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

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ABSTRACT

Integrating photovoltaic (PV) produced electricity into the electric power system is proving to be a growing challenge due to its fluctuating nature. The combination of more rigid regulation for feed-in of PV production and steadily rising electricity prices means that battery systems are becoming more attractive to private households as a way of upping their self-consumption. At the same time, batteries make the household's electricity purchasing strategy more complex. For these reasons, control concepts are required for PV + battery systems that ensure grid-friendly operation as well as considering the household's primary objectives. This paper presents a forecast-based modelling approach for the operation of a battery in combination with a grid-connected PV system. PV production and electricity demand are forecasted on an hourly time-resolution using artificial neural networks (ANN). The battery charging and discharging is optimized to maximize self-consumption, and additionally a variable feed-in tariff is considered to incentivize a grid-friendly operation. The developed model was applied for a household with 3300 kWh electricity consumption equipped with a 5 kWp PV system and a 5 kWh battery. For this case, we show that the model enables a grid-friendly operation of the battery as well as an intensified usage. However, the inevitable forecasting errors lead to overall lower economic benefits for the consumer in comparison with a simple strategy that only maximizes self-consumption. Considering the inaccuracy of forecasting, we conclude that if a grid-friendly integration of PV + battery systems is to be promoted in the future, households should be provided with better forecasting data or offered other incentives to compensate their lost benefits.

1. Introduction

PV produced electricity is an increasingly important component in the renewable energy mix. In 2015, roughly 7.5% of electricity consumption in Germany was supplied by electricity from PV systems (Wirth, 2016). Until 2020 it is estimated that a minimum share of 10% of total electricity consumption can be supplied by PV production (Bundesverband Solarwirtschaft, 2012). However, the integration of PV production into the grid poses major challenges to grid operators and electricity suppliers due to its fluctuating nature. The increased feed-in of PV production in recent years may temporarily overload parts of the grid infrastructure. About 80% of all PV systems are installed in low-voltage grids that were originally only intended to distribute electricity in one way, from the electricity provider to the consumer. Consequently, these parts of the grid are not designed to deal with reverse loads coming from the distribution grids if PV production peaks during midday hours (Kairies et al., 2016). The legislator already reacted in 2012 to counter grid overloads caused by PV 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 electric vehicles. The decentralised storage of electricity has two benefits: First, the operator of a PV + battery system can increase his/her self-sufficiency, thereby reducing the need to procure electricity from the utility and making the operator less susceptible to rising electricity prices (Kairies et al., 2016), (Praetorius et al., 2010). Second, PV + battery 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).

The mode of operation determines to which degree PV + battery systems are operated in a system-friendly way (Weniger et al., 2016). Different operating strategies have been assessed and compared for

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example by Struth and Kairies (2013), Fares and Webber (2017) and Resch et al. (2015) and are an open research subject. Like most PV + battery models in current literature, Fares and Webber (2017) and Resch et al. (2015) assume perfect foresight to facilitate the simulation of the optimal battery operation. However, in real life, forecasting algorithms are needed to obtain the time-series of electricity production and demand that are necessary to schedule the battery loads.

Due to its importance for the electric power system, forecasting is an evolving field. Particularly for PV production, many different methods have been proposed in recent years. Reviews on solar forecasting methods can be found in (Diagne et al., 2013; Inman et al., 2013; Pelland et al., 2013; Widén et al., 2015). PV production forecasting models can generally be categorized into statistical and physical models. Physical models include a physical modelling of the atmosphere and the irradiation, most commonly based on numerical weather models. The irradiation forecasts are subsequently converted into actual energy production using physical models (Lorenz et al., 2009; Mathiesen and Kleissl, 2011; Shi et al., 2012). Statistical models apply statistical methods on existing time-series of solar production and do not require any physical modelling of solar irradiation (Widén et al., 2015). Widén et al. (2015) review and compare the forecasting skills of different models and come to the conclusion that statistical methods perform better for short time horizons up to 6 h ahead, and physical methods for long time horizons. Taking this into consideration and the issue that high quality forecasts of numerical weather models are not easily obtainable for households, the focus here is on statistical methods. Among the statistical models more traditional approaches are applied for PV production forecasting such as time-series analysis (Martín et al., 2010), autoregressive models (Bacher et al., 2009) and ARIMA models (Coimbra and Pedro, 2013) as well as more recently developed approaches. The latter include fuzzy-based models (Boata and Gravila, 2012) and learning models such as artificial neural networks (ANN) (Mellit and Pavan, 2010; Yona et al., 2007). For PV production, ANN have been immensely studied and show high forecasting skills (Widén et al., 2015). Martín et al. (2010) compare the forecasting results of persistence, autoregressive, fuzzy-logical and neural 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 ANN. This result is confirmed by Pedro and Coimbra (2012), who compare forecasting results for a local PV system with a time horizon of one and two hours. Further, Fernandez-Jimenez et al. (2012) and Paoli et al. (2010) have implemented and evaluated different types of neural network to locally predict the production of PV systems. Their results show that ANN are able to serve the purposes of predicting irradiation and PV production with the lowest forecast deviations compared to other methods.

Applying forecasting algorithms in their models, Moshövel et al. (2015) and Struth and Kairies (2013) show that an operating strategy using persistence forecasts has a significantly higher potential to relieve the electric grid than a simple self-consumption strategy or a strategy with a fixed feed-in limitation of 70%. Hanna et al. (2014) use more complex irradiance forecasts from the U.S. National Centers for Environmental Prediction (NCEP) and persistence forecasts for the residential load in their battery operation model. The implemented strategy successfully reduces the household's peak demand on the grid. Apart from the evaluation of the benefits of forecast-based battery operation strategies for the energy system, Shimada and Kurokawa (2006) and Nottrott et al. (2013) use forecast-based strategies to analyse the potential benefits from a consumer's point of view. Their suggested algorithms are successful in reducing the residential consumer's electricity bill. As Ratnam et al. (2016) point out, the next step is to evaluate the trade-off between the consumer's objective to maximize self-consumption and the benefit for the electric power system. And indeed, the potential benefits of forecast-based battery operation in comparison to the effect of forecasting errors on the economic profitability from a consumers perspective is neglected so far in current research.

This study therefore aims to close this research gap and evaluate the benefits of a forecast-based battery operation in a holistic way, considering both the consumer's and the system's perspective. To do so, we developed a practical forecast-based battery operation model and applied it to calculate potential benefits. We follow these steps:

i. Forecasting PV production and household's demand: Electricity production and demand is forecasted for intervals of 24 h, using only data that is accessible for residential consumers. The forecasts serve as input to the battery optimization.
ii. Optimal battery operation: The optimal schedule of the battery's load is determined that primarily aims to maximize the consumer's self-consumption and additionally considers a time-variable feed-in remuneration that incentivizes grid-friendly feed-in of PV electricity. Every hour the schedule is adjusted to account for forecasting errors.
iii. Evaluation of benefits for the consumer and the energy system: The battery operation is simulated for an entire year in order to assess the economic benefit for the consumer. To show the impact of forecasting errors, the results from the forecast-based operation is benchmarked against a simple relay-based approach that only maximizes the household's self-consumption.

The paper is structured as follows: Section 2 describes the forecasting and optimization algorithm. Section 3 presents the simulation results of the developed forecast-basted model and compares them with the simple relay-based approach. Finally, Section 4 summarizes the findings and presents an outlook.

2. Methodology

In this study, the focus is on a single household and communities of households are not considered. Technically, the model represents a grid-connected battery, a PV system and inverters (see Fig. 1).

The model consists of 2 modules that are illustrated in Fig. 2. First, the forecasting module provides the system with 24-h forecast of household load and PV production. The forecasts are obtained from the ANN in module 1; their output is fed into module 2. This module calculates optimal schedules for the electricity flows between PV system,

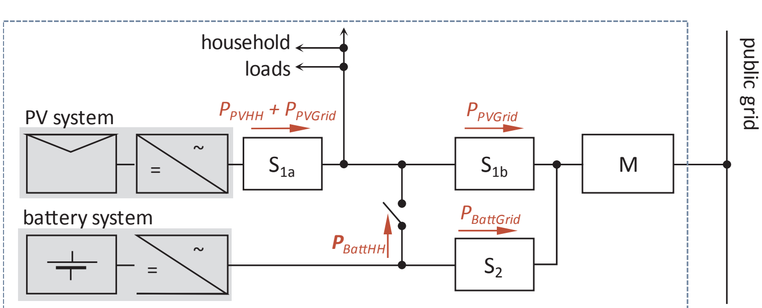

Fig. 1. AC coupled PV + battery system with sensors to measure the PV electricity production (S1a), grid feed-in from the PV system (S1b) and from the battery (S2b), and state of charge (SOC) of the battery (S2a), based on (VDE, 2016). In red: the measured variables for the battery optimization (cf. Eq. (2a)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)