price according to (BDEW, 2016)). Secondly, revenues can be made according to the market bonus scheme under the EEG, allowing the household to directly sell the electricity surplus to

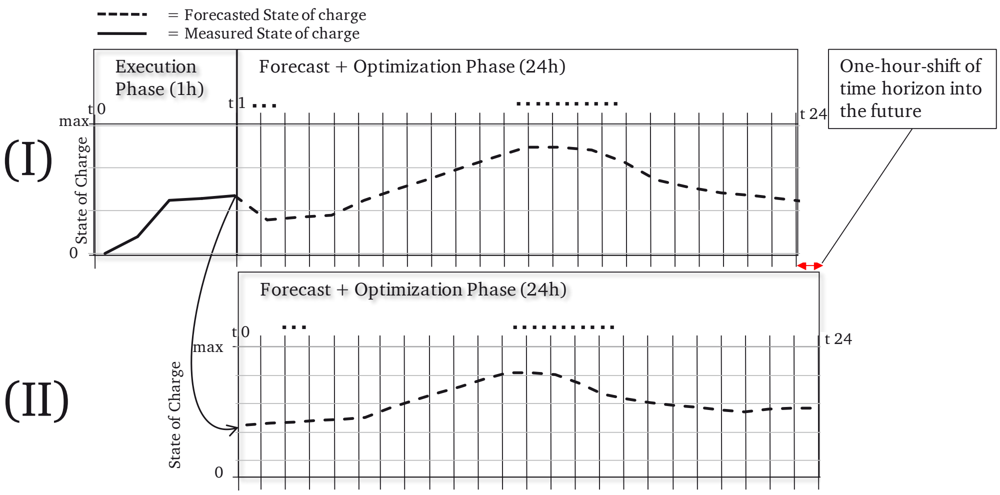

Figure 4. Illustration of one simulation step.

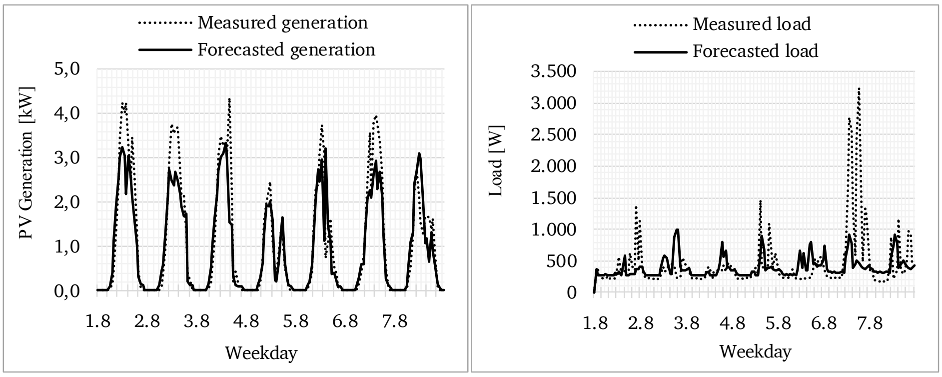

Figure 5. Forecasted / measured PV generation (left) & forecasted/measured load (right) for one week in August 1 to 7, 2014.

other market participants. In addition to the thereby realized price, a top up, the market premium, is paid. The paid market premium is the difference of the reimbursement rates specified in the EEG and a monthly average stock price. Hence, the market bonus scheme enables the individual household to make profits when feeding in at times of high prices by exceeding these average stock prices.

Results

The presented model is run in a simulation over the period of one year with 2014 prices. The simulation was run simultaneously with the controller-based model for the purpose of comparison. The simulated household, which is located in Berlin, has an annual electricity demand of 3,300 kWh and an installed rooftop PV system of 5.0 kWp. The useable lithium-ion storage battery is 5.0 kWh and grid-connected in a way that allows it to be discharged into the grid. A maximum feed-in power limit of 70 % is applied to comply with the current German Renewable Energy Act (German Renewable Energy Act 2012, p.12).

FORECASTING RESULTS

In the following, the results of the first part of the model, the forecast, are illustrated. The forecast model is able to calculate PV generation and load data with a rolling horizon of 24 hours. The forecasting quality is measured using the relative root mean square error (rRMSE), which is defined by:

$$rRMSE = \frac{1}{P_{inst}/P_{\max\_load}} \sqrt{\frac{1}{N}\sum_{N}^{1}(P_f\text{-}P_A)^2} \,,$$

where P_f is the hourly forecasted PV generation value, P_A is the hourly real measured value, N the total number of hours in the data set and P_{inst} is the rated (maximum) power of the PV modules. Alternatively, to measure the accuracy of the load forecasts, P_{inst} needs to be replaced by P_{max_load}. P_{max_load} depicts the maximum value of demand of the household. An rRMSE of 9.5 % results from predicting and testing the PV data over one year. This error causes a total error of the PV generation by 0.3 %. The results are comparable to the findings of Fernandez-Jimenez et al. (2012, p.315), who find an rRMSE of 11.8 % and an error of 0.6 % in overall PV generation data using similar forecasting and error calculation techniques. This paper achieves a slightly better performance of PV generation forecasts since Fernandez-Jimenez et al. (2012) use real and partially refined forecasted meteorological data from NWP to carry out predictions for the next hours with artificial networks. In contrast, measured meteorological data have been used for these predictions in this paper. This is due to the fact that archived forecasted meteorological data are hard to obtain in retrospect for one specified location. The irradiation data input has the strongest positive variable importance for the PV generation data, represented by an overall weight of 23.1, followed by air temperature with 11.1. The relative atmospheric humidity showed a negative, but strong, variable importance of -27.1.[1]

For the load forecast, the rRMSE is 9.3 %. The error value shows slightly better results compared to a simple weekly persistence forecast with a rRMSE of 12.0 %.

Figure 5 illustrates exemplary forecast data in comparison with measured data for one sunny week in August 2014. The prediction of PV generation is illustrated on the left and the load curve with measured and forecasted data is depicted on the right. The pattern of generation is adequately mapped, while the load pattern is more volatile and harder for the module to predict. It is remarkable that neither the peaks in real generation nor the peaks in load are adequately reflected.

Running the simulation over an entire year shows that the load and generation peaks are systemically underestimated. Here, the main problem arises from the net effect of adding up generation and load, which is carried out in every simulation step between Module 1 and Module 2. Module 1 only forecasts the PV generation and load but passes on the net differences “deficit generation” and “excess generation” to Module 2 (see Chapter Input & Output data in Forecasting with ANN). Based on this, the left-hand side of Figure 6 shows the mean excess generation for every month in the examined year. Apart from slight overestimations of the forecasts in June and July, mean excess power generation tends to be underestimated in the annual perspective. We find the same bias when analysing the forecasted mean deficit generation (right-hand side of the figure): Forecasted deficit generation is always lower than measured values. Figuratively speaking, in comparison to real data, the total annual deficit generation is underestimated by 354.1 kWh/a (-18.2 %) and the total annual excess generation is underestimated by 429.6 kWh/a (-10.0%).

1. To measure input variable importance on the output, the “Connection Weight” method is used following Olden and Jackson 2002 and Olden et al. 2004.

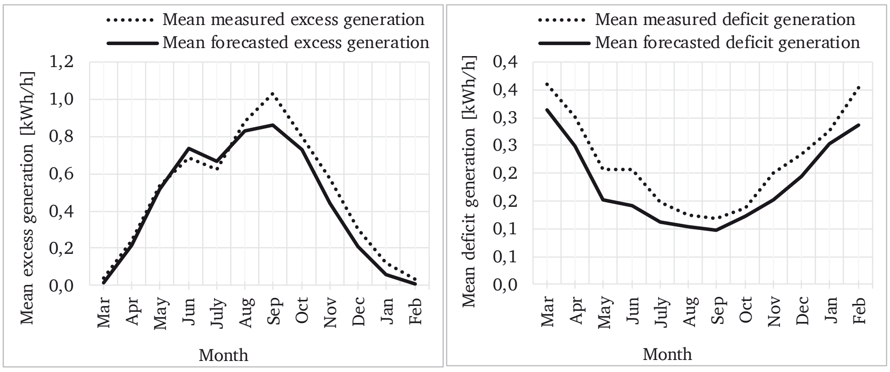

Figure 6. Forecasted/measured excess generation & forecasted/real deficit generation (monthly mean).

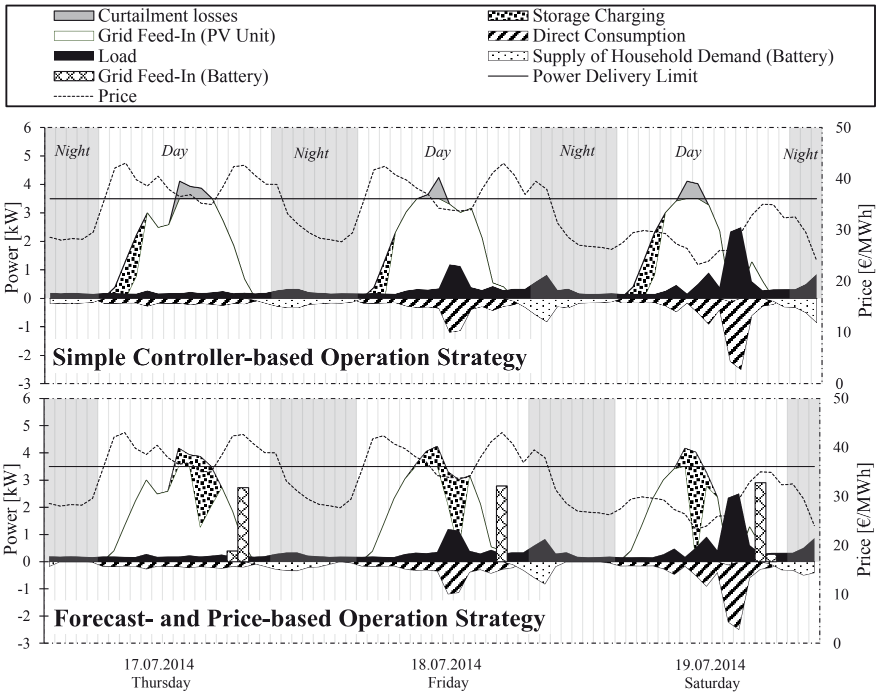

Figure 7. Comparison of three exemplary days in July with different operation strategies.

STORAGE OPERATION RESULTS

Figure 7 shows the results of the two operation strategies described above for one week in July. Positive values indicate excess power from the PV system or positive demand and battery storage values. Contrarily, negative values stand for the household's PV self-consumption either by discharging the battery or by directly consuming the generated PV power. Furthermore, the price function is illustrated by the dotted line. It can be seen that the *controller-based strategy* stores all the excess energy in the battery as soon as it occurs (and independent of the current price) which tends to be during morning hours. As a result, the battery is regularly fully charged before noon, leading to steep rises in grid feed-in and curtailment losses in the afternoon. In contrast to the controller-based operation strategy, the *price- and forecast-based operation strategy* operates the storage in a more system-friendly way. Energy storage is deferred (price-sensitively) from morning hours to hours when prices are higher (see dotted area). Secondly, the forecast-based operation system is able to detect future peaks in generation and consequently reserves battery capacity for later hours. Due to this possibility of foresight, curtailment losses are reduced or even avoided at noon and during the afternoon. Overall curtailment losses are reduced to 13.2 kWh/a (0.2 % of total real generation) in comparison to 56.2 kWh/a (1.0 % of total real generation) when using the controller-based operation strategy. Secondly, over the course of one year and in comparison to the controller-based operation strategy, the forecast-based model achieves 119.5 % more energy feed-in during times of high prices (top 50 % of prices) and 47.5 % more energy is stored in the battery during hours of low prices (bottom 50 % of prices). A side-effect of the price and forecast-based operation strategy is that the total amount of electricity stored in the battery is increased by 22.8 % compared to the controller-based model.

This effect is explained by the fact that battery discharge into the grid is allowed and the electricity market price is considered. These framework conditions lead to a higher amount of

Table 2. Overview of achievable savings and revenues with the different strategies.

Operating strategy	Savings due to direct consumption (PV system) [€]	Savings due to battery supply of household demand [€]	Revenue due to feed-in of battery [€]	Revenue due to feed-in of PV system [€]	Electricity bill [€]
No PV System	–	–	–	–	**964.90**
Controller-based strategy	398.91	273.61	–	464.96	**-172.58**
Forecast-based strategy	398.91	230.93	56.41	443.37	**-164.72**

energy which is not fed into the grid directly when it is generated, but stored temporarily in the battery to benefit from higher prices later. It has already been discussed that the forecast-based strategy underestimates total excess and deficit generation over the year (see chapter above). One direct consequence of the underestimated *deficit generation* is that the optimization module expects lower demand in the afternoon and at night. This means the battery is often excessively discharged into the grid earlier to benefit from high prices, since electricity is not expected to be needed later to supply the household's demand. Subsequently, if the household requires more energy than expected, the battery is already empty and cannot meet the demand. Forecast errors in *excess generation* are an indicator for failing to foresee peaks in generation. Since the goal of the model is to use the battery as intensively as possible, too high rates of loading capacities are scheduled too early during the day. Later, if solar radiation is higher than planned, no free battery capacity is available to offset the peaks.

The first effect of these forecast inaccuracies is that curtailment losses cannot be avoided entirely, resulting in total curtailment losses of 13.2 kWh/a. Secondly, as the price-based operation strategy strives to maximize income at all times, but at the same times underestimates future demand, too much energy is fed into the grid from the battery during periods of high prices. It becomes clear that the forecast-based operation strategy feeds in higher amounts of energy every month, while simultaneously fails to meet the household's demand. In an annual perspective, the grid feed-in is 5.2 % (3,377.4 kWh vs. 3,210.1 kWh) higher with the forecast-based strategy than with the controller-based strategy and the household supply using the battery is 15.6 % lower (792.5 kWh vs. 938.9 kWh). Due to the resulting undersupply of the household's demand, the self-sufficiency rate[2] is only 65.3 %. A self-sufficiency rate of 69.7 % is achieved with the controller-based strategy.

ECONOMIC CONSIDERATIONS

Table 1 summarizes the possible savings and revenues for the two operating strategies and for a standard household without a combined storage and PV system (as reference). The last column shows the electricity bill, which has to be paid to the energy supplier at the end of the year.

The annual electricity bill of both operating strategies is compared to the case with no installed PV system (reference). As the control algorithm always prioritizes the supply of the household's demand, each strategy equally saves €398.91 of electricity. The highest gains at the end of the year can be realized with the controller-based strategy, which achieves €172.58 in returns. As the table shows, this is mainly due to the fact that this strategy achieves the highest savings by using the battery supply (column 3). The overall difference here to the forecast-based strategy underlines the impact of forecast errors. At the end of the year, the forecast-based strategy loses €7.86/a (difference in electricity bills) in total compared to the controller-based strategy. This amount represents the net effect of the forecast errors. As already illustrated above, the forecast errors strongly affect the supply of the household's demand and the self-consumption rate because too much energy is discharged from the battery and PV system into the grid too early during the day. This results in higher revenues of €499.78/a (vs. €464.96/a) from the feed-in of the battery (column 4) and the PV system (column 5), but much lower savings due to the battery supply (column €3, 230.93/a vs. €273.61/a). Hence, the losses outweigh the efficiency gains of a more price-sensitive feed-in. Beside the above described effects, this is particularly since the opportunity cost for undersupplying a household's demand is valued with a flat tariff at €29.14Cent/kWh, whereas energy fed into the grid was remunerated with a maximum of €19.83 Cent/kWh in 2014.

Conclusion and outlook

An operating model was developed for a single household's combined PV-storage system. The developed operating strategy is able to control energy flows with a forecast horizon of 24 hours and in an hourly resolution based on demand and generation forecasts and the price function of the European Energy Exchange. Artificial neural networks are used to forecast PV generation and load and a quadratic optimization approach is applied to control energy flows. The neural networks are updated every hour with recent measured data from the household and a meteorological station. Deviations from forecasted values are taken into account using a control algorithm. The system's performance is compared to a standard controller-based strategy. We were able to show that the forecast- and price-based strategy is more system-friendly because power storage is deferred price-sensitively from morning hours to hours with high solar irradiation. This results in higher grid feed-in during hours of higher prices and increased amounts of stored energy during hours of low prices. 119.5 % more energy was feed-in during times of high prices and €56.41/a could be earned in revenues by discharging surplus energy from the battery into the grid. Our strategy also intensifies overall stored electricity to the battery by 22.8 %. At the same time, the forecast-based optimization algorithm

2. The self-sufficiency rate is defined as the share of the household's electricity demand which is supplied either by discharging the battery or by directly consuming PV-generated power.

is able to store energy in the battery for later peaks in demand while simultaneously reducing curtailment losses to a minimum of 0.2 % of total real generation. On the downside, the model suffers from excessive grid feed-in from the battery and therefore falls short in supplying the household's power demand due to forecast errors. The economic evaluation of these errors shows that the total efficiency gains from the system feeding power into the grid are outweighed by losses in savings due to undersupplying the household. Even though revenues of grid feed-in are in total higher by €34.82/a in comparison to the controller-based strategy, the price-based strategy saves substantially less (€42.68/a) due to forecasting errors. To sum up, this paper shows that even small forecast errors render system-friendly models with quite sophisticated forecasting algorithms financially disadvantageous in comparison to simpler controller-based approaches. A supposed financial advantage is further ruled out by the additional cost (e.g. interfaces to data providers, more computing power) of complex forecasting method like a neural network. Hence, if policy makers want to support the further development of system-friendly strategies and profitability cannot be achieved directly during daily operation, they need to offer private households more attractive remuneration schemes (e.g. by higher price top-up payments at peak demand or supply).

References

Bacher, P.; Madsen, H.; Nielsen, H. Aalborg (2009), *Online Short-term Solar Power Forecasting*. In: Solar Energy, Vol. 83 (10), p.1772–1783.

BDEW (2016), Averaged Electricity Prices for German Households. Bundesverband der Energie- und Wasserwirtschaft. https://www.bdew.de/internet.nsf/id/20160122-pi-steuern-und-abgaben-erreichen-neues-rekordhoch-de/.

Boata, R. St; Gravila, P. (2012), *Functional Fuzzy Approach for Forecasting Daily Global Solar Irradiation*. In: Atmospheric Research, Vol. 112, p.79–88.

Bundesverband Solarwirtschaft (2012), *Statistische Zahlen der deutschen Solarstrombranche (Photovoltaik)*.

Dreyfus, Gérard (2005), Neural networks: methodology and applications, Springer Science & Business Media.

einleuchtend e.V. (2016), Sonn-ja, Beschreibung der Daten. http://einleuchtend.org/sonn-ja/das-projekt/.

Fernandez-Jimenez, L. Alfredo; Muñoz-Jimenez, A.; Falces, A.; Mendoza-Villena, M.; Garcia-Garrido, E.; Lara-Santillan, P. M. et al. (2012), *Short-term Power Forecasting System for Photovoltaic Plants*. In: Renewable Energy, Vol. 44, p. 311–317.

German Meteorological Service (2016), Weather and Climate, archive for hourly values. http://www.dwd.de/DE/leistungen/klimadatendeutschland/.

German Renewable Energy Act (2012), Act on the Development of Renewable Energy Sources. https://www.erneuerbare-energien.de/EE/Redaktion/DE/Dossier/eeg.html?cms_docId=71802

Kairies, Kai-Philipp; Haberschusz, David; van Ouwerkert, Jonas; Strebel, Jan; Wessels, Oliver; Magnor, Dirk et al. (2016), Wissenschaftliches Mess- und Evaluierungsprogramm Solarstromspeicher, Aachen, RWTH Aachen.

Kern, F. (2013), *Wechselrichter-Kommunikation und Solarleistungsprognose*, Masterthesis at AFIB, Karlsruher Institut für Technologie, Karlsruhe.

Lorenz, E.; Hurka, J.; Heinemann, D.; Beyer, H. Georg (2009), *Irradiance forecasting for the power prediction of grid-connected photovoltaic systems*. In: IEEE Journal of selected topics in applied earth observations and remote sensing, Vol. 2 (1), p. 2–10.

Martín, L.; Zarzalejo, L. F.; Polo, J.; Navarro, A.; Marchante, R.; Cony, M. (2010), *Prediction of global solar irradiance based on time series analysis: application to solar thermal power plants energy production planning*. In: Solar Energy, Vol. 84 (10), p. 1772–1781.

Mathiesen, P.; Kleissl, J. (2011), *Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United States*. In: Solar Energy, Vol. 85 (5), p. 967–977.

Mellit, A.; Shaari, S. (2009), *Recurrent neural network-based forecasting of the daily electricity generation of a Photovoltaic power system*. In: Ecological Vehicle and Renewable Energy (EVER), Monaco, March, p. 26–29.

Moshövel, J.; Kairies, K.-P.; Magnor, D.; Leuthold, M.; Bost, M.; Gährs, S. et al. (2015), *Analysis of the maximal possible grid relief from PV-peak-power impacts by using storage systems for increased self-consumption*. In: Applied Energy, Vol. 137, p. 567–575.

Mubiru, J. (2008), *Predicting total solar irradiation values using artificial neural networks*. In: Renewable Energy, Vol. 33 (10), p. 2329–2332.

National Centers for Environmental Prediction. (2016), Global Forecasting System. http://www.emc.ncep.noaa.gov/.

Navigant Research (2015), *Energy Storage for Renewables Integration*.

Olden, J. D.; Jackson, D. A. (2002), *lluminating the "black box": a randomization approach for understanding variable contributions in artificial neural networks*. In: Ecological Modelling, Vol. 154, p. 135–150.

Olden, J. D.; Joy, M. K.; Death, R. G. (2004), *An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data*. In: Ecological Modelling, Vol. 178 (3–4), p. 389–397.

OpenWeatherMap (2016), Weather API. http://openweathermap.org/api.

Paoli, C.; Voyant, C.; Muselli, M.; Nivet, M.-L. (2010), *Forecasting of Preprocessed Daily Solar Radiation Time Series Using Neural Networks*. In: Solar Energy, Vol. 84 (12), p. 2146–2160.

Pedro, H. T. C.; Coimbra, C. F. M. (2012), *Assessment of forecasting techniques for solar power production with no exogenous inputs*. In: Solar Energy, Vol. 86 (7), p. 2017–2028.

Publikationen – Intelliekon (2016), ISOE: Publikationen Intelliekon. http://www.isoe.de/projekte/abgeschlossene-projekte/energie-und-klimaschutz-im-alltag/.

Resch, M.; Ramadhani, B.; Bühler, J.; Sumper, A. (2015), *Comparison of Control Strategies of Residential PV Storage Systems*. In: 9th International Renewable Energy Storage Conference and Exhibition, Düsseldorf, 9.03.–11.03.

Safi, S.; Zeroual, A.; Hassani, M. (2002), *Prediction of global daily solar radiation using higher order statistics*. In: Renewable Energy, Vol. 27 (4), p. 647–666.

Shi, J.; Lee, W.-J.; Liu, Y.; Yang, Y.; Wang, P. (2012), *Forecasting power output of photovoltaic systems based on weather classification and support vector machines*. In: IEEE Transactions on Industry Applications, Vol. 48 (3), p. 1064–1069.

Sözen, A.; Arcaklioğlu, E.; Özalp, M. (2004), *Estimation of solar potential in Turkey by artificial neural networks using meteorological and geographical data*. In: Energy Conversion and Management, Vol. 45 (18), p. 3033–3052.

Struth, J.; Kairies, K.-P. (2013), *PV-Benefit: A Critical Review of the Effect of Grid Integrated PV-Storage-Systems*. In: 8th International Renewable Energy Storage Conference and Exibition, Berlin.

Tymvios, F. S.; Jacovides, C. P.; Michaelides, S. C.; Scouteli, C. (2005), *Comparative study of Ångström's and artificial neural networks' methodologies in estimating global solar radiation*. In: Solar Energy, Vol. 78 (6), p. 752–762.

Weniger, J.; Tjaden, T.; Quaschning, V. (2014), *Sizing of residential PV battery systems*. In: Energy Procedia, Vol. 46, p. 78–87.

Weniger, Johannes; Bergner, Joseph; Tjaden, Tjarko; Quaschning, Volker (2016), 50%-Studie: Effekte der 50%-Einspeisebegrenzung des KfW-Förderprogramms für Photovoltaik-Speichersysteme, Berlin, Hochschule für Technik und Wirtschaft Berlin.

Wirth, Harry (2016), Aktuelle Fakten zur Photovoltaik in Deutschland, Freiburg, Fraunhofer ISE.

Yona, A.; Senjyu, T.; Saber, A. Yousuf; Funabashi, T.; Sekine, H.; Kim, C.-H. (2007), *Application of Neural Network to One-Day-Ahead 24 hours Generating Power Forecasting for Photovoltaic System*. In: International Conference on Intelligent Systems Applications to Power Systems, 05.11.–08.11.