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Risk-Aware Rolling-Horizon Scheduling of a PV–Battery–EV Charging Station via Adaptive Conformal Prediction

Baihan Cheng, Laiqing Yan *, Xiaorui Nan and Boya Sun

College of Electric Power and Architecture, Shanxi University, Taiyuan 030006, China

* Correspondence: yanlq@sxu.edu.cn

Abstract

To mitigate the impact of inaccurate forecasts of electric vehicle charging load and photovoltaic power generation on the operation of PV–storage–charging systems, a risk-aware adaptive conformal rolling-horizon scheduling method is proposed. First, a net-load point forecast is constructed from the forecasts of electric vehicle charging load and photovoltaic generation, and a one-sided conformal upper bound is derived using historical forecast residuals. Subsequently, the conformal calibration parameter is updated online based on the miscoverage outcomes of completed forecasts, enabling the net-load upper bound to adapt to recent changes in forecast errors. Finally, the dynamic upper bound is incorporated into model predictive control to achieve rolling-horizon optimization of battery charging and discharging as well as grid power purchase and sale. The results show that, compared with the fixed conformal method, the proposed method improves the event-period coverage rate and reduces the number of event-period miscoverage instances. Compared with the point-forecast method, it reduces low-SOC exposure and enhances the system’s capability to cope with net-load forecast errors at a relatively low cost.

Keywords: PV–storage–charging station; net-load forecasting; adaptive conformal prediction; model predictive control; rolling optimization

1. Introduction

With the continued growth in electric vehicle ownership, PV–storage–charging stations integrating photovoltaic generation, battery energy storage, and charging facilities have increasingly become an important means of enhancing renewable energy accommodation, alleviating grid load pressure, and reducing charging energy costs [1,2]. Affected by factors such as vehicle arrival time, initial state of charge, charging demand, and dwell time, EV charging load exhibits considerable randomness and variability, and related research has gradually expanded from deterministic forecasting to probabilistic forecasting and risk assessment [3,4]. Meanwhile, PV power output is also subject to substantial forecast errors due to solar irradiance, cloud cover, and other meteorological conditions [5]. The operational scheduling of PV–storage–charging systems generally relies on forecasts of future load and PV power output. When the actual EV charging load exceeds its forecast, or the actual PV power output falls below its forecast, the actual net load will exceed the predicted value. If such deviations persist over multiple consecutive time periods, they may lead to insufficient advance preparation of the battery energy storage system, a sustained decline in its state of charge, and increased grid electricity purchases during high-price periods. Therefore, appropriately characterizing net-load forecast risk and incorporating



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it into rolling-horizon scheduling is an important issue for improving the operational performance of PV–storage–charging systems.

For the optimal operation of PV–storage–charging systems, existing studies have developed optimization models for charging-load management, energy-storage configuration, and station-level energy management [6]. In particular, the coordinated configuration of PV generation and energy storage can reduce peak grid power and operating costs, while the joint optimization of charging-load profiles and battery charging and discharging schedules can improve PV utilization and equipment utilization efficiency [6,7]. However, such day-ahead or open-loop optimization methods generally generate a complete schedule in a single run based on a given forecast trajectory. When the actual load, PV power output, or battery state deviates from the forecast, the original schedule may be difficult to revise in a timely manner.

Model predictive control can re-solve the optimization problem at each operating time using the latest forecasts and system states, while implementing only the first control action for the current period. It is therefore well suited to the continuous operation of PV–storage–charging systems. In recent years, MPC has been applied to grid-connected charging microgrids, DC fast-charging stations with embedded PV and energy storage systems, and fast-charging systems with reconfigurable battery storage to achieve peak shaving, PV self-consumption, and battery energy management [8–10]. However, the effectiveness of closed-loop MPC scheduling still depends on the forecast inputs. When EV charging-load or PV forecast errors remain persistently biased in the same direction, rolling updates can correct state deviations that have already occurred but cannot directly provide a risk margin against future net-load underestimation. Consequently, the battery energy storage system may still be insufficiently prepared.

To address uncertainties in renewable generation and charging demand, existing studies have employed stochastic optimization to formulate multi-scenario scheduling models [7], two-stage robust optimization to improve the adaptability of scheduling decisions to adverse scenarios [11], and data-driven distributionally robust optimization to characterize uncertainty in the underlying probability distribution [12]. Related reviews and methodological studies have further summarized the modeling and solution approaches of stochastic programming and robust optimization for uncertainty management in power systems [13,14]. Recent research has also considered the joint uncertainties of vehicle-side demand and renewable generation in coupled microgrid–transportation systems, using uncertainty-aware energy management to balance operational risk and conservativeness [15]. These methods can improve the operational security of scheduling decisions. However, stochastic optimization generally requires a prespecified probability distribution or the generation of representative scenarios, whereas robust and distributionally robust optimization require the construction of uncertainty sets or ambiguity sets, with their risk levels and degrees of conservatism generally determined in advance.

In recent years, conformal prediction has increasingly been applied to uncertainty quantification in energy forecasting. It augments an existing point-forecast model with a calibration step and constructs prediction intervals that attain a target marginal coverage level based on historical nonconformity scores. Its main features include model agnosticism, weak distributional assumptions, and a clear finite-sample coverage interpretation [16]. In the energy sector, conformal calibration has been used to improve the reliability of probabilistic PV forecasts [17], and the resulting PV forecast bounds have been further incorporated into stochastic decision-making in electricity markets [18]. Related methods have also been applied to electricity price forecasting and energy storage arbitrage [19], very-short-term solar power forecasting [20], building heating and cooling load forecasting [21], and wind-speed and wind-power forecasting [22,23]. These studies demonstrate that

conformal prediction can not only characterize forecast errors but also provide risk bounds with explicit coverage interpretations for subsequent operational optimization. For PV-storage-charging systems, underprediction of EV charging load and overprediction of PV power output both cause the actual net load to exceed its point forecast. Therefore, constructing a one-sided upper bound directly for the net load more closely targets the risk of insufficient energy supply from the energy storage system than constructing separate two-sided intervals for load and PV generation.

However, fixed conformal methods typically determine empirical quantiles using a fixed calibration set and a fixed target miscoverage rate. When charging demand, weather conditions, or forecast-error characteristics undergo temporal drift, the resulting fixed bounds may experience consecutive miscoverage over short periods. To address non-stationary time series and online distributional changes, recent studies have extended conformal prediction through horizon-wise independent calibration for multi-step-ahead forecasting [24], joint construction of multi-horizon prediction intervals [25], learning-rate-free adaptive updating [26], online coverage control under arbitrary distribution shifts [27], adaptation to change points [28], and the construction of prediction regions for multivariate time series [29]. Studies on adaptive conformal prediction for time series and weighted calibration for non-exchangeable data have also provided a methodological basis for miscoverage feedback and distribution-shift handling [30,31]. Existing studies mainly focus on the coverage and width of prediction intervals themselves or incorporate conformal outputs into decisions such as electricity market trading. Research on the “dynamic one-sided net-load upper bound-energy storage MPC-closed-loop state feedback” framework for PV-storage-charging systems remains relatively limited, particularly regarding systematic analysis of the relationships among event-period coverage, low-SOC exposure, battery energy throughput, and economic cost under persistent net-load underestimation.

To this end, this paper proposes a risk-aware adaptive conformal rolling-horizon scheduling method for PV-storage-charging systems. First, a net-load point forecast is constructed from the forecasts of EV charging load and PV power output, and horizon-specific historical residual calibration sets are established to form fixed one-sided conformal upper bounds. Second, miscoverage is identified using forecasts for which the corresponding actual observations have become available, and the conformal calibration parameter for each forecast lead is updated online to generate a dynamic net-load upper bound that reflects recent changes in forecast errors. Finally, the dynamic upper bound is incorporated into model predictive control to perform rolling-horizon optimization of battery charging and discharging as well as grid power purchase and sale decisions. Point-forecast MPC, fixed conformal MPC, and adaptive conformal MPC are compared to evaluate how different risk characterization methods affect the closed-loop operation of the PV-storage-charging system in terms of net-load upper-bound coverage, battery state of charge, battery energy throughput, and operating economics.

2. Operational Model of the PV-Storage-Charging Station

2.1. System Configuration and Net Load

The system configuration and information flows of the PV-storage-charging station are shown in Figure 1. The system consists of the utility grid, PV generation system, battery energy storage system, and a cluster of EV chargers. Forecasts of EV charging load and PV power output are first fed into the risk forecasting module to generate the future net-load trajectory. The rolling-horizon optimization module then determines the battery charging and discharging schedule as well as the grid power purchase and sale schedule based on the current state of the battery energy storage system and the time-of-use electricity tariff. In this study, EV charging load is treated as an exogenous forecast quantity, and vehicle

charging schedules are not further optimized. The main decision variables are battery charging and discharging power and grid power purchase and sale.

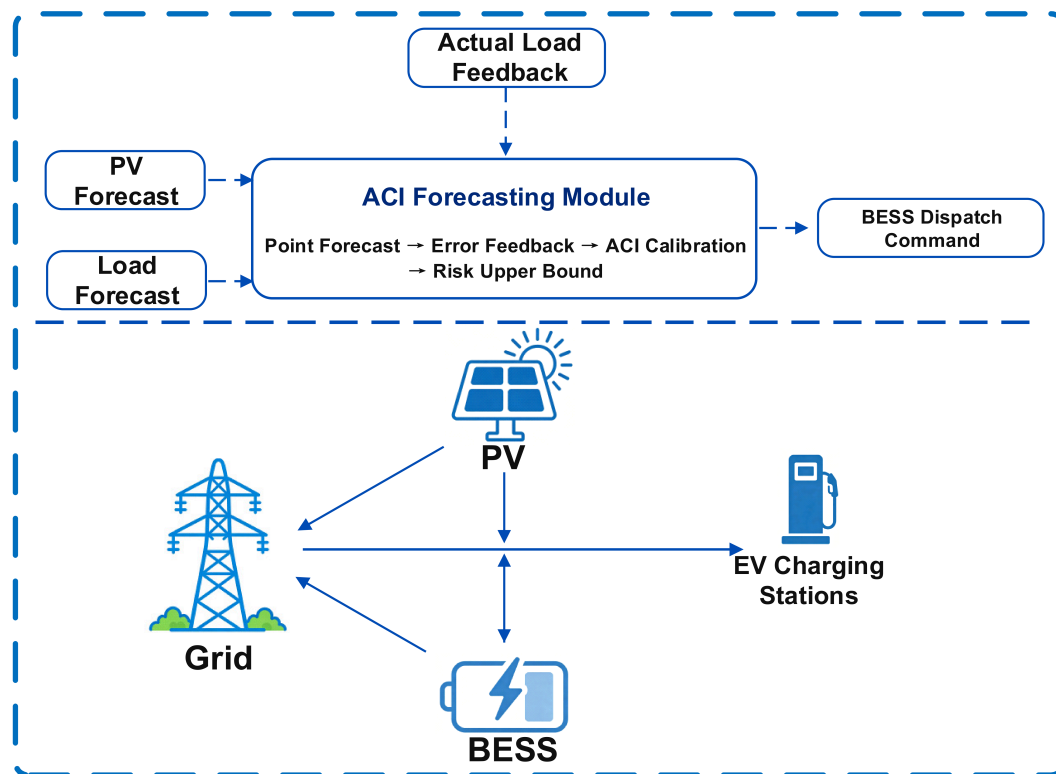


Figure 1. System configuration and scheduling framework of the PV-storage-charging station.

When PV power output is insufficient to meet the charging demand, the power deficit is supplied by battery discharging and grid power purchase. When PV power output exceeds the charging demand, the surplus energy can be used to charge the battery or be sold to the grid. To provide a unified representation of variations in EV charging load and PV power output, net load is used to characterize the power deficit or surplus within the station.

The actual net load in period t is defined as follows:

$$L_t = P_t^{\text{EV}} - P_t^{\text{PV}} \quad (1)$$

where P_t^{EV} and P_t^{PV} denote the EV charging power and PV power output in period t , respectively, and L_t is the corresponding net load. When $L_t > 0$, the system has a power deficit that must be supplied by the battery energy storage system or the grid; when $L_t < 0$, surplus PV power is available. Underprediction of EV charging load and overprediction of PV power output both cause the actual net load to exceed its forecast. Therefore, the subsequent conformal method directly constructs a one-sided risk upper bound for the net load.

2.2. Power Balance and Battery Energy Storage Model

Within each scheduling period, the system must maintain the balance between power supply and demand. Grid power purchase and battery discharging constitute the power inputs, which are used to meet the net load, battery charging demand, and grid power export. The power balance relationship is given by the following:

$$P_t^{\text{buy}} + P_t^{\text{dis}} = L_t + P_t^{\text{ch}} + P_t^{\text{sell}} \quad (2)$$

where P_t^{buy} and P_t^{sell} denote the grid power purchase and sale, respectively, and P_t^{ch} and P_t^{dis} denote the battery charging and discharging power, respectively. This relationship applies both to the actual operating period and as a fundamental constraint for each period within the rolling prediction horizon.

The stored energy is updated according to the charging and discharging power and the corresponding efficiencies in the current period. The state transition equation is given by the following:

$$E_{t+1} = E_t + \eta_c P_t^{\text{ch}} \Delta t - \frac{P_t^{\text{dis}} \Delta t}{\eta_d} \quad (3)$$

where E_t and E_{t+1} denote the stored energy in two consecutive periods, η_c and η_d denote the battery charging and discharging efficiencies, respectively, and Δt is the scheduling interval. During charging, the effective energy stored in the battery is determined by the charging efficiency; during discharging, the energy consumed on the battery side is greater than the energy delivered to the system.

To ensure that the battery energy storage system operates within its allowable range, the state of charge and charging/discharging power satisfy the following:

$$\text{SOC}_t = \frac{E_t}{E^{\text{cap}}}, \quad \text{SOC}^{\min} \leq \text{SOC}_t \leq \text{SOC}^{\max} \quad (4)$$

$$\begin{cases} 0 \leq P_t^{\text{ch}} \leq P^{\text{ch},\max}, \\ 0 \leq P_t^{\text{dis}} \leq P^{\text{dis},\max}. \end{cases}$$

where E^{cap} denotes the rated energy capacity of the battery energy storage system, SOC_t is the state of charge in period t , $\text{SOC}^{\min}$ and $\text{SOC}^{\max}$ denote the allowable lower and upper SOC limits, respectively, and $P^{\text{ch},\max}$ and $P^{\text{dis},\max}$ denote the maximum charging and discharging power, respectively. The SOC limits prevent overcharging and overdischarging, while the power limits represent the actual regulation capability of the battery energy storage system.

In addition, to avoid simultaneous charging and discharging within the same period, a binary status variable z_t is introduced together with the following mutually exclusive constraints:

$$\begin{cases} 0 \leq P_t^{\text{ch}} \leq z_t P^{\text{ch},\max}, \\ 0 \leq P_t^{\text{dis}} \leq (1 - z_t) P^{\text{dis},\max}, \end{cases} \quad z_t \in \{0, 1\} \quad (5)$$

When $z_t = 1$, battery charging is allowed while discharging is prohibited; when $z_t = 0$, battery discharging is allowed while charging is prohibited. Equations (3)–(5) describe the state evolution and operating limits of the battery energy storage system during rolling-horizon scheduling.

2.3. MPC-Based Rolling-Horizon Optimization Model

At rolling instant t , the model takes the current stored energy as the initial state and jointly optimizes battery charging and discharging as well as grid power purchase and sale over the next H periods. The objective is to minimize the net electricity purchase cost over the prediction horizon, and the objective function is given by the following:

$$\min J_t = \sum_{h=1}^H \left(c_{t+h}^{\text{buy}} P_{t+h}^{\text{buy}} - c_{t+h}^{\text{sell}} P_{t+h}^{\text{sell}} \right) \Delta t \quad (6)$$

where c_{t+h}^{buy} and c_{t+h}^{sell} denote the electricity purchase price and selling price, respectively, in the h -th future period. Electricity purchase costs are included in the operating cost, while revenues from electricity sales are deducted. Since the electricity purchase price is no lower

than the selling price within the same period, the optimal solution generally does not result in economically ineffective simultaneous power purchase and sale.

To compare the effects of different risk characterization methods on closed-loop operation, three methods are considered: point-forecast MPC, fixed conformal MPC, and adaptive conformal MPC. The three methods use the same objective function, equipment parameters, and physical constraints, and differ only in the future net-load trajectory introduced into the MPC power-balance constraints:

$$\begin{aligned} L_{t+h|t}^{\text{in,Point}} &= \hat{L}_{t+h|t} \\ L_{t+h|t}^{\text{in,FCP}} &= U_{t+h|t}^{\text{FCP}} \\ L_{t+h|t}^{\text{in,ACI}} &= U_{t+h|t}^{\text{ACI}} \end{aligned} \quad (7)$$

where $\hat{L}_{t+h|t}$ denotes the h-step-ahead net-load point forecast issued at time t , and $U_{t+h|t}^{\text{FCP}}$ and $U_{t+h|t}^{\text{ACI}}$ denote the fixed conformal upper bound and adaptive conformal upper bound, respectively. Point-forecast MPC represents economic operation without explicitly accounting for forecast risk, whereas fixed conformal MPC and adaptive conformal MPC use higher future net-load inputs to induce advance adjustments in the battery charging and discharging schedule. The construction of the two types of upper bounds is presented in Section 3.

Each rolling-horizon optimization yields a complete optimal control sequence for the next H periods, but only the first control action corresponding to the current period is implemented in actual operation:

$$u_t = u_{t|t}^* \quad (8)$$

During actual execution, the upper-bound net load is used only for anticipatory MPC scheduling and is not treated as the realized demand. The BESS charging/discharging decision of the first MPC step is implemented, while grid exchange compensates for the difference between the predicted risk trajectory and the realized net load to maintain the power balance in Equation (2). The SOC and operating cost reported in the case study are updated according to the realized closed-loop dispatch.

Where $u_{t|t}^*$ contains the battery charging and discharging decisions as well as the grid power purchase and sale decisions for the current period. After the first control action is implemented, the system obtains the updated actual net load and battery state, shifts the prediction horizon forward by one period, and then updates the forecast inputs and re-solves the optimization problem.

3. Adaptive Conformal Net-Load Forecasting

The rolling-horizon optimization model requires a future net-load trajectory as input, and its scheduling decisions are directly affected by forecast errors. When the actual EV charging load exceeds its forecast or the actual PV power output falls below its forecast, the actual net load becomes higher than the point forecast, which may result in insufficient preparation of the battery energy storage system. To characterize this one-sided underestimation risk, a fixed conformal upper bound is first constructed based on the net-load point forecast. The calibration parameters are then adjusted online using recent miscoverage outcomes to generate an adaptive net-load upper bound that can be directly incorporated into the MPC model.

3.1. Net-Load Point Forecasting and Residual Calibration

At rolling instant t , the point-forecast module generates 24 h ahead forecasts of EV charging load and PV power output. EV charging load and PV power are forecast using horizon-specific direct-horizon ridge regression models, with a regularization coefficient

of $\lambda = 0.01$. A temporal resolution of 15 min is adopted in this study. The h-step-ahead net-load point forecast is given by the following:

$$\hat{L}_{t+h|t} = \hat{P}_{t+h|t}^{\text{EV}} - \hat{P}_{t+h|t}^{\text{PV}} \quad h = 1, \dots, H \quad (9)$$

where $\hat{P}_{t+h|t}^{\text{EV}}$ and $\hat{P}_{t+h|t}^{\text{PV}}$ denote the forecasts issued at time t for EV charging power and PV power output, respectively, in the h -th future period, and $\hat{L}_{t+h|t}$ denotes the corresponding net-load point forecast. This forecast serves as the common baseline input for both the fixed conformal and adaptive conformal methods.

In multi-step-ahead forecasting, forecast errors may differ between short and long forecast leads. To preserve the dependence of forecast errors on the forecast lead, residuals are calculated separately for each lead. Let τ denote the historical forecast issuance time. The h-step-ahead forecast residual is defined as follows:

$$r_{\tau,h} = L_{\tau+h} - \hat{L}_{\tau+h|\tau} \quad (10)$$

where $L_{\tau+h}$ denotes the actual net load in the target period, and $\hat{L}_{\tau+h|\tau}$ denotes the point forecast for that target period issued at historical time τ . A positive residual indicates that the actual net load exceeds the point forecast, corresponding to net-load underestimation; a negative residual indicates that the point forecast exceeds the actual value.

For each forecast lead h , a calibration set is constructed separately using the available historical residuals:

$$\mathcal{R}_h = \{r_{\tau,h}\}_{\tau=1}^{N_h} \quad (11)$$

where N_h denotes the number of valid samples for forecast lead h . Using a separate residual set for each forecast lead avoids treating all forecast steps as having the same error distribution. For each forecast lead h , the calibration set contains $N_h = 2878$ historical residuals and remains fixed throughout the evaluation period. The same calibration set is used for Fixed CP and ACI. Fixed CP keeps the miscoverage parameter fixed, whereas ACI updates only $\alpha_{t,h}$ online after the corresponding actual observation becomes available. Because the rolling residuals are temporally dependent, the standard exchangeability assumption of conformal prediction is not strictly satisfied. Therefore, the coverage results reported in this study are interpreted as empirical coverage rates rather than strict finite-sample coverage guarantees.

3.2. Fixed Conformal Net-Load Upper Bound

The fixed conformal method determines the risk margin above the point forecast using empirical quantiles of historical residuals. Given a target miscoverage rate α^* , the calibration residuals for forecast lead h are sorted in ascending order. Under finite-sample conditions, the quantile index and the corresponding residual are given by the following:

$$k_h = \min\{N_h, \lceil (N_h + 1)(1 - \alpha^*) \rceil\}, \quad q_{h,1-\alpha^*} = r_{(k_h),h} \quad (12)$$

where k_h denotes the quantile index after finite-sample correction, $r_{(k_h),h}$ denotes the corresponding ordered sample in the residual set for forecast lead h , and $q_{h,1-\alpha^*}$ denotes the associated empirical quantile. This correction incorporates the effective sample size into the quantile selection, providing an explicit representation of the target coverage level under a finite calibration sample.

On this basis, the fixed one-sided conformal upper bound for the net load is expressed as follows:

$$\begin{aligned} U_{t+h|t}^{\text{FCP}} &= \hat{L}_{t+h|t} + b_h^{\text{FCP}} \\ b_h^{\text{FCP}} &= \max\{0, q_{h,1-\alpha^*}\} \end{aligned} \quad (13)$$

where b_h^{FCP} denotes the fixed conformal margin, and $U_{t+h|t}^{\text{FCP}}$ denotes the fixed upper bound for forecast lead h issued at time t . The nonnegative correction $\max\{0, \cdot\}$ ensures that the upper bound is no lower than the net-load point forecast. Since each forecast lead uses its own residual set, the margin of the fixed upper bound can vary with the forecast lead. However, the target miscoverage rate and quantile-selection rule remain unchanged during operation. Therefore, when recent forecast errors exhibit a persistent upward shift, the fixed method cannot promptly enlarge the upper bound in response to newly observed miscoverage.

3.3. ACI Online Calibration and Dynamic Upper Bound

To improve the adaptability of the prediction upper bound to recent changes in forecast errors, adaptive conformal inference (ACI) is employed to update the calibration parameter for each forecast lead online. ACI uses the observed miscoverage outcomes as feedback: the subsequent risk margin is enlarged when coverage is insufficient, while the calibration parameter is gradually restored under consecutive coverage, thereby balancing coverage performance and upper-bound width.

At current time t , the miscoverage indicator corresponding to forecast lead h is defined as follows:

$$e_{t,h} = \mathbb{I}\{L_t > U_{t|t-h}^{\text{ACI}}\} \quad (14)$$

The miscoverage indicator $e_{t,h}$ takes the value 1 when the actual net load exceeds the ACI upper bound previously issued for the corresponding target time, and 0 otherwise. This evaluation uses the actual value that has become available at the target time.

Based on the miscoverage feedback, the calibration parameter for each forecast lead and the projection operator are given by the following:

$$\begin{aligned} \alpha_{t,h} &= \Pi_{\mathcal{A}}[\alpha_{t-1,h} + \gamma(\alpha^* - e_{t,h})] \\ \Pi_{\mathcal{A}}(x) &= \min\{\alpha^{\max}, \max\{\alpha^{\min}, x\}\} \end{aligned} \quad (15)$$

where $\alpha_{t,h}$ denotes the adaptive calibration parameter for forecast lead h at time t , γ is the update step size, and $\mathcal{A} = [\alpha^{\min}, \alpha^{\max}]$ is the allowable parameter range. Initially, the calibration parameter for each forecast lead is set equal to the target miscoverage rate α^* . When miscoverage occurs, the update reduces $\alpha_{t,h}$, which subsequently selects a higher residual quantile and increases the upper-bound margin. When no miscoverage occurs, the parameter gradually recovers. The projection operator constrains the parameter within the prescribed range, preventing repeated feedback from driving it outside a reasonable interval.

The update step size γ determines how rapidly the parameter responds to recent forecast errors. A larger γ allows the upper bound to expand more rapidly after consecutive miscoverage events but may increase fluctuations in both the calibration parameter and the upper-bound width. A smaller γ leads to smoother updates but a slower response to persistent forecast deviations. In this study, a separate calibration parameter is maintained for each forecast lead, allowing different forecast horizons to be adjusted independently according to their respective miscoverage outcomes.

After the online update, the ACI-based dynamic one-sided net-load upper bound is given by the following:

$$\begin{aligned} U_{t+h|t}^{\text{ACI}} &= \hat{L}_{t+h|t} + b_{t,h}^{\text{ACI}} \\ b_{t,h}^{\text{ACI}} &= \max\left\{0, q_{h,1-\alpha_{t,h}}\right\} \end{aligned} \quad (16)$$

where $b_{t,h}^{\text{ACI}}$ denotes the adaptive margin that varies with the rolling instant and forecast lead, and $U_{t+h|t}^{\text{ACI}}$ denotes the corresponding dynamic upper bound. Compared with the fixed conformal method, ACI uses a time-varying calibration parameter to select the empirical quantile, enabling the upper bound to expand or contract in response to recent miscoverage feedback. The method therefore updates the subsequent risk bound online after actual forecast deviations have been observed.

At each rolling instant, Equation (16) generates dynamic upper bounds for the next H forecast steps, which are used as the net-load inputs to the adaptive conformal MPC in Equation (7) of Section 2. The system sequentially performs point forecasting, residual updating, miscoverage evaluation, parameter calibration, upper-bound generation, MPC optimization, and implementation of the first control action. After the updated actual net load and battery state are obtained, the prediction horizon is shifted forward by 15 min, and the optimization problem is re-solved, thereby linking risk forecasting with rolling-horizon scheduling.

4. Case Study

To validate the effectiveness of the proposed risk-aware adaptive conformal rolling-horizon scheduling method, ten synthetically constructed nonstationary stress events are introduced during the test period to evaluate the response of the proposed method to persistent net-load underestimation, and three methods—point-forecast MPC, fixed conformal MPC, and adaptive conformal MPC—are compared. The three methods use the same actual EV charging load, PV power output, time-of-use electricity tariff, battery energy storage parameters, and physical constraints, while differing only in the future net-load inputs used in the rolling-horizon optimization. Therefore, the differences in the results primarily reflect the effects of different risk characterization methods on closed-loop scheduling.

The case study is conducted at both the forecasting and scheduling levels. At the forecasting level, the overall coverage rate, event-period coverage rate, event-period average interval width, and number of event-period miscoverage instances are compared to evaluate the capability of the fixed and dynamic upper bounds to characterize persistent underestimation risk. At the scheduling level, grid power purchase, battery state of charge, low-SOC duration, battery energy throughput, and operating cost are further compared to analyze the effects of net-load risk bounds on operational control decisions. Finally, the power-balance results for a representative event day are used to illustrate the coordinated operation of PV generation, battery energy storage, and the grid after the adaptive conformal upper bound is incorporated into the MPC framework.

4.1. Case Study Setup

The case study adopts a temporal resolution of 15 min, with 96 periods per day. The test period extends from 1 April to 30 May 2026. The forecasting models are trained using data from July 2025 to February 2026, while March 2026 is used for conformal calibration. The evaluation period is 1 April–30 May 2026. The training, calibration, and evaluation datasets are chronologically separated, and no future evaluation observations are used for model training or conformal calibration. At each rolling instant, the MPC solves a 24 h ahead optimization problem based on the latest forecast information and the

current battery state, and only the first control action corresponding to the current period is implemented. The optimization problem is then re-solved using the updated actual net load and battery state.

To evaluate the performance of the proposed method under persistent net-load under-estimation, ten mutually separated synthetic stress events are introduced during the test period, with an interval of at least four days between consecutive events. Both weekdays and weekends are included. For each event, the EV charging load is gradually increased around the daily peak, with an average increase of approximately 20%, while PV generation is reduced by 30% during the corresponding period. Additional correlated fluctuations are introduced to represent temporal variability. All perturbations are applied only to the test period, while the training and calibration data remain unchanged.

The main system and algorithm parameters are listed in Table 1. In this study, the BESS is considered to be in a low-SOC state when the SOC falls below 25%, and the corresponding duration is used as an indicator of the available energy reserve. The rated energy capacity of the battery energy storage system is 200 kWh, and the maximum charging and discharging power are both 80 kW. The allowable SOC range is 10–90%. The rated PV power is 250 kW, and the electricity purchase prices are set to 0.94, 1.12, and 2.42 CNY/kWh for different time periods. The three methods use the same initial conditions, forecasting model, and test data to ensure a fair comparison. The forecasting metrics are used to evaluate whether the upper bounds cover the actual net load, while the scheduling metrics reflect the effects of different risk inputs on battery preparation, operating cost, and battery usage intensity.

Table 1. Main system and algorithm parameters.

Parameter	Value	Parameter	Value
Time resolution	15 min	SOC operating range	10–90%
Rated PV power	250 kW	Electricity purchase price	0.94/1.12/2.42 CNY·kWh ^{−1}
Maximum charging/discharging power	80/80 kW	Selling price	80% * Electricity purchase price
Rated battery energy capacity	200 kWh	Low-SOC threshold	25%
Initial SOC	60%	$\alpha_{\max}$	0.04
$\alpha_{\min}$	0.005		

4.2. Net-Load Upper-Bound Forecasting Results

The reported coverage rate represents the empirical marginal coverage over individual forecast targets and should not be interpreted as the probability that all 96 forecast steps within a 24 h MPC horizon are simultaneously covered.

The forecasting performance of Fixed CP and ACI is evaluated using the empirical coverage rate, event-period coverage rate, event-period mean upper-bound width, number of event-period miscoverage instances, and longest consecutive event-period miscoverage. Table 2 summarizes the results over the full evaluation period and the 10 nonstationary stress-test events.

Table 2. Forecasting performance of the fixed and adaptive conformal methods.

Method	Overall Coverage Rate/%	Event-Period Coverage Rate/%	Event-Period Average Width/kW	Event-Period Miscoverage Instances
Fixed conformal	94.618	91.167	126.140	53
Adaptive conformal	96.701	95.000	150.427	30

As shown in Table 2, the overall empirical coverage rate increases from 94.618% for Fixed CP to 96.701% for ACI, corresponding to an increase of 2.083 percentage points.

The difference becomes more pronounced during the stress-test events, where the event-period coverage rate increases from 91.167% to 95.000%. Meanwhile, the number of event-period miscoverage instances decreases from 53 to 30, a reduction of 43.4%, and the longest consecutive miscoverage duration decreases from 105 to 90 min. These results indicate that ACI provides stronger protection against persistent net-load underestimation, particularly during periods in which forecast errors remain biased in the same direction over consecutive intervals.

The improvement in coverage is accompanied by a wider risk bound. The event-period mean upper-bound width increases from 126.140 kW for Fixed CP to 150.427 kW for ACI, corresponding to an increase of 24.286 kW or 19.25%. Therefore, the reduction in miscoverage cannot be interpreted as a cost-free improvement in forecasting performance. Instead, the results show a trade-off between empirical coverage and upper-bound conservativeness: ACI reduces both the frequency and persistence of miscoverage by allocating a larger risk margin during periods with stronger underestimation risk.

Figure 2 further illustrates the adaptive behavior using the representative synthetic stress event, Event 4. During this event, the actual net load remains above the point forecast over multiple consecutive periods, producing repeated violations of the fixed upper bound. The empirical event-period coverage rate of Fixed CP is 86.667%, with eight miscoverage instances and a longest consecutive miscoverage duration of 75 min. Under ACI, the event-period coverage rate increases to 95.000%, the number of miscoverage instances decreases to three, and the longest consecutive miscoverage duration is shortened to 30 min. The corresponding mean upper-bound width is 153.157 kW for ACI, compared with 126.140 kW for Fixed CP.

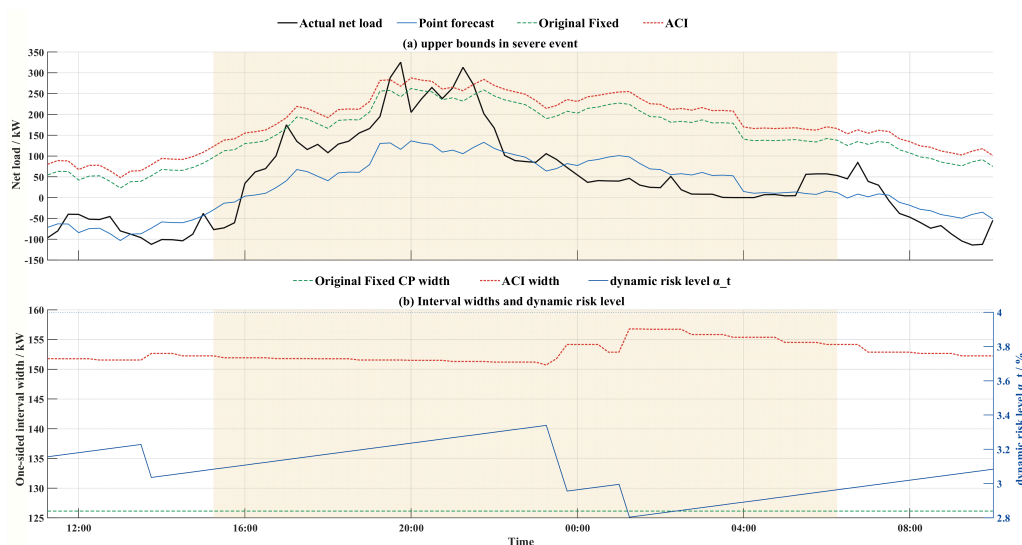


Figure 2. Net-load upper bounds and dynamic adjustment of Fixed CP and ACI under a representative stress event.

The lower panel of Figure 2 shows that the Fixed CP margin remains nearly unchanged, whereas the ACI upper-bound width varies with the online evolution of the calibration parameter α_t . When miscoverage is observed, the adaptive update modifies the subsequent calibration level and enlarges the corresponding risk margin; as the recent forecast-error condition changes, the margin is adjusted accordingly. ACI therefore does not identify the stress event in advance. Rather, it uses the outcomes of completed forecasts to modify subsequent net-load upper bounds. The results for event 4 are consistent with the aggregate results in Table 2: adaptive calibration reduces persistent miscoverage, but this improvement is accompanied by an increase in upper-bound width.

4.3. Rolling-Horizon Scheduling Results

Point-forecast MPC, Fixed CP-MPC, and ACI-MPC are applied to the same actual net-load trajectory using identical electricity prices, BESS parameters, and physical constraints. The three strategies differ only in the future net-load trajectories used by the rolling-horizon optimization. Figure 3 presents the grid-purchase power and BESS SOC trajectories under representative stress event 4, while Table 3 summarizes the closed-loop scheduling results over the complete evaluation period.

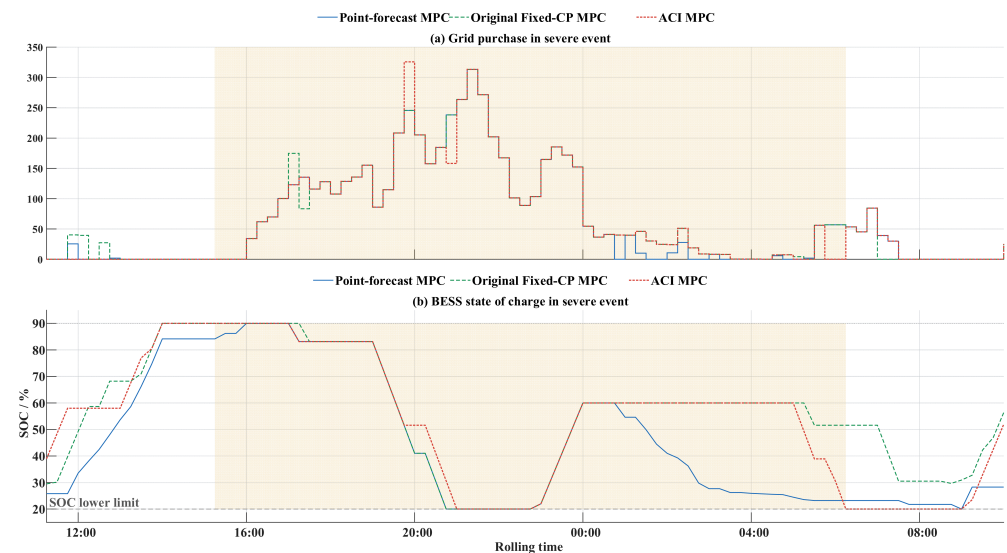


Figure 3. Closed-loop scheduling results of the three methods under a representative stress event.

Table 3. Comprehensive results of the three rolling-horizon scheduling methods.

Method	Total Cost/CNY	Event-Period Cost/CNY	Pre-Event SOC/%	Low-SOC Duration/Min	Battery Energy Throughput/kWh
Point-forecast MPC	53,635.22	15,959.88	60.63	2145	26,151.66
Fixed conformal MPC	54,206.37	16,302.38	77.00	1500	25,554.60
Adaptive conformal MPC	54,271.46	16,127.69	76.03	1485	25,675.44

For stress event 4, the three methods exhibit similar grid-purchase trends over most periods, but differences appear in the timing of energy preparation and release. The mean pre-event SOC is 57.103% for point-forecast MPC, 67.001% for Fixed CP-MPC, and 69.406% for ACI-MPC. Correspondingly, the event-period low-SOC duration decreases from 225 min under point-forecast MPC to 150 min under Fixed CP-MPC and 135 min under ACI-MPC. These results indicate that the use of an upper net-load bound modifies the intertemporal allocation of BESS energy and allows more stored energy to be retained before sustained net-load underestimation develops.

The differences in grid-purchase power are concentrated in several periods rather than appearing as a uniform reduction throughout the event. In particular, the maximum grid purchase during event 4 is 313.18 kW for both point-forecast MPC and Fixed CP-MPC and 325.67 kW for ACI-MPC. Therefore, the benefit of ACI should not be interpreted as a reduction in peak grid purchase. Instead, the adaptive risk input changes when grid energy is purchased and when stored energy is retained or released. For this event, the operating cost of ACI-MPC is CNY 2321.29, compared with CNY 2381.70 for Fixed CP-MPC, corresponding to a reduction of approximately 2.54%.

As shown in Table 3, point-forecast MPC achieves the lowest total operating cost of CNY 53,635.22, but its mean pre-event SOC is only 60.63%, and the accumulated low-SOC

duration reaches 2145 min. In comparison, ACI-MPC increases the mean pre-event SOC to 76.03%, an increase of 15.40 percentage points, while reducing the low-SOC duration to 1485 min. This corresponds to a reduction of 660 min, or 30.77%. The total operating cost increases to CNY 54,271.46, which is CNY 636.24 higher than that of point-forecast MPC, corresponding to an increase of approximately 1.19%. Battery throughput decreases from 26,151.66 to 25,675.44 kWh. These results indicate that incorporating the adaptive upper bound leads to greater BESS energy preparation and lower low-SOC exposure at a relatively limited increase in operating cost.

The differences between Fixed CP-MPC and ACI-MPC are smaller. ACI-MPC increases the full-period operating cost from CNY 54,206.37 to CNY 54,271.46, a difference of CNY 65.09 or approximately 0.12%. In contrast, the accumulated event-period cost decreases from CNY 16,302.38 to CNY 16,127.69, corresponding to a reduction of CNY 174.69 or approximately 1.07%. The low-SOC duration decreases from 1500 to 1485 min, whereas the mean pre-event SOC decreases slightly from 77.00% to 76.03%. A prolonged low-SOC state reduces the available energy reserve of the BESS and limits its flexibility in responding to subsequent net-load deviations, which may increase grid purchases during high-price periods. Battery throughput increases from 25,554.60 to 25,675.44 kWh, an increase of 120.84 kWh. The mixed changes in these indicators suggest that adaptive calibration primarily modifies the timing of BESS energy retention and release rather than uniformly improving all scheduling metrics.

Over the complete evaluation period, the maximum grid-purchase power is 749.571 kW for all three methods. Therefore, the scheduling results do not indicate a reduction in the maximum grid-purchase requirement. Taken together, the results show that point-forecast MPC retains a cost advantage but is associated with greater low-SOC exposure, whereas the conformal-based strategies maintain higher BESS energy reserves before stress periods. ACI-MPC further adjusts this risk preparation in response to updated net-load bounds, resulting in a trade-off among low-SOC exposure, operating cost, and battery-energy utilization.

4.4. Sensitivity Analysis of the ACI Update Step Size

To examine the sensitivity of the proposed method to the ACI update step size, γ was varied from 0.0005 to 0.01 while the remaining forecasting, BESS, and MPC settings were kept unchanged. Table 4 reports the resulting forecasting and scheduling performance. The tested values cover both relatively slow and relatively fast adaptive updates and are used to evaluate the influence of γ on coverage behavior, upper-bound conservativeness, BESS reserve, and operating cost.

Table 4. Sensitivity analysis results for different ACI update step sizes.

γ	Overall Coverage Rate/%	Event Coverage Rate/%	Event Misses	Low-SOC Duration/Min	Total Cost/CNY
0.0005	96.545	94.667	32	1665	54,290.25
0.001	96.615	95.000	30	1620	54,307.96
0.002	96.701	95.000	30	1485	54,271.46
0.005	96.823	94.667	32	1395	54,309.70
0.01	96.910	94.833	31	1485	54,301.07

As γ increases from 0.0005 to 0.01, the overall coverage rate increases from 96.545% to 96.910%, corresponding to an increase of 0.365 percentage points. Over the same range, the event-period mean upper-bound width increases from 144.995 to 159.740 kW, an increase of 14.745 kW or approximately 10.17%. In contrast, the event-period coverage rate does

not increase monotonically. Its maximum value of 95.000% is obtained at ($\gamma = 0.001$) and ($\gamma = 0.002$), for which the number of event-period miscoverage instances is also minimized at 30. When γ reaches 0.005 and 0.01, further increases in the upper-bound width do not produce additional improvement in event-period coverage. These results indicate that increasing the update step size strengthens the response of the adaptive bound, but an excessively large step size mainly increases the risk margin rather than continuously improving event-period coverage.

The effect of γ is also reflected in the persistence of miscoverage and BESS operation. At ($\gamma = 0.0005$) and 0.001, the longest consecutive event-period miscoverage remains 105 min, whereas it decreases to 90 min when ($\gamma = 0.002$). The low-SOC duration decreases from 1665 min at ($\gamma = 0.0005$) to 1485 min at ($\gamma = 0.002$), a reduction of 180 min or approximately 10.81%. A further increase to ($\gamma = 0.005$) reduces the low-SOC duration to 1395 min, but the event-period coverage rate simultaneously decreases from 95.000% to 94.667%, and the number of event miscoverage instances increases from 30 to 32. This result suggests that a shorter low-SOC duration alone does not imply a uniformly better risk-control performance, because changes in the adaptive upper bound affect both BESS energy preparation and subsequent energy release.

The total operating cost remains comparatively stable over the tested range. The five cases vary between CNY 54,271.46 and CNY 54,309.70, corresponding to a maximum difference of only CNY 38.24, or approximately 0.07%. Among the tested values, ($\gamma = 0.002$) yields an event-period coverage rate of 95.000%, 30 event miscoverage instances, a longest consecutive miscoverage duration of 90 min, a low-SOC duration of 1485 min, and the lowest total operating cost of CNY 54,271.46. Although it does not minimize every individual metric, it avoids the longer consecutive miscoverage observed at smaller step sizes and the wider risk bounds without further event-coverage improvement observed at larger step sizes. Therefore, ($\gamma = 0.002$) is adopted as the baseline setting in this study as a balanced choice among coverage performance, persistent miscoverage control, BESS reserve, upper-bound conservativeness, and operating cost.

4.5. Power Balance Analysis for a Representative Event Day

Figure 4 presents the real-time power balance of ACI-MPC under representative stress event 4. Supply-side power is defined as positive and includes PV generation, BESS discharge, and grid purchase, whereas demand-side power is defined as negative and includes the actual EV charging load, BESS charging, and grid export. The supply- and demand-side components remain balanced at each 15 min control interval within numerical tolerance, confirming that the closed-loop scheduling results satisfy the station-level power-balance constraint.

The power trajectories shown in Figure 4 are based on the realized closed-loop dispatch using the actual EV charging load and PV generation. Before the stress period, the grid and available PV generation jointly supply the EV charging demand while part of the available energy is allocated to BESS charging. This energy allocation is consistent with the higher BESS reserve observed before the stress event in Section 4.3. As the actual net load increases during the stress period, grid purchase becomes the main source for meeting the sustained power deficit, while the BESS discharges during selected high-demand intervals to supplement grid supply. The stored energy prepared before the event is therefore gradually released as the net-load condition becomes more demanding. After the stress period, the reduction in charging demand and the recovery of available generation allow the BESS energy level to be restored through subsequent charging.

The power-flow results indicate that the adaptive net-load upper bound influences the temporal allocation of grid energy and BESS charging/discharging while preserving

the instantaneous supply-demand balance. Figure 4 is therefore mainly used to illustrate the physical implementation and energy-flow characteristics of the ACI-MPC schedule. Differences in forecasting performance and scheduling performance among point-forecast MPC, Fixed CP-MPC, and ACI-MPC are evaluated separately using the quantitative results reported in Tables 2 and 3 rather than inferred from the power-balance trajectory alone.

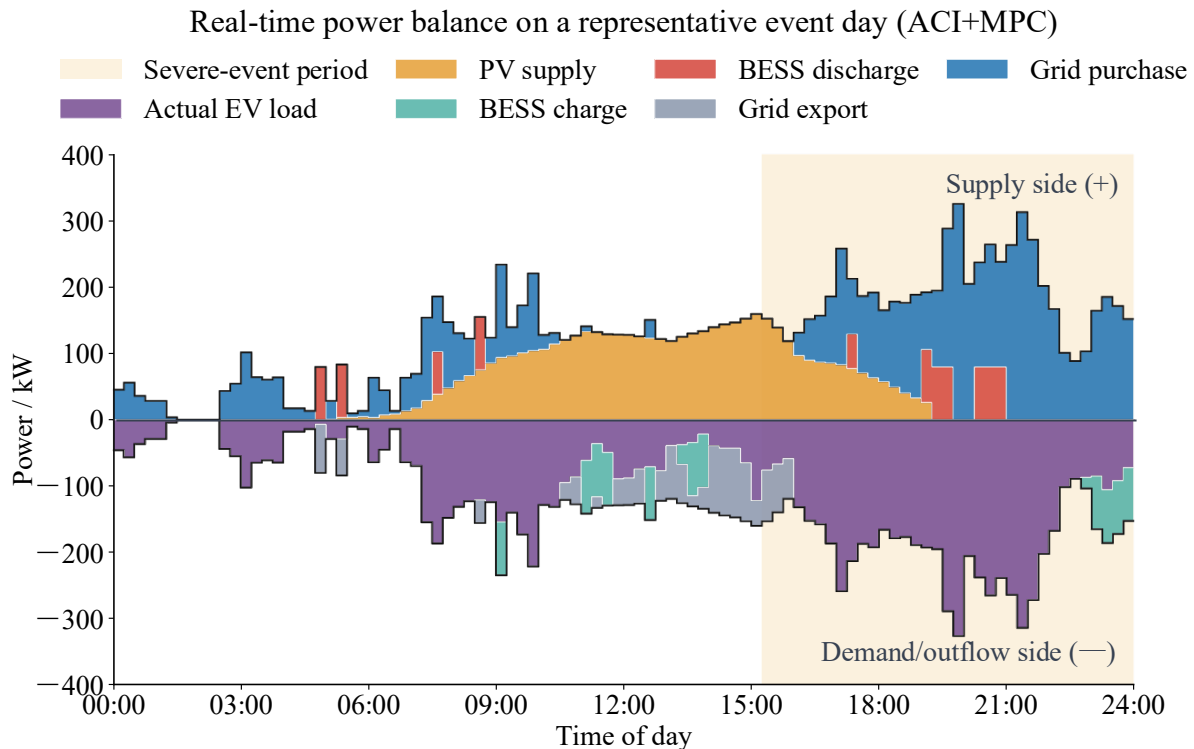


Figure 4. Real-time power balance of ACI-MPC on a representative event day.

5. Discussion

The results indicate that adaptive conformal inference changes the way forecast uncertainty is represented under persistent net-load underestimation. Fixed CP relies on a relatively stable calibration rule and therefore has limited ability to respond promptly when recent forecast errors shift in the same direction. In contrast, ACI updates subsequent upper bounds according to observed miscoverage feedback. Under the tested configuration, this mechanism improves empirical coverage and reduces persistent miscoverage, but the improvement is accompanied by a wider net-load upper bound. The forecasting benefit should therefore be interpreted as a trade-off between risk protection and conservativeness rather than as a cost-free increase in coverage. This distinction is important because a wider upper bound directly changes the risk information passed to the subsequent scheduling problem.

The effect of this risk adjustment is reflected in the intertemporal use of the BESS. When the MPC receives a higher future net-load trajectory, it tends to retain more stored energy or replenish the BESS before periods of sustained net-load underestimation. The resulting reserve can then be released as the actual net load remains above its point forecast, thereby reducing prolonged low-SOC exposure. However, the comparison with Fixed CP-MPC shows that adaptive calibration does not uniformly improve all operational indicators. Changes in operating cost, pre-event SOC, and battery throughput are mixed, suggesting that the main scheduling effect of ACI is to modify the timing of energy retention, grid purchase, and BESS discharge rather than to reduce every operating metric simultaneously. The power-balance analysis further confirms that these adjustments remain consistent with

the station-level physical constraints, while the comparative performance itself should be assessed from the quantitative forecasting and scheduling metrics reported in Section 4.

ACI should not be interpreted as an event-prediction mechanism. The calibration parameter is updated only after the corresponding observations of completed forecasts become available, so the method responds to persistent forecast deviations rather than identifying a stress event in advance. In addition, the nonstationary stress-test events used in the case study are synthetically constructed to examine the response of the proposed framework under sustained net-load underestimation. They are therefore intended for stress-performance evaluation rather than for estimating the occurrence probability of real disturbance events. The current study is also limited to a single PV-storage-charging station, treats EV charging load as an exogenous forecast quantity, and does not explicitly include battery degradation costs or distribution-network operating constraints. Future work may extend the validation to longer-term measured and multi-station datasets and investigate the integration of adaptive conformal prediction with charging-load optimization, battery degradation modeling, and distribution-network security constraints.

The present model assumes that grid exchange remains available to maintain instantaneous power balance. Therefore, low-SOC duration is not interpreted as load-supply failure, but as an indicator of reduced BESS energy reserve and weaker flexibility against subsequent net-load deviations.

6. Conclusions

This paper proposes a risk-aware adaptive conformal rolling-horizon scheduling framework for PV-storage-charging systems under net-load forecast uncertainty. Net load is used as a unified risk variable, and horizon-specific residual calibration is employed to construct one-sided conformal upper bounds. ACI further updates the calibration parameter according to observed miscoverage outcomes, and the resulting dynamic upper bound is incorporated into MPC to coordinate BESS charging and discharging and grid power exchange at a 15 min rolling interval.

The experimental results show that ACI increases the overall empirical coverage rate from 94.618% to 96.701% relative to Fixed CP. Across the 10 nonstationary stress-test events, the event-period coverage rate increases from 91.167% to 95.000%, while the number of miscoverage instances decreases from 53 to 30 and the longest consecutive miscoverage duration decreases from 105 to 90 min. These improvements are accompanied by an increase in the event-period mean upper-bound width from 126.140 to 150.427 kW, corresponding to 19.25%, indicating a trade-off between coverage performance and upper-bound conservativeness. At the scheduling level, compared with point-forecast MPC, ACI-MPC increases the mean pre-event SOC from 60.63% to 76.03% and reduces the low-SOC duration from 2145 to 1485 min, a reduction of 30.77%, while increasing the total operating cost by 1.19%. Compared with Fixed CP-MPC, ACI-MPC reduces the event-period operating cost by approximately 1.07% and the low-SOC duration by 15 min, while increasing the total operating cost by approximately 0.12% and battery throughput by 120.84 kWh.

Overall, the proposed framework improves protection against persistent net-load underestimation and links adaptive forecast-risk quantification with closed-loop BESS scheduling. The results should be interpreted as a trade-off among empirical coverage, upper-bound conservativeness, BESS reserve, and operating cost rather than as uniform improvement across all performance indicators. The present validation is limited to a single PV-storage-charging station and synthetically constructed nonstationary stress-test events. Future work may extend the analysis to longer-term measured and multi-station datasets

and incorporate charging-load optimization, battery degradation costs, and distribution-network operating constraints.

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