

# Integration of PV power and load forecasts into the operation of residential PV battery systems

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**Abstract**—This paper analyzes forecast-based operation strategies for residential PV battery systems which have the capability of feed-in peak shaving and self-sufficiency optimization as well. To evaluate the robustness of these operation strategies, simulations in one minute resolution are carried out over a period of one year, taking real PV power and load forecasts into account. The impact of forecast inaccuracies on the performance is assessed from the energetic and economic perspective. The results highlight that already simple forecasts based on the approach of persistence facilitate an economic benefit compared to conventional operation strategies neglecting forecasts. By implementing forecast-based operation strategies into residential PV battery systems, the decentralized usage of PV generated energy and the grid integration of PV is improved.

*Keywords*-PV battery systems; grid integration; peak shaving; feed-in limitation; forecasts

## I. INTRODUCTION

Given the increasing number of installed PV systems in Germany, new challenges with regard to the grid integration of PV generated electricity are coming up. Amongst those challenges is the issue of ramps and peaks of the injected PV power into low voltage grids. One option to tackle this challenge consists in the approach of restricting the PV power fed into the grid. Since the revision of the German Renewable Energy Act (EEG) in 2012, either taking part in the so-called feed-in management, or limiting the maximum feed-in power to 70% (0.7 kW/kWp) of the rated power is mandatory for PV systems below 30 kWp in Germany. In general, a limitation of the grid feed-in of PV systems can be achieved by different measures. Firstly, already the simultaneous direct use of PV power by the electrical loads can reduce the injected PV power. Due to diurnal and seasonal fluctuations in both the PV generation and load demand, the direct use of PV energy is limited, though. Nevertheless, shifting the consumption of deferrable loads may also reduce the injected feed-in peaks.

Another approach to limit the feed-in power consists in using battery systems for that purpose. This has already been incentivized by the renewable energy storage program of the German government-owned development bank (KfW) since May 2013. The utilization of the funding program requires limiting the feed-in power of grid-connected PV battery systems to 0.6 kW/kWp. Additionally, further reductions in the feed-in power can also be achieved by charging electric vehicles or by the thermal usage at times of high PV production. Ultimately, the PV power output could be diminished to prevent the feed-in power from exceeding the stipulated maximum threshold value.

By implementing such feed-in limitation measures, a higher number of PV systems can be connected to the grid. In this way, a slowdown of the future PV expansion in highly penetrated low voltage grids for reasons of limited

grid capacity can be reduced. From the grid operator's point of view, the lower the overall maximum feed-in power, the higher the hosting capacity of the grid for additional PV systems. Hence, strengthening existing PV feed-in limitation requirements is worthwhile to realize an energy supply covered mostly by renewables in Germany.

This paper focuses on the contribution of residential PV battery systems to limit the PV injection. In Section II, the characteristics of distinct operation strategies are analyzed. Section III describes the input data and models used in the simulation study. The simulation results for different operation strategies are assessed from the energetic and economic perspective in Section IV and Section V, respectively. Finally, Section VI concludes this paper.

## II. OPERATION STRATEGIES FOR PV BATTERY SYSTEMS

In general, residential PV battery systems can be operated with different objectives in mind. This can be achieved by controlling the charging power of the battery systems with distinct algorithms. Fig. 1 provides a schematic overview of different operation strategies and their characteristic properties. The primary objective of residential PV battery systems is to increase the self-sufficiency of the household equipped with the system. This is accomplished by storing surplus PV power during the day and using it later to supply the loads after sunset. If storing surplus power is the only objective, the battery is usually charged with the first available surplus PV energy in the morning. By charging the battery in this way, the battery frequently reaches its maximum state of charge before noon, especially on clear days. Afterwards, the PV peak production is injected into the grid around midday. As a consequence, operating a PV battery system without feed-in limitation does not relieve the grid from PV feed-in spikes. Hence, to utilize the capability for feed-in peak shaving while preserving the advantages regarding self-sufficiency optimization, more sophisticated grid-compatible modes of operation are needed.

■ Battery charge  
■ Grid feed-in  
■ Curtailment  
--- Feed-in limit

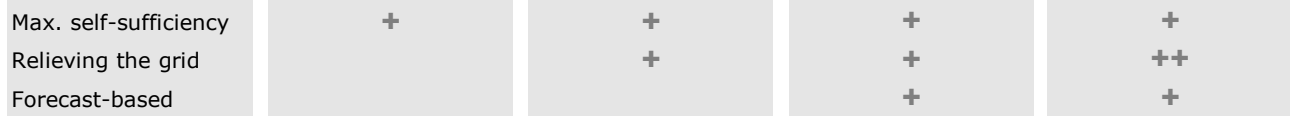


Figure 1. Schematic overview of different operation strategies for PV battery systems and their characteristic properties

Maintaining a fixed feed-in limit is conventionally achieved by curtailing surplus PV power that exceeds this limit. In that case, the battery charging behavior does not differ from those of the operation strategy without feed-in limitation. Nevertheless, the resulting curtailment losses reduce the power output of the PV system. As such, this operation strategy can only limit the feed-in power but not optimally utilize the PV energy.

A more advantageous feed-in limitation approach is obtained by charging the battery with PV energy that exceeds the permitted feed-in limit. For this purpose, it is necessary to previously determine the amount of PV energy to be shaved through charging the battery by taking forecasts about the future PV production and electricity consumption into account. The residual battery capacity can already be charged in the morning. This forecast-based operation strategy mitigates undesired feed-in peaks, but does not utilize the entire peak shaving potential of the battery system.

A second forecast-based operation strategy is the approach of limiting the feed-in power dynamically. The feed-in limit is ideally set each day based on the forecasts such that the battery is completely charged with energy that exceeds the limit. In this way, the maximum daily feed-in power can be minimized and the self-sufficiency is optimized. As this forecast-based operation strategy seems to be the most promising one, this paper focuses on the implementation of the dynamic feed-in limitation. A more detailed comparison of different forecast-based operation strategies can be found in [1].

### III. MODELLING OF PV BATTERY SYSTEMS WITH FORECAST-BASED OPERATION STRATEGIES

This section describes the used input data, simulation model and control scheme to implement forecast-based operation strategies. The procedure of such operation strategies can be distinguished into different steps, as shown in Fig. 2.

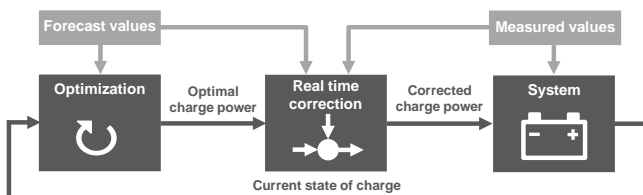


Figure 2. Control scheme of forecast-based operation strategies

In the first step, an optimization is carried out based on the current battery's state of charge and the forecasted values. After that, the optimized charging power is corrected by a real time correction unit considering differences between the forecasted and measured values. Finally, the battery system is instructed to operate according to the corrected charging power. The components of the control scheme as well as the simulation assumptions are described in the following subsections.

#### A. Measured Input Data

The simulations are based on measured annual time series of the load demand and PV power output. The 1 min averaged measurements of the output power of a PV system were recorded in 2012. The PV system is located in southern Germany next to Munich and is south-east oriented with a 35° tilt angle. The maximum PV power output is restricted to 1 kW/kWp and the annual PV energy yield amounts to 1150 kWh/kWp. For the load consumption, a minutely resolved load profile of a single-family home with 5300 kWh of annual load demand is used [2].

#### B. PV Power and Load Forecasts

Three different types of PV power forecasts are considered in this study (see Fig. 3). Firstly, a commercially available forecast product, which was delivered to the considered PV system within the period of measurement by enercast GmbH. Thus, the time series of the measured PV power output correlates with the time series of the forecast values. The commercial PV forecast has a 15 h forecast horizon with both an update interval as well as a time step resolution of 15 min. The second type of PV forecasts is derived from historical measurements using the approach of persistence; i.e. the PV forecast for the current day is based on the measured PV power output time series from the preceding day. To ensure comparability between both types of PV forecasts, the persistence also has a temporal resolution of 15 min and a forecast horizon of 15 h. Furthermore, perfect forecasts that exactly match the measured values are taken into account, both for the PV power output and load demand.

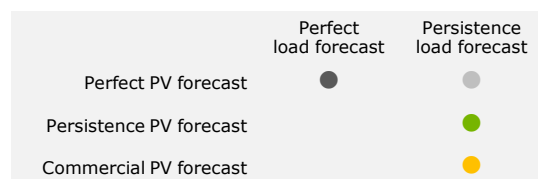


Figure 3. Investigated combinations of different PV and load forecasts

The approach of persistence is also used to establish the real forecasts about the future load demand. As the load profile of households often implies a dependency on the weekday, the load prediction is based on the mean daily load profile of the same weekday during the previous three weeks. The time step resolution amounts to 15 min and no updates within the day for both persistence forecasts are considered. Fig. 3 highlights the different forecast combinations which will be analyzed. The persistence PV and persistence load forecast are used as the reference in this study.

### C. System Model

As measured and forecasted PV power output are used as inputs, no model of the PV system is needed. The measured and forecasted time series of the PV power output are scaled to 5 kWp of rated PV power. The AC-coupled battery system based on lithium-ion batteries has been modeled by a simple approach with constant efficiency factors [3]. The batteries are modelled with a watt-hour efficiency of 95%. Additionally, the bidirectional battery inverter is assumed to be constantly 94% efficient. These losses result in an overall round-trip efficiency of about 84%. The state of charge of the battery is restricted to a range between 20% and 80% of the nominal battery capacity, i.e. the usable battery capacity amounts to 60% of the nominal capacity and is set to 5 kWh. As the battery capacity is reduced during the useful life, it is assumed that on average only 90% of the usable capacity can indeed be utilized. The maximum charge and discharge power is restricted to 5 kW.

The system model also depicts the possible energy flows between the different system components. Fig. 4 illustrates the relevant energy flows of grid-connected PV battery systems. The electricity generated from the PV system can be used in different ways. Primarily it is directly used to supply the electrical demand. The direct use of PV energy results from the simultaneity of the PV production and load demand. When the current PV power output exceeds the load, the available surplus PV power can potentially be stored in the battery system for later consumption. If the battery is fully charged, the remaining excess PV power will be injected into the grid without violating the defined maximum feed-in limit. According to the requirements of the renewable energy storage program, the stipulated feed-in limit is set to 0.6 kW/kWp. To prevent the feed-in power from exceeding this threshold value, curtailment of PV power is required in the case in which the battery is fully charged and the surplus PV power exceeds the limit. Throttling the PV power output is realized in practice by operating the PV generator out of the maximum power point. This way, the exceedance of the stipulated feed-in limit can be prevented either by adjusting the battery charging power or by curtailing surplus PV power.

The loads of the household can be supplied through different sources and are preferably covered by the instantaneous use of PV energy. The battery starts to discharge when the PV output is insufficient to satisfy the electrical demand of the consumers. As soon as the battery is completely discharged, the residual load demand is covered by electricity drawn from the grid. Power exchange between the battery system and the grid is not taken into account in this study.

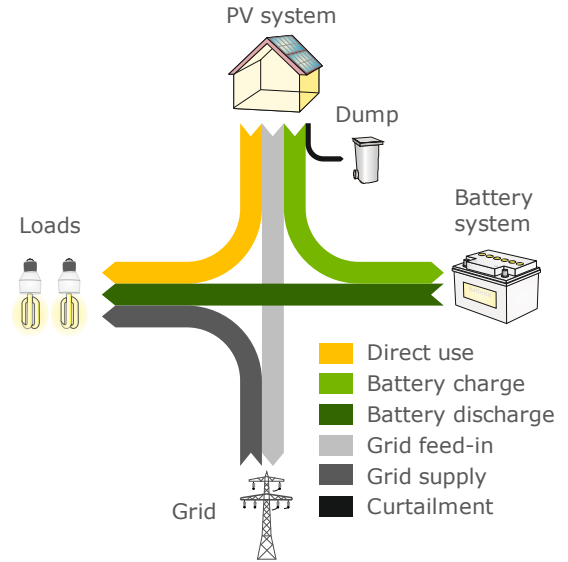


Figure 4. Relevant energy flows in grid-connected PV battery systems

### D. Optimization

The forecast-based operation strategy with a dynamic feed-in limitation can be mathematically formulated as a linear optimization problem. The linear optimization algorithm aims to minimize the feed-in limit such that the battery system reaches its maximum possible state of charge over the forecast horizon. This is done by taking the energetic and technical constraints of the system model into account. The optimization computes the optimal battery charging power at each time step over the forecast horizon based on the remaining free battery capacity. The optimal schedule of the battery charging is recalculated every 15 min considering possible forecast updates as well as updated measurements of the state of charge. Further details of the optimization approach are specified in [4].

### E. Real Time Correction Unit

In the case of accurate forecasts the optimization results can directly be used to control the charging power of the battery system. However, due to the inherent variability of both PV output and load, deviations between the forecasted and measured values are inevitable. To compensate forecast errors in real time, a downstream correction unit is required to maintain the predetermined feed-in limit. This is accomplished by correcting the optimized battery charge power  $P_{BC,OPT}(t)$  in response to the difference between the real and forecasted surplus PV power. The corrected charge power  $P_{BC}(t)$  is determined from the current measured values of the PV power  $P_{PV}(t)$  and load  $P_L(t)$  as well as from their respective forecast values  $P_{PV,F}(t)$  and  $P_{L,F}(t)$  at each time step  $t$  at which  $P_{PV}(t)$  is greater than  $P_L(t)$ .

$$P_{BC}(t) = \max \begin{pmatrix} 0, P_{BC,OPT}(t) \\ +(P_{PV}(t) - P_L(t)) \\ -(P_{PV,F}(t) - P_{L,F}(t)) \end{pmatrix} \quad (1)$$

The real time correction unit aims to balance short-term forecast errors until the optimized charging schedule is updated by repeating the optimization procedure. Thereby, the exceedance of the predefined feed-in limit can be instantaneously avoided.

#### IV. ENERGETIC ASSESSMENT OF FORECAST-BASED OPERATION STRATEGIES

Based on the assumptions and models described above, simulations of a PV battery system considering different forecast approaches and operation strategies have been performed. In this section, the simulation results are assessed from an energetic perspective.

##### A. Assessment Criteria

In order to evaluate the annual operational results, three energetic assessment criteria should be defined. The first one is the degree of self-sufficiency, which specifies the fraction of the total load demand covered by the PV battery system. The degree of self-sufficiency  $d$  is obtained by dividing the sum of the directly used PV energy  $E_{DU}$  and the energy discharged from the battery  $E_{BD}$  by the load demand  $E_L$ .

$$d = \frac{E_{DU} + E_{BD}}{E_L} \quad (2)$$

The second evaluation parameter is the self-consumption rate  $s$ , which is equal to the share of PV generated electricity  $E_{PV}$  that is either directly used  $E_{DU}$  or stored in the battery  $E_{BC}$ .

$$s = \frac{E_{DU} + E_{BC}}{E_{PV}} \quad (3)$$

Restricting the feed-in power to a stipulated limit can lead to curtailment of PV power in order to comply with the threshold value. As a result, energy losses due to curtailment will occur. The curtailed PV energy  $E_{CT}$  and the curtailment losses  $l$  can be determined by subtracting the directly used energy  $E_{DU}$ , the energy used to charge the battery  $E_{BC}$  and the energy fed into the grid  $E_{GF}$  from the total generated PV energy  $E_{PV}$ .

$$l = \frac{E_{CT}}{E_{PV}} = \frac{E_{PV} - E_{DU} - E_{BC} - E_{GF}}{E_{PV}} \quad (4)$$

##### B. Assessment Results

This subsection focuses on the impact of forecast inaccuracies on the performance of forecast-based operation strategies. Forecast errors can be found either in the load forecast or in the PV forecast. As the battery is only charged with PV energy that exceeds the load, the resulting difference between the PV power forecast and the load forecast is decisive. As a result, errors in the projected PV power and load demand can also counteract and can compensate each other [1]. In general, two different cases in terms of forecasting the surplus PV energy can be distinguished:

- Under-forecasting of the surplus PV energy: The real surplus PV energy exceeds the predicted value caused by too low forecasted PV energy or by too high forecasted load.
- Over-forecasting of the surplus PV energy: Less excess PV energy is available than anticipated caused by too high forecasted PV energy or too low forecasted load.

Both types of forecast errors have different consequences on the operational behavior of forecast-based operation strategies. The impact of under-forecasted surplus PV energy on the energy flows of a PV battery system operated with the dynamic feed-in limitation is depicted in the course of one exemplary day in Fig. 5. Besides the realized energy flows, also the results of the optimization at 5:00 am are shown. The optimization is performed using the state of charge at this instant of time as well as the persistence PV and persistence load forecast of the next 15 h. According to the predicted time series of the differential power between PV and load, the optimization algorithm calculates the optimal battery charging sequence during the forecast horizon resulting in an initial feed-in limit of 2 kW on this day. The realized energy flows highlight that the battery starts to charge after the surplus PV power exceeds the predefined feed-in limit.

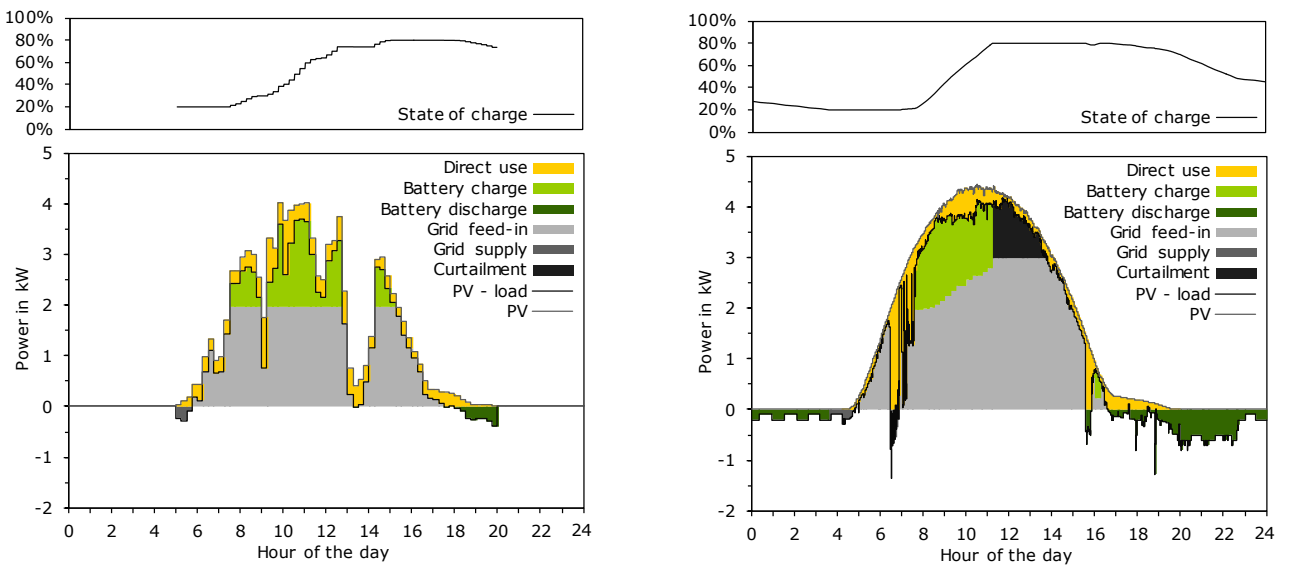


Figure 5. Forecasted and optimized energy flows at 5:00 am (left) and realized energy flows (right) of a PV battery system with a dynamic feed-in limitation based on persistence forecasts in the case that the surplus PV energy is under-forecasted

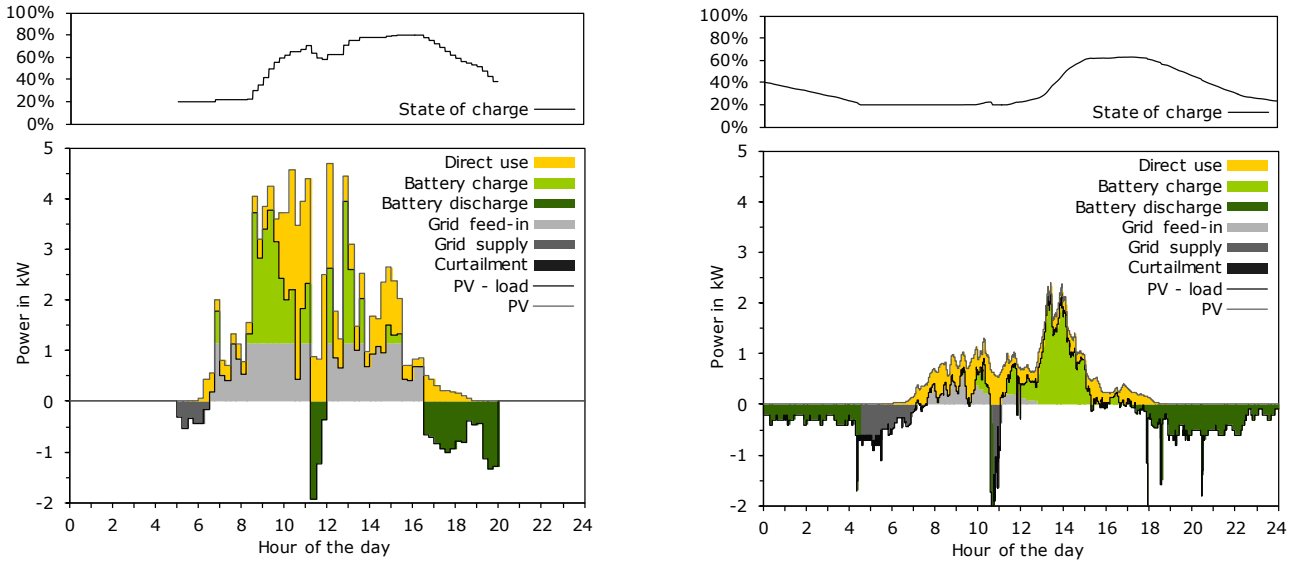


Figure 6. Forecasted and optimized energy flows at 5:00 am (left) and realized energy flows (right) of a PV battery system with a dynamic feed-in limitation based on persistence forecasts in the case that the surplus PV energy is over-forecasted

If the forecasted surplus PV power matches perfectly with the measured surplus PV power at each instant of time, the feed-in limit will remain constant throughout the day. Nevertheless, to maintain the predetermined feed-in limit in the case that more surplus PV energy is available than expected, more PV energy has to be charged into the battery system. Thereby, the under-forecasting of the surplus PV energy results in a faster ascending state of charge than expected. Thereafter, the remaining free battery capacity is inadequate to observe the previously defined feed-in limit. In response to this, the feed-in limit is subsequently elevated throughout the day by adjusting the optimized charging power. After reaching the maximum state of charge, the curtailment of surplus PV power is enforced to preserve the imposed maximum feed-in limit of 3 kW (0.6 kW/kWp). As a result, higher losses due to curtailment of PV energy occur on days on which more excess PV energy is available than predicted which corresponds to the findings presented in [5].

The impact of over-forecasted surplus PV energy on the operational behavior of a PV battery system with a dynamic feed-in limitation is displayed for an exemplary day in Fig. 6. It is evident that the occasional over-forecasted load demand partially compensates the significantly over-forecasted PV output. On this day, an initial maximum feed-in power of roughly 1 kW is established by the optimization subject to the forecasts at 5:00 am. However, it can be observed that the real surplus PV energy is significantly lower than expected due to prolonged overcast conditions. Therefore, the initial feed-in limit is set too high and is only slowly diminished due to the expectation of higher future PV surpluses. Consequently, this results in a loss of stored PV energy, as not the entire surplus PV energy is used to reach the maximum possible state of charge on this day. Hence, a lower fraction of the surplus PV energy is stored in the battery and hence a higher amount of PV energy is injected into the grid, compared to the operation supposing perfect forecasts.

The previously analyzed simulation results highlight the distinct consequences of the two types of forecast errors on the operational behavior on two exemplary days. Fig. 7 illustrates the impact of forecast errors on the increased stored and reduced curtailed PV energy of every day

obtained by an annual power flow simulation. The operational results based on persistence forecasts are assessed in comparison to an ideal case that takes perfect forecasts into account. This allows to determine changes in the stored and curtailed PV energy as a function of the difference between the forecasted and measured surplus PV energy each day. Negative values of this difference correspond to under-forecasted surplus PV energy and positive values are equal to over-forecasted. As expected, the reductions in the battery charge occur commonly on days on which more PV surpluses are forecasted than measured. As a reduced stored PV energy increases the amount of energy that must be drawn from the grid, besides the self-consumption rate, also the degree of self-sufficiency is reduced by the over-forecasting of the surplus PV energy. In contrast, the amount of curtailed energy shows a distinct tendency to be enhanced with an increasing under-forecasting. This allows to draw the general conclusion that the degree of self-sufficiency and self-consumption rate are negatively affected by over-forecasted PV surpluses, whereas higher curtailment losses are attributable to under-forecasted PV surpluses.

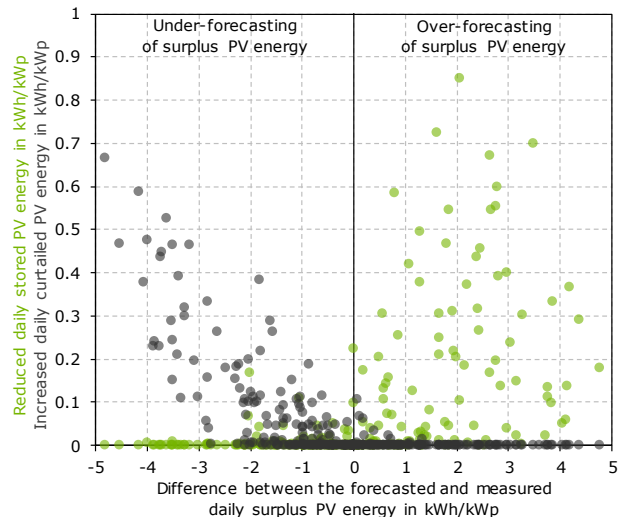


Figure 7. Impact of under- and over-forecasted daily surplus PV energy on the daily stored and curtailed energy with the dynamic feed-in limitation based on persistence forecasts compared to perfect forecasts

After figuring out the impact of forecast errors on the daily performance, the simulation results of different forecast approaches are analyzed on an annual basis. As the losses in the self-consumption rate are directly proportional to the losses in the degree of self-sufficiency, only the annual average values of the degree of self-sufficiency are investigated in the following. Fig. 8 displays the annual degree of self-sufficiency as well as curtailment losses of the dynamic feed-in limitation, applying different PV and load forecasts. For purpose of comparison, the performance of the conventional operation strategy of fixed feed-in limitation through curtailment is also depicted. As this operation strategy acts in a way to charge the battery system as soon as possible, the highest degree of self-sufficiency is obtained by this strategy. However, the early battery charging results in the highest curtailment losses of 3.6%, whereas the battery is frequently fully charged before the peak has passed.

In the case that the PV battery system is operated with a dynamic feed-in limitation supposing perfect PV and load forecasts, the curtailment of PV energy can almost be completely avoided. Thus, perfect forecasts allow realizing the highest degree of self-sufficiency as well as the lowest curtailment losses. Because PV and load forecasts are inherently erroneous, the real operational performance deviates from this ideal case. Operating the PV battery system with a dynamic feed-in limitation integrating perfect PV and persistence load forecasts reduces the degree of self-sufficiency to 56.3% and increases the curtailment losses to 0.5%. The resulting losses are only induced by imperfect load forecasts so that these simulation results can be considered as the benchmark for different PV forecast approaches assuming that the same load forecast is used.

The annual performance has also been determined considering the commercial PV forecast which results in 1.0% curtailment losses and a self-sufficiency of 56.1%. Moreover, it can be seen that the reference simulation based on the persistence PV and load forecasts involves the lowest degree of self-sufficiency of 55.6% and highest curtailment losses of 1.4% for the dynamic feed-in limitation. Nevertheless, the differences in the energetic performance compared with the commercial PV forecast are quite small.

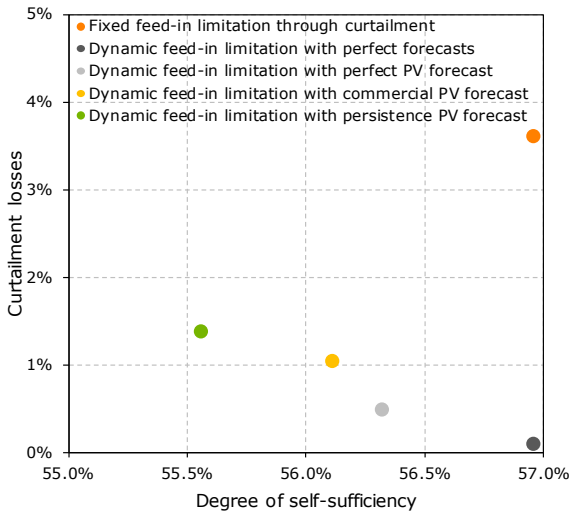


Figure 8. Assessment of the energetic performance of different operation strategies and forecast approaches with regard to the obtained annual degree of self-sufficiency and curtailment losses

In comparison with the conventional operation strategy of fixed feed-in limitation through curtailment, the advantage of using forecasts consists in reducing the curtailment losses; also in the case of error-prone forecasts. However, losses in the degree of self-sufficiency incurred by forecast errors emerge. In real conditions, the impact of the forecast accuracy on the performance is also dependent on the implemented control strategy [6]. Moreover, the grid feed-in is smoothed more strongly operating a PV battery system with a dynamic feed-in limitation, compared to the operation strategy of a fixed feed-in limitation [1]. But besides that, as the battery charging is delayed by the dynamic feed-in limitation, the dwell time at high states of charge is reduced which can also enhance the calendar life of lithium-ion battery systems [7, 8].

## V. ECONOMIC ASSESSMENT OF FORECAST-BASED OPERATION STRATEGIES

The performance of different operation strategies and forecast approaches are evaluated from the economic perspective in this section.

### A. Assessment Criteria

In order to assess the economics of different operation strategies, a cost-benefit analysis concerning the cash flows due to the energy exchange with the grid is carried out. This is performed by calculating the annual operational costs  $C$  considering the expenses for the grid supply  $C_{GS}$ , additionally reduced by the revenues from the grid feed-in  $R_{GF}$ . The annual costs for electricity supplied by the grid  $C_{GS}$  are obtained from the retail electricity price  $p_{GS}$ , the annual load demand  $E_L$  and the degree of self-sufficiency  $d$ . The revenues from selling PV energy can be calculated using the feed-in tariff  $p_{GF}$  and the annual PV energy output  $E_{PV}$  lowered by the self-consumption rate  $s$  and curtailment losses  $l$ .

$$C = C_{GS} - R_{GF} = E_L \cdot (1-d) \cdot p_{GS} - E_{PV} \cdot (1-s-l) \cdot p_{GF} \quad (5)$$

For comparability of different operation strategies, the difference in the operational costs  $C_{FIXED}$  and  $C_{DYN}$  applying a fixed feed-in limitation through curtailment and a dynamic feed-in limitation is analyzed, respectively. This allows to calculate the saved profit in the annual operational costs  $S_{DYN}$  by operating a PV battery system with the dynamic feed-in limitation compared to the conventional operation strategy.

$$S_{DYN} = C_{FIXED} - C_{DYN} \quad (6)$$

In order to evaluate the economic benefit from implementing the different strategies or from purchasing external PV forecasts, only the differences in the energetic performance of the distinct operation strategies should be monetarily assessed.

### B. Assessment Results

To reveal the present cost reduction potential of the dynamic feed-in limitation, the reference cost scenario in this study considers the current retail electricity price of roughly 0.28 €/kWh and feed-in tariff of 0.12 €/kWh.

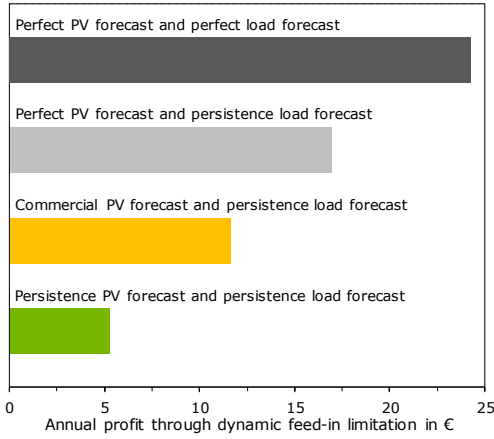


Figure 9. Annual profit of the dynamic feed-in limitation taking account of the different forecast approaches compared to the fixed feed-in limitation through curtailment

Fig. 9 compares the annual savings that can be gained by applying the dynamic feed-in limitation based on different load and PV forecasts. It is clearly visible that the dynamic feed-in limitation realizes a positive benefit in the reference scenario compared to the fixed feed-in limitation through curtailment, regardless of the considered forecasts. The highest annual savings potential of almost 25 € is obtained in the ideal case of perfect PV and load forecasts. Nevertheless, as forecast errors increase the curtailment losses and decrease the self-sufficiency, the annual savings are also affected by imperfect forecasts. Thus, the forecast errors induced by the persistence load forecast already reduce the annual profit to 17 €. This savings gained by the perfect PV forecast and persistence load forecast can be considered as the maximum possible profit which can be obtained by using real PV forecasts.

The utilization of the commercial PV forecast results in annual operational costs between the perfect and persistence PV forecast. In the case of persistence PV forecast, the annual cost reduction potential is lowered to 5 €. Nevertheless, the annual economic advantage of involving the commercial PV forecast compared to the persistence PV forecast amounts to only 6 €. Because of this, one can suppose that it is hard to attain a business case to incorporate external PV forecast information into the control of residential PV battery systems with forecast-based operation strategies. Nevertheless, more precise commercial forecast information could enhance the annual economic benefit in comparison with the persistence PV forecast to up to 12 € for the investigated system configuration. But besides that, the difference in the annual operational costs of distinct operation strategies depends further on the size of the PV system and battery capacity [9]. Consequently, higher possible savings by purchasing high-quality external PV forecasts can be achieved at larger-sized PV systems.

Considering these facts, the approach of persistence based on historical measurements seems to be an encouraging alternative to external PV forecasts. Hence, Fig. 10 finally highlights the sensitivity of the resulting annual profit obtained by the persistence PV and load forecasts in the case that the retail electricity price and feed-in tariff deviate from the reference cost scenario. In general, higher feed-in tariffs increase the economic benefit of the dynamic

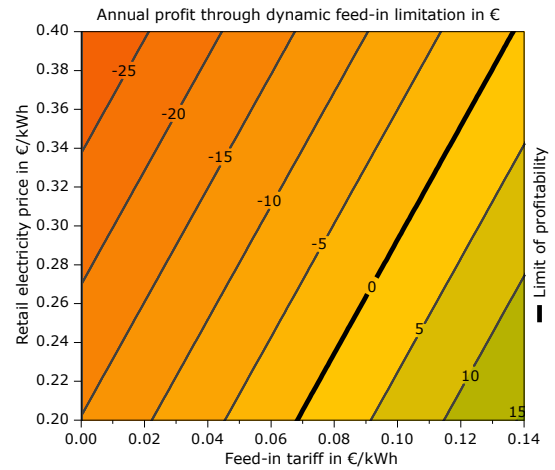


Figure 10. Annual profit of the dynamic feed-in limitation with persistence forecasts compared to the fixed feed-in limitation through curtailment as a function of the feed-in tariff and retail electricity price

feed-in limitation, as lower curtailment losses are obtained compared to a fixed feed-in limitation through curtailment (see Fig. 8). Moreover, increasing retail electricity prices lower the annual profit of the dynamic feed-in limitation due to losses in the degree of self-sufficiency incurred by forecast errors. As long as the difference in the operational costs is positive, the dynamic feed-in limitation is economically more viable than the fixed feed-in limitation through curtailment. However, in the case that the cost situation in terms of feed-in tariff and retail electricity price undercuts the limit of profitability, the annual operational costs of the dynamic feed-in limitation are higher. As a result, it can be seen that a sufficient remuneration of the grid feed-in is decisive for realizing a profitable operation with the dynamic feed-in limitation.

Reducing curtailment losses with forecast-based operation strategies is only beneficial in cases in which the grid feed-in is sufficiently remunerated. Otherwise curtailing surplus PV energy is more practicable to observe a defined feed-in limit as no losses in the degree of self-sufficiency due to forecast inaccuracies occur. Thus, it can be concluded that adequate feed-in tariffs are worthwhile to enhance the introduction of more grid-compatible operation strategies for PV battery systems. Furthermore, higher savings can be achieved by improving the persistence PV forecasts or by reducing the maximum feed-in limit in future [10, 11]. Additional benefits using the forecast-based operation strategies can also be obtained from using them in a way to reduce also the peak demand and possible demand charges [12].

## VI. CONCLUSION

This paper analyzes the performance of operation strategies for residential PV battery systems that use load and PV forecasts. For the operation strategy with a dynamic feed-in limitation the robustness in regard to dealing with forecast errors has been demonstrated. Imperfect forecasts are compensated through adjustments to the feed-in limit during the day depending on whether the surplus PV energy is over- or under-forecasted. The performed simulations highlight that over-forecasting the daily surplus PV energy is negatively affecting the degree of self-sufficiency with respect to a perfect forecast, whereas under-forecasting

events result in higher curtailment losses. By applying a dynamic feed-in limitation instead of a conventional fixed feed-in limitation through curtailment, savings in terms of the annual operational costs can be achieved at present. Nevertheless, only small financial benefits by adding commercial PV forecasts instead of persistence PV forecasts were identified. Consequently, improvements in the forecast accuracy of locally created PV forecasts may render the purchase of externally provided PV forecasts in residential applications obsolete. In addition, such forecasts based on historical measurements seem to be much easier to implement compared with external forecast information. In this way, operating PV battery systems with forecast-based operation strategies can enhance the local use of PV generated energy and reduce the magnitude of the feed-in peaks. The dynamic feed-in limitation can thus be seen as an economically efficient measure to improve the grid integration of PV and hence increases the hosting capacity of distribution grids for the future PV expansion.

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