FEED-IN POWER LIMITATION OF GRID-CONNECTED PV BATTERY SYSTEMS WITH AUTONOMOUS FORECAST-BASED OPERATION STRATEGIES

Joseph Bergner, Johannes Weniger, Tjarko Tjaden, Volker Quaschning
HTW Berlin - University of Applied Sciences
Wilhelminenhofstraße 75A, 12459 Berlin, Germany
Email: joseph.bergner@htw-berlin.de

ABSTRACT: Considering the challenges of grid integration, battery systems could be used to smooth the infeed of PV systems. This paper presents autonomous forecast-based operation strategies for residential PV battery systems that can be used to improve grid integration of PV systems. Simulation calculations on a timescale of one minute were performed to determine the impact of error-prone forecasts of the PV generation and load demand. Like load forecasts which need to be calculated on-site, also PV forecasts can be autonomously derived from measurements to avoid costs from forecast services. For the purpose of dealing with forecast errors a model predictive controller is implemented which can compensate the essential undesired effects of forecast errors. In this paper basic forecast approaches were assessed to show that even simple prediction models result in an economic feasible and autonomous grid relieving operation of residential PV battery systems.

Keywords: PV Battery Systems, Battery Storage, Economical Analysis, Forecast, Operation Strategy

1 MOTIVATION

As feed-in tariffs decrease faster than the levelized costs of PV generated electricity in many countries, new operational concepts for photovoltaic (PV) systems are needed. A potentially huge market could be the on-site consumption of locally generated PV power. Because local demand and PV generation are limited in simultaneity with regard to their diurnal and seasonal course, storages could increase the usage on-site by storing surplus PV energy for later consumption. Furthermore, battery storages could play a major role for grid integration of renewables and especially residential PV [1,2]. The majority of PV systems is connected to the low voltage grid so that the avoidance of voltage rises is the crucial issue for PV grid integration [3,4]. In order to develop promising operation strategies for residential PV battery systems recent work gives a wide spectrum of approaches. Most authors agree on one point: PV batteries will not relieve the grid, as they will be fully charged as soon as possible, often before feed-in reduction is necessary [1–10].

Moreover many causes for peak shaving applications from a grid operator's point of view have been identified in recent work [1–10]. Hence the reduction of feed-in to a certain amount of power is mandatory in Germany. However the feed-in limitation through curtailment leads to unnecessary losses whereas curtailment occurs when energy could be fed into the grid with power above the mandatory feed-in limit. To eliminate this drawback of that nowadays conventional operation, forecast-based operation strategies were proposed, which fulfills the balancing act of peak shaving feed-in, increasing the self-sufficiency on-site and avoiding curtailment as illustrated schematically in Figure 1.

The previously published studies differ in their forecast assumptions; some use perfect forecasts for investigation [1,5,6], others synthetic forecasts (modified measured time series) [2,7] or forecasts by meteorological services [9,11,12]. Finally there are studies that use simple persistence models such as [10] or more complex models such as [2,13,14]. For that reason the results are not overall comparable. While perfect forecasts contribute to a conceptual development showing possible gains from different approaches, error-prone forecasts become necessary for the implementation of forecast algorithms in real PV battery systems.

Autonomous forecasts, based on measurements are freely available, in contrast to forecasts of meteorological services. Nevertheless implementation constraints could arise from a lack of knowledge. Therefore simple but accurate approaches are in favor and need to be developed. This paper shows how residential PV battery systems could be easily equipped with autonomous forecasts to relieve the grid without additional costs.

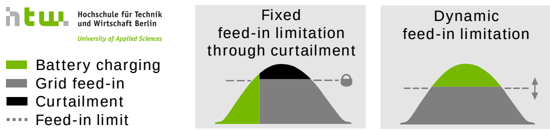

Figure 1: Schematic representation of different operation strategies

2 MODEL DESCRIPTON

2.1 System model and input data

The system model investigated in this paper can be described with four components: input data, a PV- and battery model and finally the control scheme. The input data to simulate the PV system is based on measurements of the diffuse and global irradiance as well as ambient temperature from 25 weather stations recorded by the German weather service (DWD) in 2013. The temporal resolution of the irradiance data is one minute and ten minutes for the temperature data. For the case study in this paper the meteorological observatory Lindenberg, Germany was chosen as representative in comparison to the other weather stations. To depict the temporal course of typical residential load demand, minutely resolved load demand data of a household is taken into account, referring to [15]. The load profile is characterized by an annual load demand of 5282 kWh.

The model of the PV system is based on the work presented in [16] and [17]. The required model parameters are specified by characteristic curves of a multi-crystalline module and a transformer-less inverter. Besides that the PV generator is assumed to be southoriented with a 35° declination. Furthermore the rated power of the PV generator is considered to be 5.3 kWp, which results in a PV system size to annual load demand ratio of about 1 kWp/MWh. The maximum PV inverter power output is restricted to 5.3 kW. This results in a specific annual energy yield of the PV system of 1002 kWh/kWp. In this paper the maximum feed-in power is restricted to 50% of the rated PV power for that it is comparable with [2,3,6,7].

In order to get general insights into the system operation a simple storage model is used that depicts the general characteristics of a lithium-ion battery [1]. It is assumed that the AC-coupled battery system has a constant watt-hour efficiency of 95% and an additional 6% of conversion losses in the battery inverter, so that the round tip efficiency is roughly 84%. The maximum power output and input of the battery inverter related to the usable capacity is limited to 1 kW/kWh. Accordingly to [1] the usable battery capacity is set to 1 kWh/MWh annual load demand, i.e. 5.3 kWh of usable battery size is considered. In order to take aging into account it is assumed that on average 90% of the usable capacity was available over the operation time. Note that the battery is not allowed to feed energy into the grid or draw energy from the grid.

2.2 Control Scheme

Additionally the control algorithm, which implements forecast-based peak-shaving by dynamically limiting the feed-in, has to be described. The controller is based on a linear optimization approach which consists of basic balancing equations and is solved by the simplex algorithm. Therefore it is expected that the PV power output P_{pv} is primary used to meet the load demand P_{load}. Hence only the residual surplus PV power output could be used to charge the battery P_{bc}, feed into the grid P_{gf} or at last option be curtailed P_{ct}.

$$P_{\mathrm{pv}} - P_{\mathrm{load}} = P_{\mathrm{bc}} + P_{\mathrm{gf}} + P_{\mathrm{ct}} \;\; (P_{\mathrm{pv}} > P_{\mathrm{load}}) \tag{1}$$

If the PV supply is lower than the demand, the residual load will be supplied either through discharging the battery P_{bd} or through drawing from the grid P_{gl}.

$$P_{\mathrm{pv}} - P_{\mathrm{load}} = P_{\mathrm{bd}} + P_{\mathrm{gl}} \quad \left(P_{\mathrm{pv}} < P_{\mathrm{load}}\right) \tag{2}$$

Further the battery balance is described by equation (3) at the first time step of the optimization and by equation (4) for further steps. Therefore the actually stored energy E_{b0} and time step length Δt is needed.

$$\eta_{\mathrm{bc}} P_{\mathrm{bc}} + \frac{1}{\eta_{\mathrm{bd}}} P_{\mathrm{bd}} - \frac{1}{\Delta t} E_{\mathrm{b}} = -\frac{1}{\Delta t} E_{\mathrm{b0}} \tag{3}$$

$$\eta_{\mathrm{bc}} P_{bc} + \frac{1}{\eta_{\mathrm{bd}}} P_{\mathrm{bd}} + \frac{1}{\Delta t}\left(E_{\mathrm{b}}^{t-1} - E_{\mathrm{b}}\right) = 0 \tag{4}$$

Although $P_{\mathrm{gf,max}}$ has to be calculated so that the battery is fully charged at the lowest possible feed-in power with sparse curtailment at least one equation for a peak-shaving grid feed-in limit is needed. Besides that, the feed-in limit is assumed to be constant over the whole optimization horizon.

$$P_{\mathrm{gf}} - P_{\mathrm{gf,max}} \leq 0 \tag{5}$$

For shortage, the system boundary conditions such as e.g. lower and upper limitation due to inverter size, were left out. The cost function considers the retail electricity price and feed-in tariff. Additionally, lower feed-in and curtailment losses are valued qualitatively.

In order to compensate possible forecast errors in terms of deviations between the predicted and measured surplus PV power, a real-time correction unit is needed. An equation is developed to realize the optimized feed-in when PV-power is greater than load demand or the feed-in is greater than the maximum. Note that the index f marks the forecasted values.

$$P_{\mathrm{bc}} = \max\left(0,\ \begin{matrix} P_{\mathrm{bc,f}} \\ +\left(P_{\mathrm{pv}} - P_{\mathrm{load}}\right) \\ -\left(P_{\mathrm{pv,f}} - P_{\mathrm{load,f}}\right) \end{matrix}\right) \tag{6}$$

If the PV output is below the load demand; the battery discharge should follow the load precisely until the state of charge (SOC) has reached the minimum value.

$$P_{\mathrm{bd}} = P_{\mathrm{pv}} - P_{\mathrm{load}} \tag{7}$$

The entire control algorithm is depicted in Figure 2. At first; the optimization is carried out based on the current SOC of the battery and forecasts about the future load demand and PV-generation. The output is an optimized schedule of the battery charging power within the optimization horizon. To balance forecast errors in real time, the actual optimal charge power is adjusted by the real-time correction unit based on equation (6). Finally, the battery is charged with the corrected value. The optimization is done every 15 minutes, with 15 minutes of forecast resolution and 15 hours of optimization horizon. A detailed model description can be found in [18].

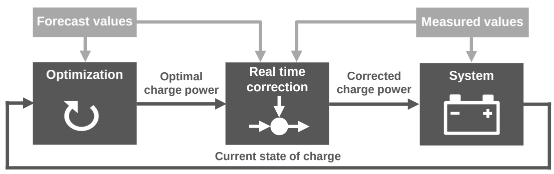

Figure 2: Control scheme of the forecast-based operation strategies .

3 ENERGETIC EVALUATION

3.1 Energetic evaluation criteria

Simulation results considering different forecast approaches were assessed by the comparison of two dimensionless quantities. First the degree of self-sufficiency d is used which specifies the fraction of the total load demand covered by the PV battery system. Hence d is obtained by dividing the sum of directly used PV energy E_{du} and energy discharged from the battery E_{bd} by the load demand E_{load}.

$$d = \frac{E_{\mathrm{du}} + E_{\mathrm{bd}}}{E_{\mathrm{load}}} \tag{8}$$

If losses in the degree of self-sufficiency emerge, less PV-energy will be used for charging the battery and in consequence more electricity has to be drawn from the grid. Nevertheless, as the amount of PV energy that is stored in the battery decreases, a higher amount could be injected into the grid.

Secondly the rated curtailment losses l is investigated which reveals the percentage of unused PV energy. It could be determined from the curtailed energy E_{ct} divided by the total theoretical PV production E_{pv}.

$$l = \frac{E_{\mathrm{ct}}}{E_{\mathrm{pv}}} \tag{9}$$

A reduction of curtailment losses results in an increase of the grid feed-in, which enhances the financial benefit for the operator of the PV battery system, thus it needs to be minimized. In principle, both assessment criteria vary with a number of parameters. The impact of the system configuration in terms of PV and battery size on these operational results was analyzed in [1].

3.2 Energetic evaluation results

In this section the impact of different approaches for the load and PV generation forecasts on the operational results are assessed from the energetic perspective. To reveal the reasons for changes in the energetic criteria, different forecast approaches for the load and PV prediction will be combined with each other. This has been performed for perfect, persistence and energy forecasts. Perfect forecasts precisely coincide with the real time series of load and PV. Nevertheless the temporal resolution of the perfect forecasts is reduced to 15 minutes, as the optimization is done on this time scale.

Furthermore the most simple stochastic technique of forecasting is the extrapolation of recent values, called persistence [19]. In this paper persistence forecasts are used to determine PV power forecasts based on the measured time series of the past day. This approach is also applicable for load forecasts. As load profiles of households often imply a dependency on the weekday, the load prediction is based on the measured load of the same day of the former week. For simplicity, this approach for load forecasts is also referred to as persistent or real forecast.

Due to the variability of the load and PV generation time series, it can be assumed that forecasting only daily energy amounts of load demand and PV generation is easier than the prediction of the time series. Accordingly, the projected energy could be applied on characteristic curves such as clear-sky or standard load profiles to forecast the time series. In this paper, this method is defined as energy forecast.

Before revealing the impact of the different forecast approaches on the performance, the conventional operation strategy of charging the battery as soon as possible should be compared with the dynamic feed-in limitation. Considering perfect forecasts for the dynamic feed-in limitation, both operation strategies result in a degree of self-sufficiency of 54.4%. In Figure 3 the curtailment losses for both operation strategies are depicted. Limiting the PV feed-in to 50% of the rated PV power causes about 7% less usage of PV energy in the case of conventional battery operation. This is due to the fact that the battery is often fully charged before generation peaks, which have to be curtailed afterwards. If the battery is operated with a dynamic feed-in-limitation, curtailment losses will be reduced more or less by the factor seven considering perfect forecasts. Using error-prone persistence forecasts, the energy losses due to curtailment can only be halved compared to the conventional operation strategy. Even with perfect forecasts curtailment losses could emerge. This is explicable with insufficient spare capacity in the battery

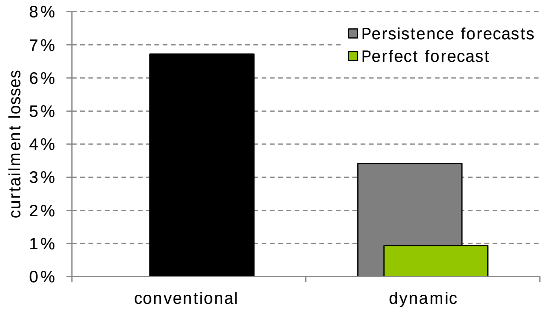

Figure 3: Curtailment losses in relation to the annual PV energy output for different operation strategies.

due to an incomplete discharging in the night through lowest consumption or due to small installed battery capacity. Since the persistence forecast is the benchmark of a naive forecast, Figure 3shows the range for the curtailment with a more intelligent battery operation.

Furthermore persistence forecasts induce only good results if the weather situation is similar to the day before, otherwise forecast errors occur that have to be corrected by the control algorithms. For example; optimizing energy flows in expectation of a clear sky day while clouds cover the sun leads to higher expected feed-in and therefore battery charging is delayed till noon. If the power output stays below the limit, the optimization adapts in terms of fully charging the battery on the remaining forecasted clear sky day but could fail to reach the maximum degree of self-sufficiency concerning the small PV supply. Thus error-prone forecasts do not only affect the curtailment losses but also the degree of self-sufficiency.

In order to illustrate the impact of forecast quality on the dynamic feed-in limitation, Figure 4 shows the correlation of different forecast models to curtailment losses and to the degree of self-sufficiency. It is obvious that operational strategies are affected by forecast errors with differences in the forecasted quantities. A perfect forecast could reach the highest rate in the degree of self-sufficiency while preserving lowest curtailment. Despite that, persistence PV and load forecasts deliver the lowest degree of self-sufficiency and highest curtailment among the dynamically operated PV battery systems, which is also displayed in Figure 3. To conclude, forecast induced losses emerge compared to perfect forecasts, hence the household could be less supplied by the PV battery system and more PV energy is curtailed, although a higher feed-in could be achieved. If only a persistence PV forecast and a precisely known time series of the load are applied, the degree of self-sufficiency slightly increases and a reduction of curtailment losses of about 0.7% can be obtained. Besides that, the assumption of perfect PV and persistence load forecasts absolutely increases the degree of self-sufficiency d by about 0.5% and decreases curtailment losses by about 1.5% compared to complete persistence forecasts.

This indicates that PV forecasts have a stronger impact on the simulation than load forecasts and that persistence fits better for residential load than for PV generation. Moreover, errors of both forecasts together do not increase the losses as much as both errors in sum; hence it is obvious that forecast errors could interfere positively. The comparison to perfect forecast operational results should be the benchmark for an improvement of the prediction approaches.

Figure 4: Annual energetic evaluation criteria in dependence of the forecast quality for dynamic feed-in limitation.

The results reveal that the gain of dynamic operation can be obtained by avoiding curtailment, varying in the range of 50% to 90% depending on the forecast technique, feed-in-limit and overlap of load demand and PV generation. Secondly, PV forecasts have a stronger impact on the results of that application than load forecasts, consequently this paper focuses on improvements of PV forecasts.

3.3 Improvements in PV forecasts

In comparison to other quantities that could be forecasted, solar power has the advantage that the possible appearance is well known. Various models for the calculation of the sun position and clear sky radiation have been developed over the past century. Especially the fracture of actual irradiance to the possible maximum clear sky irradiance k_{T}, is advantageous for forecasting. If the value is known, the bell-shaped-curve of solar radiation results by multiplying it with clear sky irradiation. Analogous to the irradiation the fraction of PV power k_{pv} could be defined as:

$$k_{\mathrm{pv}} = \frac{\int_{t_1}^{t_2} P_{\mathrm{pv}}\, dt}{\int_{t_1}^{t_2} P_{\mathrm{pv,max}}\, dt} \tag{10}$$

While P_{pv} is the actual PV power output, $P_{\mathrm{pv,max}}$ is the expected maximum PV power at the same time. $P_{\mathrm{pv,max}}$ can be obtained from measured values of the past which has prevailing positive properties. On the one hand it incorporates orientation, shadow situation and temperature dependence at a specific site. On the other hand, small errors occur because sunrise and sunset were not depicted correctly and could differ by a few minutes.

$$P_{\mathrm{pv,max}}(t) = P_{\mathrm{pv}}\big(t - (n \cdot 24\ \mathrm{h})\big) \tag{11}$$

Therefore n is the number of days backwards, chosen by the criterion (12). It depends on the maximum energy yield at a time interval t_1 and t_2 around the actual time t and at a day of the year (doy) that is less than $n_{\max}$ days close to the current doy.

$$n \text{ chosen by: } \max_{n=1\ldots n_{\max}} \int_{t_1}^{t_2} P_{\mathrm{pv}}(t, doy - n)\,\mathrm{d}t \tag{12}$$

Although this approach seems laborious, it is easier to implement into the practical operation than the alternative of clear sky irradiance calculation which needs site and system specific input parameters. With only a one year database no negative effects on the simulation were obtained compared to the usage of a clear sky model and in fact the maximum fit gets better with each year running. Nevertheless a bell-shaped production curve as maximum could not be guaranteed with such a poor database. For the simulation the period for look up $n_{\max}$ is limited to ten days backwards and the energy of criterion (12) is evaluated for hourly intervals which show sufficiently precise results. A forecast could be acquired by multiplying a forecasted $k_{\mathrm{pv,f}}$ over the entire forecast horizon with the maximum generation time series.

$$P_{\mathrm{pv,f}}(t) = k_{\mathrm{pv,f}} \cdot P_{\mathrm{pv,max}}(t) \tag{13}$$

Assuming that the yield of the next day could be known precisely, a forecast could be derived that is correct in overall energy but differs in shape. If the operational result of perfect PV and persistence load forecasts are compared to a perfect forecast of the overall energy, with the same load forecasts, curtailment losses increase only by about 0.5% while the degree of self-sufficiency remains steady which implies the forecast of the overall energy fits very well for this application.

In order to investigate the influence of forecast accuracy, a bias deviation and a stochastic variation has been determined. In Figure 5 and Figure 6, the absolute losses compared to perfect forecast are shown. Therefore, in Figure 5 the predicted energy varies by a fixed factor (bias variation) where 100% signifies a perfect energy forecast. It becomes apparent that forecasting less energy causes higher curtailment losses and an increasing degree of self-sufficiency due to earlier charging of the battery. Furthermore, in the case in which more energy is forecasted than measured, the amount of peak energy is too small to fully charge the battery. Consequently the feed-in limit is adapted dynamically, so that less curtailment losses but increasing losses in the degree of self-sufficiency occur. Moreover the standard deviation of normally distributed forecast errors shifts the operational results toward persistence forecast which is depicted in Figure 6. As a consequence of this analysis, forecast errors could be classified as a function of the energetic criteria d and l.

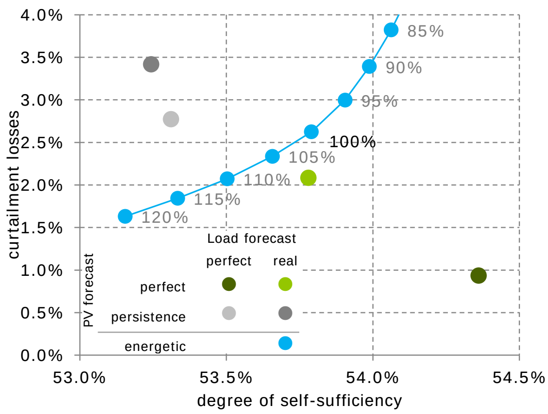

Figure 5: Influence of systematic forecast errors on energy PV forecasts for dynamic feed-in limitation.

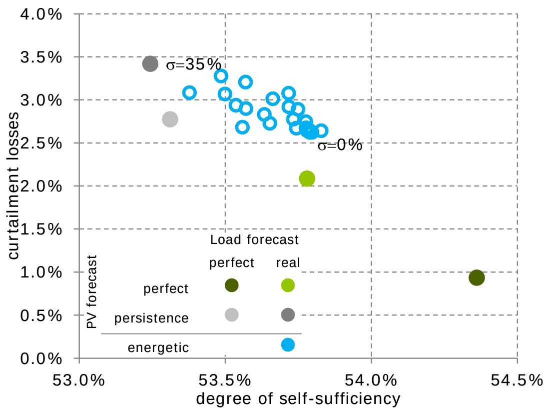

Figure 6: Influence of stochastic forecast errors on energy PV forecasts for dynamic feed-in limitation.

Furthermore, it is commonly known that the persistence approach is suitable for short time scales of PV forecasting [19]. Hence, it can be assumed that further forecast accuracy could be achieved by updating the PV forecasts during the day taking more recent measurements into account. This allows adapting the forecasts in the event of weather changes despite day ahead forecasts used before that have a constant accuracy over the forecasted period. In the following section such an adaptive approach is developed and applied to the operation strategy.

To implement the adaptive approach, a moving horizon $k_{\mathrm{pv,f}}$ over a horizon h is calculated with equation (14) to predict the upcoming generation output.

$$k_{\mathrm{pv,f}} = \frac{\int_{t-h}^{t} P_{\mathrm{pv}} dt}{\int_{t-h}^{t} P_{\mathrm{pv,max}} dt} \tag{14}$$

Note that the nighttime is excluded from the moving horizon so that only meaningful measurements are evaluated. It could be guessed that, if a short horizon is applied, the forecast adapts very quickly to changing weather conditions. Hence each cloud changes the forecast of the next 15 h. Whereas a greater h causes more average weather forecasts, which therefore are not affected by smaller bands of clouds. Figure 7 shows the influence of the horizon on the operational results. It is obvious that the horizon influences the operational behavior and leads to different combinations of curtailment losses and degrees of self-sufficiency nevertheless with a variation in the range of 0.15%.

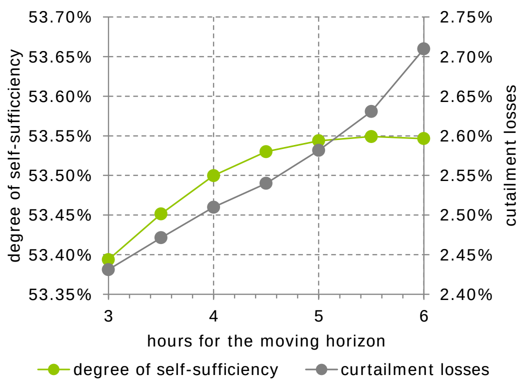

Figure 7: Energetic evaluation for an adaptive moving horizon PV-forecast for dynamic feed-in limitation.

An appropriate horizon could be obtained by following considerations; the system operation aims on the maximization of the degree of self-sufficiency, while minimizing curtailment losses. As a forecast with longer horizons is more average, less energy is forecasted and the battery starts charging earlier, hence the degree of self-sufficiency is increased but the forecast adaption to measurements is damped. Besides that, the minimum of curtailment can be found with shorter horizons and fast adaption. The opposed influence of the horizon length causes a problem of optimization. Apparently a horizon below 5 h shows a visible increase in the degree of self-sufficiency and a longer horizon will only increase curtailment losses. Therefore the optimum could be found at the break point of the curve. For that purpose a horizon h in the range of 4.5 h shows best annual performance for the case study. The performance of the investigated forecast approaches are finally compared in Figure 8. The advantage from the usage of adaptive PV forecast is compared to the PV persistence and real load forecasts a 1% higher infeed and a decrease of 0.3% in terms of grid supply. The gap towards operation with perfect PV and real load forecasts is decreased to 0.5% more curtailment and a 0.25% lower degree of self-sufficiency, which is close to the results of a commercial PV forecast investigated here [12]

The before mentioned results lead to the conclusion that energy forecasts are a simple but appropriate method as only a single value has to be forecasted. Secondly persistence forecasts are proper for shorter timescales and could therefore be used in a moving horizon to predict the near future with the nearby past. At least distinct improvements compared with persistence forecasts are possible using adaptive forecasts based on measured data.

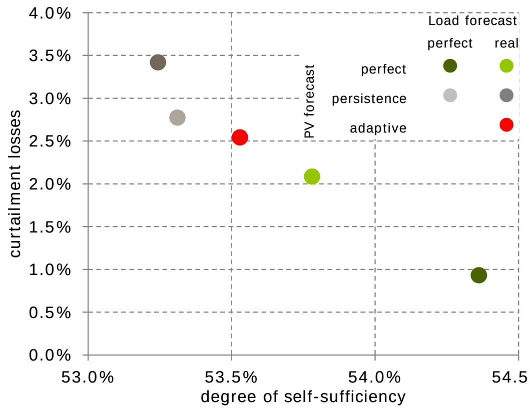

Figure 8: Comparison of the operational results of the adaptive forecast approach.

4 ECONOMIC EVALUATION

From a business economists point of view there are two perspectives on the operation of a PV battery system. First the investment decision with variability of system sizing, resulting in mean electricity costs over a given period [1,20]. The second perspective covers only the optimization of operational costs which includes the minimization of curtailment losses and maximization of the degree of self-sufficiency. In the previous section different forecast approaches were compared to rate their efficiency on energetic criteria within a dynamic feed-in operation. This section focuses on the comparison with the competitive conventional operation strategy.

4.1 Economic evaluation criteria

Regarding to the energetic criteria defined in section 3, operational results for different battery operation strategies could be financially valued. The differences of the curtailment losses Δl and the degrees of self-sufficiency Δd expose the benefits and disadvantages of the operation strategy with identical boundary assumptions.

$$\Delta l = l_{\text{conv}} - l_{\text{dyn}} \tag{15}$$

$$\Delta d = d_{\text{conv}} - d_{\text{dyn}} \tag{16}$$

Furthermore, the investigations in section 3 showed that dynamic feed-in causes a decreasing degree of self-sufficiency as well as decreasing curtailment losses. This could be financially expressed with; additional feed-in that increases the financial benefit while losses in the degree of self-sufficiency lead to a higher electricity bill because more energy has to be drawn from the grid. In order to illustrate this relation the balance of payment flows for adaptive PV forecast and real load forecasts is displayed in Figure 9.

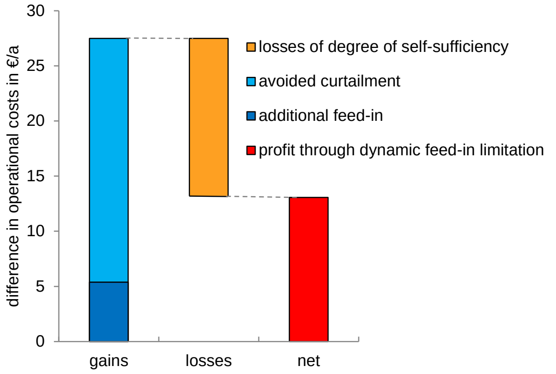

Figure 9: Balance of payment flows for the comparison of different operation strategies.

Furthermore this balance allows discounting the differences in the operational costs Δp.

$$\Delta p = \left(\Delta l \cdot E_{\text{pv}} + \frac{\Delta d}{\eta_{\text{bat}}} \cdot E_{\text{load}}\right) r_{\text{pv}} - \Delta d \cdot E_{\text{load}} c_{\text{gl}} \tag{17}$$

Therefore the feed-in-tariff r_{pv} multiplied with the total generated energy E_{pv} is the annual revenue from an only grid-feeding PV-system. The total load demand E_{load} multiplied with the retail electricity price c_{gl} marks the total annual electricity costs without a PV battery system. The expression $\Delta d/\eta_{\text{bat}} \cdot E_{\text{load}}$ calculates additional feed-in from the loss of degree of self-sufficiency by dividing it through the battery round tip efficiency. With that equation, relative expressions are possible were a positive Δp means that dynamic feed-in-limitation has economic advantages compared with conventional operation and money could be saved.

The economic evaluation is based on the assumptions shown in Table I. It is assumed that the feed-in tariff is 0.10 €/kWh and the retail electricity price is 0.32 €/kWh.

Table I: Assumption of the basic scenario

Retail electricity price	0.32 €/kWh
Feed-in-tariff	0.10 €/kWh

4.2 Economic evaluation results

The results of the economic evaluation in terms of differences in the annual operational costs compared with the conventional operation strategy are depicted in Figure 10. As the balance of the operational costs is positive for all forecast approaches, the dynamic feed-in limitation is more rewarding than the conventional operation strategy, independent of the forecast accuracy. Furthermore, Figure 10 shows that maximum potential gain is about 30 € per year whereas load forecast errors cause losses of about 12 €. When the persistence approach is also used for the PV forecast the profit margin is reduced to 5 € and adaptive PV forecasts could increase that margin up to 13 €.

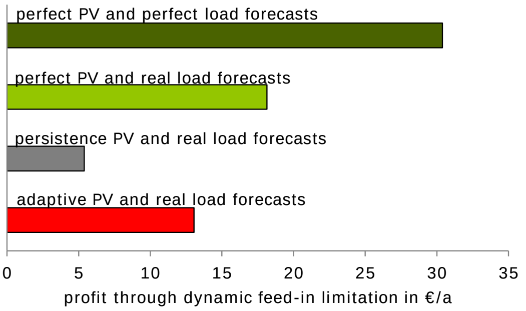

Figure 10: Annual profit through dynamic feed-in limitation considering different forecast quality.

Nevertheless, the aforementioned differences in the annual operational costs depend on the cost assumptions. With zero differences in the operational costs, the limit of profitability $c_{\text{gl,limit}}$ of the dynamic feed-in limitation can be calculated by transforming equation (17).

$$c_{\text{gl,limit}} = \left(\frac{\Delta l \cdot E_{\text{pv}}}{\Delta d \cdot E_{\text{load}}} + \frac{1}{\eta_{\text{bat}}}\right) \cdot r_{\text{pv}} \tag{18}$$

As the feed-in tariff r_{pv} is varied, the limit of profitability could be calculated for different cost assumptions, which is depicted in Figure 11, considering the simulation results of the adaptive PV forecast and real load forecast. It has to be pointed out that nowadays in Germany the feed-in-tariff depends only on the date of installation while the retail electricity price could change during the operational lifetime. Hence it is obvious that in this case study a system installed in the upcoming years should be operated with the dynamic feed-in-limitation in order to maximize the profits. It also reveals that sufficient remuneration for feed-in is needed; otherwise the effort for grid integration is reduced to the minimum.

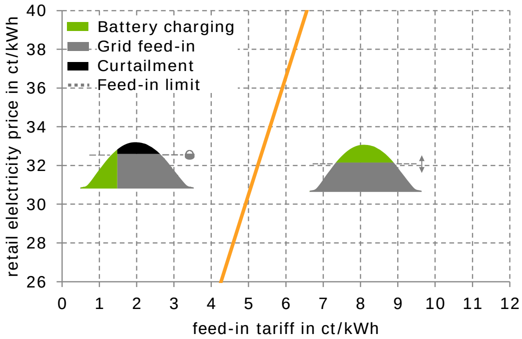

Figure 11: Limit of profitability of dynamic feed-in limitation.

Finally; a crucial point can be found in the assumption of a 50% feed-in-limitation despite that it is not comprehensively mandatory yet. In order to analyze the effect of divergent maximum feed-in on the economic results, the annual profit through dynamic feed-in limitation is plotted in Figure 12 with different regulatory feed-in limits. It reveals that an intelligent battery operation could be profitable over the spectrum of relevant feed-in limits. Since curtailment losses increase exponentially with conventional battery operation and decreased feed-in limits, dynamic feed-in limitation has an increased economic benefit because curtailment can be reduced minimum.

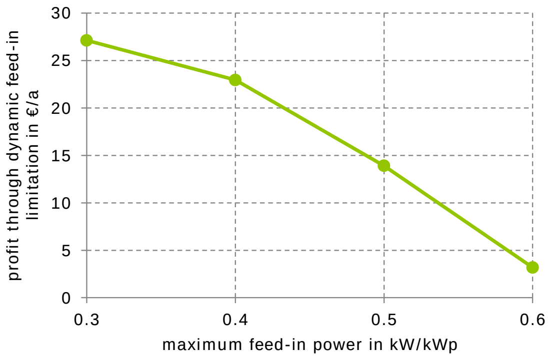

Figure 12: Annual profit through dynamic feed-in limitation as a function of the maximum feed-in limits.

The economic results can be summed up as follows; for the economic assessment of different operation strategies it is necessary to value the energy flows precisely and to take positive as well as negative aspects into account. Additionally, it could be shown that the reduction of curtailment is the major cost driver, which makes a dynamic feed-in limitation profitable even with persistence PV forecasts. Finally, the case study reveals that an intelligent battery operation with adaptive PV forecasts is economically reasonable over a long term considering the limit of profitability.

5 DISCUSSION

The results of this paper should be compared to the results of recent work and be classified in order to estimate whether they are sensitive or solid results.

First, the energetic assessment could be done by comparing the results to other studies, evaluating perfect and real forecasts. Riesen et al. show that forecast errors cause a loss in the degree of self-sufficiency of about 4% which could be lower with a 50% feed-in-limitation [11]. On the other hand, Williams et al. show 0.2-0.3% losses of the self-supply regarding a different operation strategy [2]. Zeh and Witzmann, but also Braam et al. agree on about 1.4-3% losses due to peak shaving operation with realistic forecasts in the middle of these results [7,8]. Especially the results of Moshövel et al. are interesting because they use persistence forecasts and are therefore a congruent approach with this paper. With slightly higher feed-in limits they found curtailment losses in the same range but higher losses in the degree of self-sufficiency regarding forecast errors [10]. To summarize, the energetic assessment could be found in the spectrum of recent work so that results seem to be comparable.

Due to the conception of case studies, they are not representative but they give a hint which paths should be further investigated. Therefore, model assumptions and input-data need to be proofed. First; the load profile could be called representative because characteristic quantities lay in the center of 75 measured households, referring to recent work of [21]. Secondly; also sizing of the system seems representative recognizing [1], hence it is not further discussed. Thirdly; as mentioned before, the site was chosen as representative comparing 25 weather stations in Germany. Fourthly; the economic validation could be done by comparison with results of [2]. It shows that similar assumptions deliver similar results, despite the forecast approach and control algorithm differs.

Whereas the assumptions and results seem to be reasonable, a critical view should be taken on the discounting approach. Besides the payment flow considering grid exchange, other economic quantities were neglected that were positively influenced by dynamic feed-in limitation. E.g., Li and Danzer pointed out that due to reduced dwelling time, the battery life time could be enhanced [5], hence the investment period could be extended. Furthermore reduced infeed could be the basis for further PV expansion in areas with depleted hosting capacity [9], which could enhance the value of peak shaving operation enormously.

6 CONCLUSION

The upcoming market of PV self-sufficiency submits new opportunities for PV grid integration. Thereby it is more than reasonable to operate batteries based on forecasts in a grid relieving mode. The discussed approaches need to prove feasible with regard to error-prone forecasts. This contribution could show what the inevitable losses due to simple load forecasts are and that even PV persistence is applicable with the developed algorithm. But a further development towards adaptive forecasts increases the advantages of a forecast based operation distinctly. On the basis of short time weather persistence a moving horizon forecast was developed which only needs measurement of the PV power time series. Further, the economic benefit of an adaptive forecast compared to persistence could be doubled up to tripled, which leads to the conclusion that modest forecast improvements have a significant impact. This implies that a commercial PV forecast product must be cheap to compete with autonomous forecasts.

Despite the advantages in the grid operator’s point of view for dynamic feed-in limitation it could be proven as beneficial for the system owner. The limit of profitability indicates up to what retail electricity price the PV battery system should be operated reasonably from an economical point of view, with a dynamic feed-in limitation. Current battery systems with a feed-in limit below 70% of the installed PV capacity could be operated economically over the next years with a dynamic feed-in limitation. For future systems it is essential that feed-in is sufficiently remunerated otherwise there is no incentive for improved grid integration. Finally, a revealing insight of Figure 12 is that the feed-in-limitation seems to be a major lever for politics to decide on how PV battery systems are to be operated. While a limit of 60% does not sufficiently enforce a peak-shaving operation, the regulation of feed-in below 50% of the installed PV capacity makes an intelligent operation mandatory.

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