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Impact of Shading on Energy Management Strategies

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Abstract. The rapid expansion of photovoltaics (PV) requires intelligent operational strategies for energy storage systems. These strategies help manage PV surpluses during peak generation periods, reducing grid stress while optimising storage system performance. By minimising long periods of high state of charge and maintaining efficient operating conditions, such strategies also help to extend the lifetime of storage systems. However, effective implementation requires accurate forecasting of both PV generation and load demand. This study investigates the impact of forecast errors caused by shading, in particular by stationary objects, on storage system operation. An adaptive forecasting approach that dynamically adapts to shading conditions was developed and compared to a non-adaptive method. The analysis, based on real PV generation and load data over ten days, showed that the adaptive approach reduced grid consumption by 24% and the time spent at high state of charge by 29%. These results highlight the potential of adaptive prediction models to improve the efficiency and durability of storage systems.

Keywords: Energy Management Strategies, Forecasting, Machine Learning, Energy Storage Systems

1. Introduction

The increasing deployment of distributed PV systems highlights the need for accurate PV power forecasting to optimize energy management systems (EMS). Forecast inaccuracies, particularly those arising from shading, can significantly affect the economic efficiency of operational strategies in residential battery storage systems. In this study, we investigate the influence of shading on forecast accuracy and its impact on an age-optimized charging strategy for a real home storage system. A data-driven approach is proposed to dynamically adjust forecasts based on shading conditions, thereby reducing errors and improving storage operation, with a conventional forecast serving as a benchmark.

There are several approaches to incorporate shading into forecasting models. Physical models can compensate for shading using geometric data, as demonstrated by Mayer et al. [1], who accounted for direct obstructions from nearby PV systems. Similarly, Masa-Bote et al. [2] employed statistical ARIMA models with correction factors to adjust predictions for shading effects caused by surrounding trees. Automated prediction frameworks, such as the AutoPV approach by Meisenbacher et al. [3], improve generalization by averaging pre-trained models, although they do not explicitly account for shading variability. Despite these advances, the validation of dynamic shading effects remains underexplored, even though it is critical for accurate predictive energy management.

PV forecasting is a core component of an EMS that optimizes self-consumption and guides the intelligent operation of batteries to enhance the economic return on investment. One well-established strategy is PV peak shaving, which avoids curtailment by delaying battery charging until the midday peak rather than storing excess energy earlier in the day [4]. Alternatively, an age-optimized charging strategy aims to mitigate the effects of calendar aging in battery chemistries such as NMC, LFP, and NCA by minimizing high state-of-charge (SOC) periods [5]. Barry et al. [6] proposed a forecast-based approach that determines the last possible charge time to minimize prolonged full charge states, thereby reducing calendar aging. Although aging-optimized strategies have been validated in real-world applications [7,8], the impact of PV forecast accuracy on these strategies remains largely unexamined. Forecast errors can lead to suboptimal energy dispatch, making it essential to incorporate advanced error mitigation techniques. For example, Stein et al. [9] compared different load forecasting models for small EV charging stations and evaluated their influence on operational costs. Their results indicate that precise load and generation forecasts reduce costs, highlighting the importance of advanced forecasting methods in cost-efficient EV charging operations. Jiang et al. [10] further contributed by proposing a stochastic online forecast-and-optimize framework for real-time energy dispatch in virtual power plants, effectively mitigating uncertainty through optimization. Additionally, Masa-Bote et al. [11] investigated the impact of PV generation forecast uncertainties on residential energy systems equipped with Demand-Side Management (DSM) and local storage. Their study demonstrated that integrating DSM and storage reduces energy exchange uncertainty with the grid, significantly improving self-consumption and grid stability. Finally, Gandhi et al. [12] reviewed the economic implications of solar forecasting errors across various applications, emphasizing that inaccuracies can significantly impact electricity market bidding, power system operations, and household energy management, ultimately leading to increased operational costs.

In summary, these studies emphasize the critical role of accurate forecasting in EMS and present various methods to mitigate forecast-induced inefficiencies. By integrating shading-aware forecasting techniques, this work addresses a major source of prediction error in PV generation, leading to improved energy storage utilization, reduced curtailment, and enhanced economic performance.

The novelty of this research lies in the direct integration of an adaptive, shading-aware forecasting approach into a real-world EMS and the systematic assessment of its impact on storage operation and self-consumption. While previous studies have considered forecast errors in energy management optimisation, they have primarily focused on general forecast inaccuracies rather than explicitly addressing dynamic shading effects. Existing forecasting models either rely on static correction factors, or use machine learning approaches that do not continuously adapt to changing shading conditions. In contrast, this study introduces a real-time adaptation mechanism that continuously refines PV power predictions based on observed shading deviations. By incorporating an adaptive drift detection algorithm, our approach dynamically adjusts forecasts to mitigate prediction errors caused by variable shading, an aspect that has been largely overlooked in previous research. Furthermore, while forecast improvements are often evaluated in isolation, our study goes beyond forecast error metrics by analysing the direct impact of adaptive forecasting on EMS performance. We quantify how reducing forecast errors affects storage utilisation, grid interaction and economic outcomes, providing empirical evidence of the operational benefits of adaptive forecasting. By bridging the gap between forecast adaptation and real-world EMS optimisation, this work provides novel insights into how shading-aware forecasting increases self-consumption, minimizes reliance on the grid, and improves battery longevity. This research advances the field by demonstrating that the ability to dynamically learn and correct for forecast deviations is critical to maximising the efficiency of distributed PV battery systems, particularly in environments where shading effects fluctuate over time.

2. Methodology

This study examines a real-world system, consisting of a photovoltaic (PV) system and a battery storage system, operated over several days using an energy management system (EMS). The EMS was designed to maximize self-consumption while ensuring optimization of battery ageing, based on forecasts of PV generation and load demand. Two forecasting models have been used, one with and one without consideration of PV shading. The aim of this analysis is to quantify the impact of these different forecasts on actual system operation. The methodology compares a conventional PV forecasting approach with an advanced adaptive model that dynamically updates its parameters when significant deviations in forecast errors occur. The adaptive model incorporates a drift detection mechanism to identify persistent errors in predicted PV power due to environmental changes such as shading. Once a drift is detected, the model is retrained using newly available data to maintain forecast accuracy. The methodology is structured as follows:

- The first subsection describes the System Configuration and Components, which includes the PV system, battery storage, and load profile used for the study.
- The second subsection introduces the Adaptive Forecasting Model, including its ability to respond to forecast errors and adapt dynamically.
- The third subsection presents the Energy Management Strategy, explaining how the forecasting models are integrated to optimize battery operation.

2.1 System Configuration and Components

In this study, a system at the Karlsruhe Institute of Technology (KIT) was used to assess the impact of improved forecasting on the strategy of the EMS. The system consists of a PV system, a battery storage system and a building load. A characteristic of the PV system is the presence of a chimney, which casts shadows on the modules throughout the day (see Figure 1).

Figure 1. *Shaded PV System*

The PV system has an installed capacity of 7.2 kWp and is connected to the grid. As the system is undersized for the task, it is effectively scaled to a 10 kWp system for the study. The power for a sunny day, shown in Figure 1, clearly illustrates the shading effects on the modules throughout the day. To optimize the use of the PV system and increase the self-consumption, a battery storage system with a capacity of 10.2 kWh and a charging capacity of 10 kWp was integrated. Like the PV system, the battery storage system is connected to the grid on the AC side. A realistic load profile from the ADRES [13] research project at the Vienna University of Technology was used for the building load. The load data, recorded with a resolution of one second, includes both three-phase active and reactive power from 30 households. For this study, household 6 was selected as a representative profile with an annual energy consumption of 3756 kWh. This profile was chosen to ensure a sufficient load for optimal battery capacity utilization during the evaluation period.

2.2 Adaptive Forecast

Accurate solar power forecasting is essential for efficient energy management, but traditional machine learning models rely on historical training data and lack mechanisms to adapt to environmental changes such as shading. This limitation can lead to unreliable predictions when real-world conditions differ from those observed during training. To overcome this, an adaptive forecast model is proposed that incorporates a drift detection mechanism that continuously evaluates forecast errors and updates the model when persistent deviations occur.

2.1.1 Description of Dataset

The dataset used in this study consists of two separate datasets, one for the PV power forecasting and one for the drift detection.

The first dataset is used for PV forecasting. It includes meteorological weather forecasts from the ICON-D2 model, which provides forecasts with a spatial resolution of 2 km and a temporal resolution of 15 minutes, providing forecasts up to two days ahead. This dataset also includes PV power data measured on site from the previous day to improve forecast accuracy. Global Tilted Irradiance (GTI) and other irradiance variables such as Direct Tilted Irradiance and Diffuse Tilted Irradiance are calculated using PVLib [14] based on the weather forecast and location.

The following PV-specific variables are included in the forecast model in addition to the meteorological variables used in the forecast dataset to improve forecast accuracy:

- Solar elevation angle
- Solar azimuth angle
- Lagged power from the previous time step

Feature importance analysis performed on the forecast dataset shows that GTI and sun elevation are the most influential predictors, with importance scores of 0.94 and 0.90 respectively. The second dataset is used for drift detection and consists of historical weather data and corresponding historic PV power data. For drift detection, the model integrates historical weather data from the European Centre for Medium-Range Weather Forecasts - Integrated Forecasting System (ECMWF IFS). The following meteorological variables are used as inputs to evaluate differences between the ideal unshaded system power and the actual PV power output:

- Global tilted irradiance (GTI)
- Air temperature at 2 meters

These references help to identify persistent errors in PV power forecasts caused by environmental changes such as shading or other factors, thereby improving forecast accuracy over time.

2.1.2 Drift Detection and Adaptive Learning

The prediction model is pre-trained on an unshaded reference PV system with a total installed power of 10 kWp, with a tilt of 30° and a south orientation of 0°. The system described in section 2.1, which operates under an EMS, has a PV array that is affected by shading from a chimney. The shading effect results in deviations in power generation, making it different from the idealized unshaded system. In order to account for the differences between the unshaded reference system and the shaded PV system used in the EMS, the model uses a PV power model. This model generates the power of the idealized unshaded system, which is then compared with the actual measured power of the shaded PV system. This reference power output is obtained using a PV model that estimates the maximum possible power generation under given environmental conditions. The Feiman model [15] is used to estimate the module temperature T_{module} based on the ambient air temperature T_{air} and the global tilted irradiance E_n. The relationship is given by:

$$T_{\text{module}} = T_{\text{air}} + \frac{\mathrm{E}_{POA}}{U_1}$$

where T_{module} is the module temperature, T_{air} is the ambient air temperature, E_{POA} is the solar irradiance, and U_1 is the heat loss coefficient of $25\frac{\mathrm{W}}{\mathrm{m^2K}}$. While the Feiman model includes an additional term that incorporates wind speed to better account for convective heat loss, this term will be neglected in this study. This is due to the fact that the historic wind speed forecast data does not exhibit a meaningful correlation with the actual wind speed, rendering its inclusion unnecessary for the purpose of this analysis. Using the estimated module temperature, the ideal PV power output P_{ideal} is computed as:

$$P_{\text{ideal}} = \eta \times A \times E_{\text{POA}} \times \left(1 + \alpha \times (T_{\text{module}} - T_{\text{ref}})\right)$$

where η is the efficiency of the PV module, A denotes the total surface area of the PV modules, α is the temperature coefficient of power, and T_{ref} is the reference temperature. This ideal power output provides a baseline for assessing the accuracy of the forecasted power. If the measured power is significantly lower than the ideal power, it may indicate shading or other environmental disturbances affecting the PV system.

The error at time index n, denoted as e_n, is calculated as the difference between the measured PV power output, P_{measured}, and the predicted output from the PV performance model, P_{model}:

$$e_n = P_{\text{measured}_n} - P_{\text{forecasted}_n}$$

Significant and persistent deviations in e_n indicate that the model is no longer well calibrated to current conditions. To enhance sensitivity to shading-induced errors, the error is first segmented into specific time slots, reflecting typical shading patterns. This targeted approach improves drift detection by isolating periods with higher forecast deviations. The ADaptive WINdowing (ADWIN) drift detection algorithm is then applied separately to each time slot. ADWIN dynamically adjusts the window size based on the error distribution, ensuring an optimal balance between sensitivity and stability. It is based on a sliding window of past observations and detects statistically significant changes in the mean of the incoming data stream. When such a change is detected, the model is retrained using the latest available data, ensuring continuous adaptation to environmental changes.

The forecasting model is based on a neural network architecture with two LSTM layers of 60 neurons each. These layers are followed by a fully connected layer with 15 neurons, and a tanh activation function is applied between the layers. The model is trained using the Adam optimizer with a learning rate of $1 \cdot 10^{-3}$. A batch size of $96 \cdot 7$ samples is used, and early stopping is implemented with a validation patience of 10 epochs.

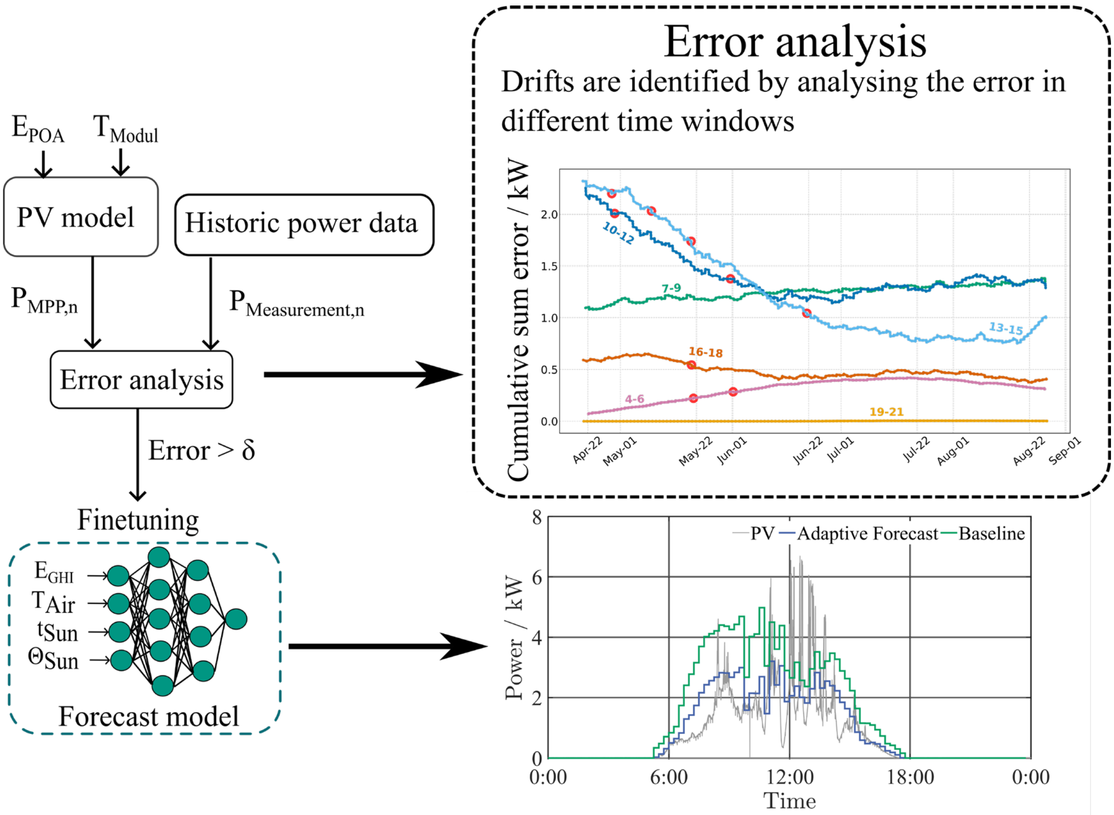

Figure 2. *Overview of proposed forecast approach*

2.3 Energy Management Strategy

The EMS used in this study can be described as a two-tier system. The higher-level control unit calculates the battery's charging and discharging power based solely on the actual PV generation and building load. In doing so, it must comply with the operational power limits in the charging direction, which are dynamically adjusted by the lower-level control unit to optimize battery aging behaviour.

In this context, the low-level control unit plays a crucial role in minimizing the operationally accelerated calendar aging of the battery. Accelerated aging occurs particularly when the lithium-ion battery (LIB) is charged to a high state of charge too early and remains unused for a significant portion of the day [5]. To mitigate this effect, the EMS schedules the charging process so that the battery is fully charged only at the latest possible time when PV surpluses are still available. To determine this point in time, the EMS utilizes forecasts of PV power generation and load demand. These forecasts are not only used to define the optimal charging time but also to recursively plan the entire charging process using a state-of-charge prediction algorithm. Such an algorithm was first introduced by Barry et al. [6] and later applied to real-world systems in studies by Palaniswamy et al. [7] and Strobel et al. [8]. In these studies, the algorithm by Barry et al. was extended with logic that considers only efficient charging power levels of the storage system. The specific methodology used by the algorithm for charge planning is described in detail in the following section.

1. Forecasting PV and Load Power: In the first step, the algorithm retrieves the forecasts for PV power generation and building load applicable to the current day. The PV power forecasts used in this study are described in Chapter 2.2. A perfect forecast is assumed for the building load, ensuring that only uncertainties in the PV forecast impact the EMS, while deviations in the load forecast are excluded. Therefore, the load forecast is defined as the actual ADRES power profile, averaged to a 15-minute resolution.

2. Calculating the optimized end of charge: To determine the last point in time with PV surplus, up to which the battery storage should be fully charged, the forecasts of load and PV power generation are compared. Starting from the end of the day, each value of the PV forecast is recursively analyzed against the load forecast. The latest time at which PV generation exceeds the load, thereby creating a surplus, defines the charging end time. After this point, no further battery charging is possible, and the storage system is only discharged until the following day.

3. SoC Prediction Algorithm: Based on the planned end of charging, the EMS predicts the battery's SoC. For this purpose, it utilizes an integrated battery model that accounts for energy content while considering inverter and battery losses. The simulation is performed recursively, starting from the planned end of charging and moving backward in time until the predicted SoC matches the current SoC. This point then defines the start of charging. In each time step, the predicted available PV surplus that can be stored in the battery is calculated. Based on this power, the initial SoC required to reach the planned end SoC, assuming charging exclusively from PV surplus, is determined. This process is iteratively repeated for all preceding time steps. The algorithm terminates under two conditions: either when the computed initial SoC matches the current system SoC, or when all time steps up to the beginning of the day have been simulated without reaching the current SoC. An additional feature of this algorithm segment is the consideration of an efficient charging power threshold to limit excessive charging rates and prevent unnecessary losses. In this study, the efficient charging power was set to -3 kW, meaning that all charging power values below this threshold are capped at -3 kW. The whole Process can be described by the diagram in fig. 3.

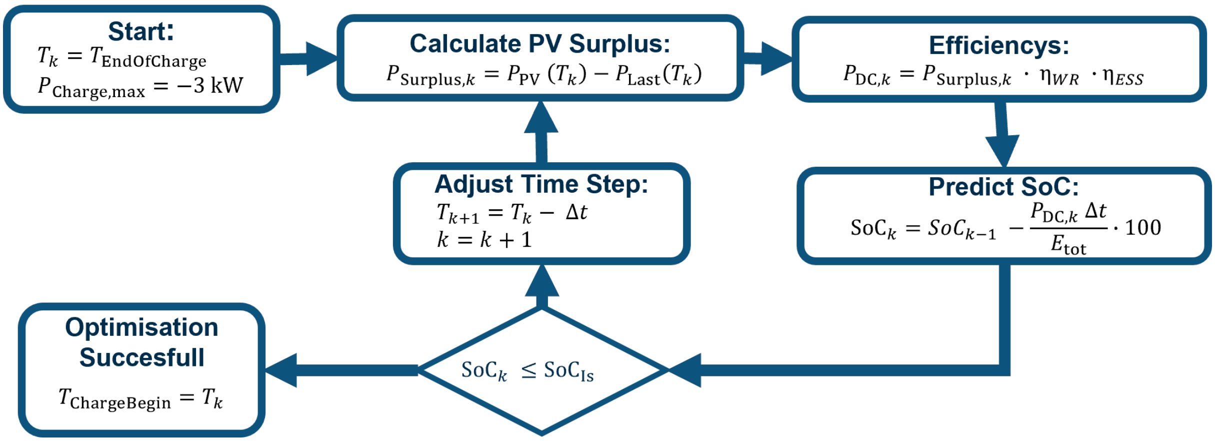

Figure 3. *SoC prediction algorithm in the lower-level controller to optimize calendar ageing*

By implementing the lower-level control unit, the start of charging is delayed to the latest possible time. Fig. 4 illustrates this behaviour and compares the simulated operation of an EMS with and without lower-level control. Without this control, the battery would be fully charged by approximately 12:00. In contrast, the optimized EMS delays the charging process to the latest possible time when PV surplus is available. This approach reduces the battery's dwell time at the maximum SoC thereby mitigating operationally induced calendar aging.

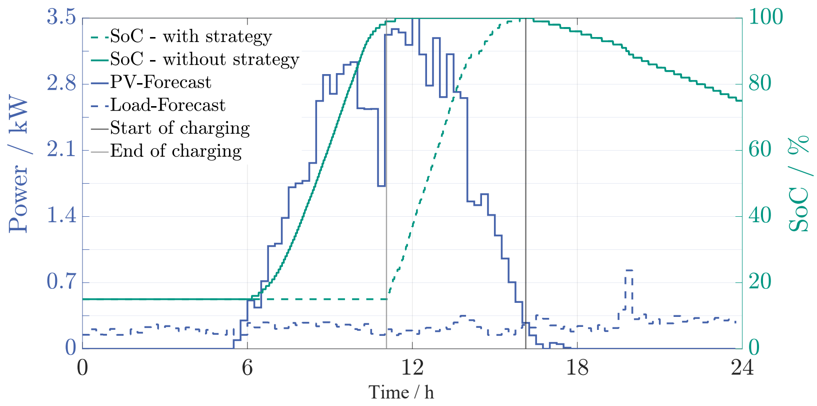

Figure 4. *Comparison of SoC development with and without lower-level controller within the EMS*

3. Results

The results are structured in two sections: first, the improvements in forecast accuracy achieved through the adaptive approach are presented, followed by an analysis of how these improvements impact the EMS.

3.1 Forecast Accuracy Improvements

In the first stage, the performance of the adaptive forecasting model is evaluated by comparing the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for both shaded and unshaded PV arrays. For the unshaded array, the MAE is 0.39 kW, and the RMSE is 0.79 kW. In contrast, for the shaded array without any adaptation, the MAE increases to 0.54 kW and the RMSE to 1.09 kW, highlighting the significant impact of shading on prediction errors. However, after applying the adaptive approach, the RMSE is reduced to 0.51 kW, and the MAE to 0.31 kW. This demonstrates a 53.2% improvement in RMSE and a 43.6% improvement in MAE, confirming the effectiveness of the drift detection and retraining mechanism in maintaining forecast accuracy under dynamic shading conditions.

3.2 Impact on Energy Management System

In the second stage, the impact of improved forecasts on EMS operation is analyzed. The SoC deviation of the battery is significantly reduced from 32% to 6.8% (see Figure 4a), ensuring more stable and reliable operation. Additionally, improved forecast accuracy leads to a reduction in overall grid consumption over a four-day period by 2 kWh, as the enhanced predictions enable better scheduling of charging and discharging processes, minimizing unnecessary reliance on the grid. This optimization also results in an increase in cost savings from -0.20 EUR to 0.86 EUR (see Figure 4b), reflecting the financial benefits of reduced grid consumption. Furthermore, the deviation in the optimal crossover time is reduced to 14 minutes, compared to 52 minutes in the baseline forecast (see Figure 4c), demonstrating the efficiency gains achieved through the adaptive forecasting approach.

The improvements in EMS performance can be directly attributed to the reduction in prediction errors caused by shading. When shading effects are not taken into account, the PV power output is systematically overpredicted. This overprediction results in a delayed start of battery charging, as the system expects higher future generation than actually occurs. As a result, the storage system is charged too late, preventing it from reaching 100% SoC. Even more critically, this delay increases the frequency of periods of low SoC, which in turn increases the risk of increased consumption from the grid in the evening, when the PV generation is no longer available. Without adaptation, the EMS operates on the assumption of inaccurate forecasts, resulting in sub-optimal charging schedules. To match the performance of the adaptive model, the start of the charge would need to be reduced by an average of 52 minutes, bringing the battery charge cycle more in line with actual PV generation. This highlights the need for an adaptive learning mechanism that continuously adapts to dynamic environmental conditions, ensuring that charging strategies remain optimal despite variations in shading patterns.

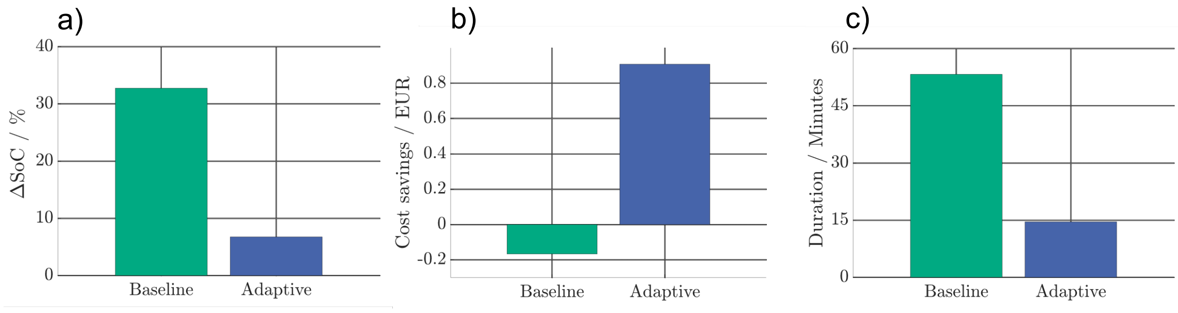

Figure 5. *a) Deviation from 100% SoC at the end of the load period for both adaptive and baseline forecasts. b) Cost savings achieved by the EMS using the adaptive and baseline forecasts. c) Deviation in true crossover time between adaptive and baseline forecasts.*

Moreover, the adaptive forecasting model improved the distribution of the SoC. Periods with a high SoC were reduced by up to 29% as seen in Figure 5 compared to a scenario without a dedicated charging strategy. In the reference forecast, inaccurate predictions often resulted in a lower SoC, forcing the system to rely more heavily on the grid. The improved forecast, however, ensured a more balanced distribution of stored energy, allowing the system to make better use of its available resources.

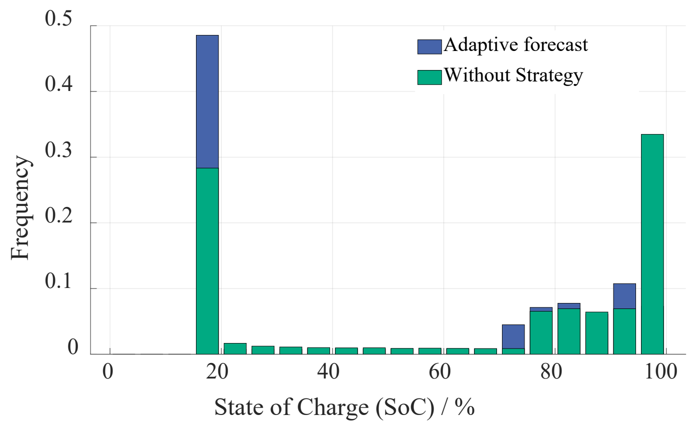

Figure 6. *Impact of adaptive forecast on SoC distribution*

The economic impact of these improvements was also substantial. High forecasting errors typically lead to increased costs, as inaccurate predictions result in suboptimal battery operation and greater grid consumption. In the reference forecast, a lower SoC meant that more electricity had to be drawn from the grid, increasing operational expenses. By reducing forecasting errors, the adaptive approach minimized these additional costs, improving the overall economic efficiency of the energy system.

These findings underscore the necessity of adaptation mechanisms in PV power forecasting. The ability to adjust to dynamic environmental changes, such as shading, not only ensures more accurate predictions but also enhances energy management and delivers significant economic benefits.

4. Discussion

The findings highlight the critical role of adaptive learning in PV power forecasting, particularly in addressing the challenges posed by environmental variability. Traditional forecasting models struggle with dynamic factors such as partial shading, as observed in this study. The chimney-induced shading introduced localized fluctuations in solar irradiation that a static model failed to capture accurately, leading to systematic forecast errors. In contrast, the adaptive model effectively detected these variations and adjusted its predictions accordingly, significantly improving forecast accuracy. Beyond predictive accuracy, the benefits of adaptive forecasting extend to energy storage optimization and grid reliance. A well-balanced SoC distribution reduces grid dependence and enhances battery utilization, leading to lower operational costs and improved system efficiency. The observed reduction in avoidable grid consumption underscores the potential for adaptive forecasting to increase self-sufficiency in PV-based energy systems. Moreover, the improvement in SoC stability ensures that stored energy is more effectively allocated, minimizing periods of low charge that could otherwise force reliance on external power sources.

However, one limitation of this approach is its reliance on real-time data availability. Any disruptions in data transmission or sensor failures could delay model retraining, temporarily reducing the effectiveness of the adaptation mechanism. Future work should focus on enhancing system resilience against data interruptions by integrating predictive maintenance for sensors or hybrid forecasting strategies that combine adaptive learning with physical modeling techniques.

In conclusion, this study demonstrates that adaptive forecasting is essential for accurate PV power predictions in dynamically changing environments. By incorporating drift detection and continuous retraining, forecasting models can maintain high accuracy, ultimately improving energy management and economic performance. Future research should explore the scalability of this approach, particularly its applicability to PV systems with more complex environmental conditions, to further optimize distributed energy resource management.

Data availability statement

The authors do not have permission to share data.

Author contributions

Tim Kappler: Conceptualization, Methodology, Software, Investigation, Writing-Original Draft, Visualization, Resources. **Lukas Strobel**: Conceptualization, Methodology, Software, Investigation, Writing-Original Draft, Visualization, Resources. **Nina Munzke**: Writing - Review & Editing, Supervision, Project administration, Funding acquisition. **Bernhard Schwarz**: Writing - Review & Editing, Supervision, Project administration. **Marc Hiller**: Project administration, Funding acquisition.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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