Research Article

Forecasting-based electricity tariff selection for resident users with photovoltaic and energy storage considering forecast uncertainties

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Abstract: With the diversification of electricity price structures, an increasing number of power utilities have incorporated demand charges into their tariff structures. Individual households equipped with photovoltaic (PV) and energy storage systems can adapt to this trend by adopting appropriate energy management strategies. Due to the high uncertainty in photovoltaic and load generation for household users, it is often challenging for them to make the most advantageous choice among the diverse electricity tariffs. This paper proposes a rolling prediction method based on Long Short-Term Memory (LSTM) networks for monthly peak power demand, taking into account historical peak power and applying corrective measures within the same month. Additionally, a profit evaluation method for electricity tariff schemes considering forecast uncertainties is presented. The predictive capabilities of load and PV power are characterized using kernel density estimation, and a large number of scenarios are generated using Monte Carlo simulation. Based on the proposed energy management strategies, a probabilistic economic evaluation is conducted for different tariff schemes, enabling the optimal selection of electricity tariffs. To validate the effectiveness of the proposed methods, analysis is performed using household data from Arizona, and the results demonstrate that the proposed methods can reduce monthly electricity expenses and assist households in choosing the correct electricity tariff scheme.
Keywords: Demand charge; Power demand forecast; Energy management strategy; Probabilistic assessment; Tariff selection

1 Introduction

The charging schemes for electricity prices are becoming increasingly diverse worldwide. The electricity tariff structure is evolving towards accurately reflecting the costs of electricity consumption from multiple dimensions, including power and energy, in a more precise manner[1]. This trend aims to more accurately reflect the actual supply and consumption of electric energy, in order to promote energy efficiency and sustainability. Electricity markets and regulations have improved their pricing models and billing mechanisms by considering factors such as demand power, peak loads, supply-demand balance, and infrastructure costs. This evolution helps incentivize users to reduce electricity loads during peak hours, optimize electricity consumption behavior, and promote the use of clean energy, laying a foundation for sustainability transition of energy systems[2-3]. Therefore, under electricity tariffs that include demand charge, a feasible method for selecting electricity tariffs has become an important issue for resident users.

Due to the correlation between the monthly demand charges for residential users and their highest power consumption within that month, it is essential to forecast the peak electricity usage power in order to make informed decisions when selecting electricity tariff plans. Concerning peak load forecasting during the month on the residential side, there are numerous existing methods known, but their application in the context of household energy management often lacks consideration for frequent updates within the current month. This limitation can result in decreased forecasting accuracy and misjudgment of power demand within the current month. References[4-5] provide a comprehensive review of the probabilistic forecasting theory and application methods in the context of renewable energy power systems. Extensive research has been dedicated to the investigation of advanced probabilistic forecasting methods in the context of typical application scenarios within emerging power systems. Specifically, significant attention has been placed on time series-based probabilistic forecasting approaches, which leverage the autocorrelation analysis of historical statistical data associated with the forecasting target. Furthermore, considerable emphasis has been placed on exploring artificial intelligence-driven probabilistic forecasting methods, such as neural networks and deep learning, which have emerged as prominent techniques in this field [6-8]. In the field of microgrids, there exist cases where probabilistic methods have been used for load forecasting[9-10]. In Reference[9], a probabilistic normal load forecasting model was built using the artificial neural network (ANN). Reference[10] proposed an adaptive data decomposition based quantile-long-short-term memory(QLSTM) probabilistic forecasting framework to reflect the future load information more comprehensively. However, forecasting the peak load of residential users within a month is more challenging compared to forecasting load of a microgrid. Therefore, in the daily rolling forecasting process within a month, forecasting refinement of peak power deamand is needed. Similar approaches can be explored by referencing literature from other domains in the power system, and applied to refine probabilistic load forecasting for residential purposes. In the field of electricity markets, a model proposed in reference[11] first used the nonlinear approximation ability of radial basis functions to forecast the load for the next day without considering the electricity price factors. Then, based on the real-time price changes of the day, an adaptive fuzzy inference system is used to adjust the load results obtained from the radial basis functions. In the field of photovoltaic forecasting, reference[12] proposed a layered correction approach where forecasts from different time periods can complement each other based on continuously updated meteorological data. In terms of park-level load forecasting, reference[13] proposed a dynamic forecasting model based on load pattern recognition and intra-day corrections,which utilizes the data from the current day to update the final forecasting results in a rolling manner. Therefore, further research and development of timely updating methods for peak power demand forecasting are necessary to enhance the effectiveness of household energy management.

For residential users, particularly those with PV and energy storage systems, the selection of electricity tariffs incorporating demand charges presents a complex challenge. To minimize demand charges and attain economic benefits, residents have to consider various factors such as energy consumption patterns, renewable energy generation capacity, and energy storage capacity. These factors influence the costs associated with different energy management strategies. Additionally, fluctuations in electricity market prices, variations in peak and off-peak electricity loads, and the accuracy of load and solar power forecasting further complicate the decision-making process. Thus, an analysis of uncertain energy costs becomes imperative when choosing the appropriate tariff tailored to the specific needs and circumstances of residential users, ultimately optimizing energy expenditures and enhancing energy utilization efficiency.

In the selection of energy usage plans for residential users, deterministic methods are commonly employed for revenue assessment[14-17]. Reference[14] investigated the application of recommender system, a fast-developing technique in machine learning, into the task of recommending electricity plans for the individual residential customer. In reference[15], the net present value analysis of potential monetary savings was considered and established as the optimization objective. An optimization strategy is developed to select the optimal scale of photovoltaic (PV) and retail electricity plans that are most suitable for this purpose. Reference[16] compares the economic viability of solar energy systems of different scales under demand charge. However, they lack an analysis of the involvement of energy storage systems in the electricity consumption behavior of residential users. Reference[17] analyzed the control strategies and configuration issues of solar storage systems for residential users under time-of-use and demand pricing scenarios, while it still lacks consideration for prediction and resource uncertainties. In addition to the deterministic analysis methods mentioned above, probabilistic evaluation methods[18-20] that consider uncertainties are also employed to assess the economic viability. But there is currently limited application in the selection of electricity price plans for residential users. Reference[21] proposed a probabilistic formula to capture uncertainty in cost and benefit data in the expansion of distribution engineering projects. Reference [22] conducted analysis and computation of the costs and benefits of regional power grids using a Gaussian statistical model. Reference[23] proposes a novel method for calculating the levelized cost of electricity (LCOE) by employing a probability model that takes into account endogenous input parameters. The method utilizes Monte Carlo simulation to analyze the economic feasibility of the project. Reference[24] proposed an economic evaluation method for microgrids that considers the dual uncertainty of both load and prediction. These methods provide references for electricity tariff selection schemes that further consider predictive uncertainty.

Therefore, the key contributions of the paper include the following:

1) A method for analyzing the economic viability of electricity tariffs with demand charge, based on long-term peak power forecasting, which is proposed for comparing the economic feasibility of different electricity tariffs in various scenarios.

2) A production simulation method that takes into account predictive uncertainties for selecting various electricity tariffs that include demand charge.

2 Electricity tariff including demand charge

The electricity bill for residents based on the current multi-rate electricity pricing tariff options includes supply charge, energy charge and demand charge. Under this pricing structure, the calculation of the monthly electricity bill can be expressed by the following formula.

$$EC = EC_{bs} + EC_{ec} + EC_d \tag{1}$$

where EC represents the total electricity cost for that month; EC_{bs} represents the basic service fee charged by the power utility for that month; EC_d represents the demand charge for residential customers for that month; and EC_{ec} represents the energy charge for residential users for that month.

2.1 Supply charge

Supply charge refers to the monthly service fee for energy supply, which is usually charged by the electricity or energy company to customers for the distribution, transmission, and storage of energy. Supply charge is often billed on a monthly basis, with a fixed monthly fee or a fee that is calculated based on the number of days in the month. When billed based on the number of days in the billing cycle, the monthly supply charge can be obtained using the following formula.

$$EC_{bs} = BS_{pd} \cdot n_d \tag{2}$$

where BS_{pd} represents the daily base service fee for the electricity pricing structure; n_d represents the number of days in the current billing cycle.

2.2 Energy charge

Time-of-use (TOU) pricing is an electricity rate structure that reflects the varying cost of electricity at different times throughout the day. TOU pricing divides the day into distinct time periods, usually categorized as peak and off-peak. In this method, the electricity cost of energy charge can be expressed as:

$$EC_{ec} = \sum_{t \in T_0} c_{buy}^t \cdot p_b^t \Delta t \tag{3}$$

where c_{buy}^t represents the unit price per kilowatt-hour (kWh) of electricity during time period t given by the grid. p_b^t represents the power imported from the grid during time period t. Δt represents the length of the time interval.

2.3 Demand charge

Demand charge includes additional expenses which are based on the consumer's peak demand during a designated time period (high-demand period) of any day over a billing cycle. In some typical electricity pricing tariffs, the calculation of demand charge is applicable for the entire day. The electricity cost of demand charge in the month can be expressed as:

$$EC_d = DC_p \cdot p_{mp} + DC_{op} \cdot p_{mop} \tag{4}$$

where DC_p represents demand charge for unit power during peak demand periods in demand-based pricing, p_{dp} represents the peak power imported from the grid during peak demand periods in the entire month; DC_{op} represents demand charge for unit power during off-peak demand periods in demand-based pricing, p_{mop} represents the peak power imported from the grid during off-peak demand periods in the entire month. And in some typical electricity pricing tariffs, DC_p equals to DC_{op}, p_{mp} equals to p_{mop}.

3 Framework for electricity tariff selection

As shown in Fig.1, for future tariff selections of households with solar PV and energy storage systems, it is necessary to make predictions based on historical data. However, these predictions often have significant uncertainties. To characterize the uncertainty in the predictions, it is necessary to recharacterize the prediction errors and consider these errors in the subsequent scenario generation. In particular, for tariff packages that include demand charges, it is crucial to also predict the maximum demand power for the current month. Based on the characterized solar PV and load predictions, appropriate energy management strategies can be employed to determine the potential electricity costs that households may incur. By comparing

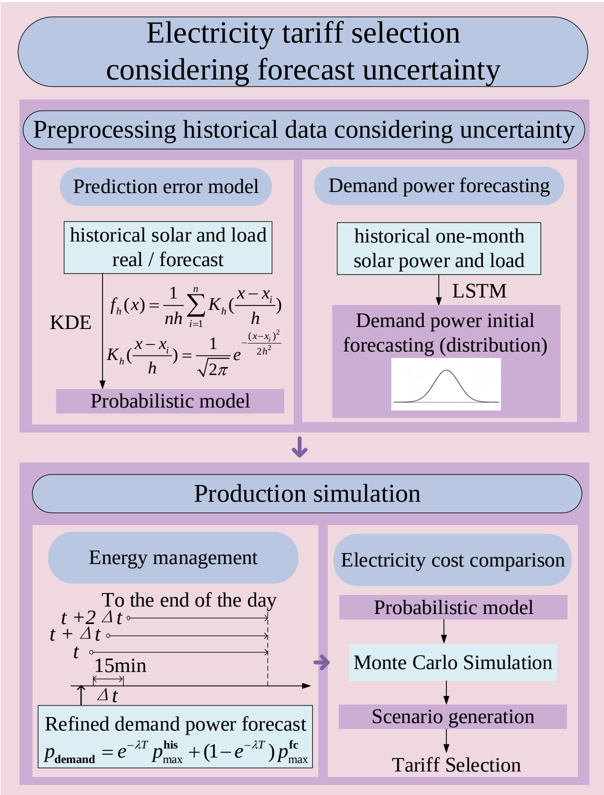

Fig. 1: Forecasting-based electricity tariff selection.

these costs, the best electricity tariff with demand charges can be identified.

The next two chapters will discuss how to select electricity tariff schemes with demand charges from the following two aspects.

Before selecting an electricity tariff, it is necessary to analyze historical data and generate the probability density function of prediction errors using kernel density estimation. At the same time, input the maximum daily grid power data from the past 30 days into a pre-trained Long Short-Term Memory (LSTM) model to obtain the probability distribution of maximum power for the next month.

When selecting an electricity tariff, two aspects need to be considered. On the one hand, the impact of the maximum power for the current month needs to be adjusted in the energy management method. On the other hand, Monte Carlo simulations are used to generate diversified application scenarios and obtain the probability distribution of potential returns under different tariffs. By comparing these probability distributions, the optimal selection plan can be determined.

4 Prediction error and demand power forecast model

When utilizing production simulation methods for electricity tariff selection, it is often based on the simulation of historical data and forecasted values. However, discrepancies between forecasts and actual values need to be characterized in order to make the simulation closely approximate real-world conditions. Additionally, in the operation of photovoltaic energy storage systems, it is necessary to consider the highest monthly power consumption and integrate it into the optimization model. Therefore, two fundamental operations that must be carried out before residential users choose an electricity tariff are the establishment of a prediction error model and a long-term scale maximum power consumption prediction model based on historical data.

4.1 Prediction error model

Compare the predicted values of load and photovoltaic generation with the actual values, and model the prediction errors. According to references [25-26], prediction errors follow certain distributions, obtaining the probability distribution of temporal power error values.

Based on accurate photovoltaic and load power data, as well as their forecast values, it is possible to obtain a probability distribution for the prediction error at each power point throughout the day. By utilizing the kernel density estimation method, this distribution can be obtained [27-28]. Because KDE (Kernel Density Estimation) does not require a prior distribution assumption, it can be used to fit the distribution of photovoltaic and load prediction errors, and it demonstrates the relatively strong autocorrelation inherent in the prediction errors.

The calculation method and simplified formula for KDE are as follows:

$$f_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K_h(\frac{x - x_i}{h}) \tag{5}$$

$$K_h(\frac{x - x_i}{h}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-x_i)^2}{2h^2}} \tag{6}$$

where K_h is the kernel function, which often uses the normal kernel for convenience; h is a smoothing parameter called bandwidth. At a specific point i, where x represents the actual power of the photovoltaic or load, x_i represents the predicted value.

4.2 Demand power forecast model based on LSTM network

The maximum monthly demand power serves as a critical constraint in the daily production simulation, and it is an uncertain quantity for each day. In the production simulation process of electricity tariff selection, it is necessary to periodically assess the potential maximum demand power for the current month within each daily cycle. This requires long-term scale forecasting of demand power and its corresponding updates to avoid imposing excessively strict or lenient constraints on the long-term scale.

Firstly, an LSTM-based probabilistic forecasting model is established to predict the daily maximum power imported from the grid for the remaining days in the current month. This model provides a probabilistic prediction interval $f(p^*_{demand})$ for the maximum imported power from the grid.

Then, the maximum imported power from the beginning of the month until the current day is taken into account to update the probabilistic model for the maximum power of the month, characterizing the probability distribution $f(p^{\mathrm{fc}}_{\max})$ of the demand power $p^{\mathrm{fc}}_{\max}$.

Finally, as time progresses, the prediction confidence k in probabilistic forecasting steadily increases. Utilizing the value of k, the maximum demand power for the current month p^*_{demand} can be calculated considering the uncertainty of the forecast . Given historical data including load power, photovoltaic power, and other relevant factors, the demand power for the entire month can be determined by applying the global optimization using the model described above.Given the complete determination of the demand charge for the current month, it is possible to determine the maximum power to be imported from the grid on a daily basis. This can be used as an essential component of the dataset required for forecasting.

Due to the temporal continuity between loads, LSTM is a commonly used network structure for load prediction[29-30]. The input of the LSTM network consists of the maximum value, minimum value, average value, and standard deviation of the power imported from the grid on a daily basis within the past 30 days, along with a time label indicating whether it is a weekday or weekend.After passing through the LSTM layer and dense layer, the output consists of the values of the 20 quantiles of the maximum purchase power for the next 30 days as shown in Fig. 2.

In a given scenario, when running into the middle of the current month, the historical maximum power consumption already generated is also an important reference for the demand power of that

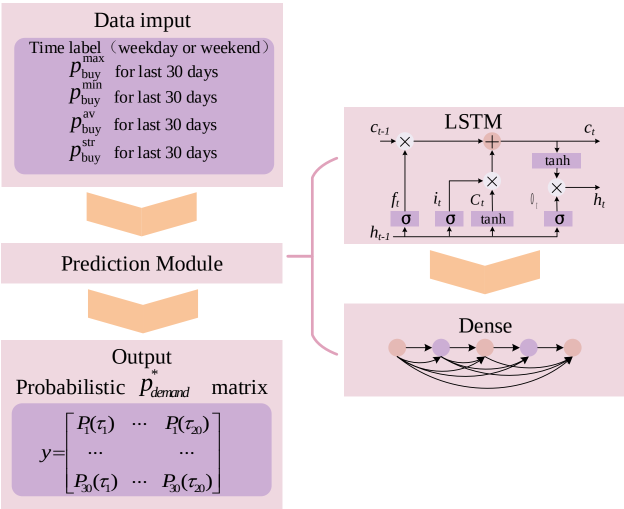

Fig. 2: Model of LSTM network.

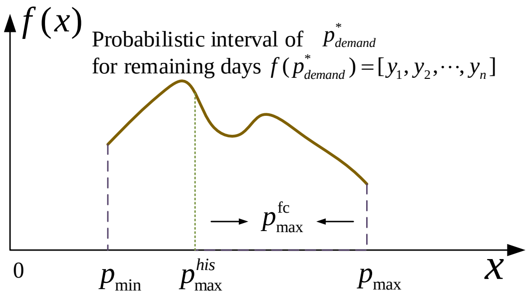

Fig. 3: Forecasting the maximum demand power for the remaining days $p_{\max}^{\text{fc}}$ on a specific day within a month.

month. When making predictions, this factor needs to be taken into consideration, and the probability distribution should be refitted by considering the probability of exceeding this value. As shown in Fig. 3, if the maximum power of electricity imported from the grid before that day $p_{\max}^{\text{his}}$ falls within the predicted interval, the probability density exceeding that value will be organized into a new probability distribution, which can be expressed as:

$$f^{re}(x) = f(x)\frac{1}{\sum\limits_{p_i \geq p_{\max}^{\text{his}}} f(p_i)} \tag{7}$$

where $f(x)$ represents the probability density function before adjustment, $f^{re}(x)$ represents the renewed probability density function. The predicted maximum power $f(p_{\max}^{\text{fc}})$ can be obtained using this new probability density function.

Simultaneously, as the production simulation in a given scenario progresses over time, there is a need for dynamic assessment of the confidence in the predictions and historical maximum power consumption. This dynamic assessment leads to refinement to the predicted demand power.

Based on the acquired values $p_{\max}^{\text{his}}$ and $p_{\max}^{\text{fc}}$, the long term constraints p^*_{demand} can be expressed as:

$$p^*_{demand} = \begin{cases} p_{\max}^{\text{his}}, \xi = k \\ p_{\max}^{\text{fc}}, \xi = 1-k \end{cases} \tag{8}$$

where ξ represents probabilities associated with the confidence of the prediction. k is a value between 0 and 1, and as time goes on, it gradually approaches 1. We can express it as:

$$k = 1 - e^{-\lambda T} \tag{9}$$

where T represents the current day of the month; λ is a fixed parameter that can be optimized based on historical data using particle swarm optimization(PSO) algorithm.

5 Electricity tariff selection

The method for household users to choose electricity tariffs with demand charges can be divided into the following three steps:

First, based on the predicted values, utilize the error distribution to generate a large number of uncertainty scenarios with different prediction errors using Monte Carlo simulation[31-32].

Then, apply the energy management method considering demand charge to simulate production and obtain a probabilistic electricity charge distribution for comparing different tariff profits.

5.1 Scenario generation based on Monte Carlo simulation

Leveraging kernel density estimation of prediction errors, a Monte Carlo simulation approach is adopted to generate a large ensemble of operational scenarios. This entails augmenting the original forecast results with uncertain prediction errors, thereby incorporating probabilistic discrepancies into profit evaluation.

For a given moment t, R represents the ensemble of aggregate prediction errors under the load and new energy integration mode, as shown in equation (27).

$$R = \sum_{x \in X} F_{Load} + F_{PV} = \{R_j\} \qquad j = 1, 2, 3, \cdots, n \tag{10}$$

where F_{Load} and F_{PV} represent the prediction errors associated with all loads and new energy sources, respectively. X represents the distribution space of prediction errors for both loads and new energy sources. R_j represents the error range corresponding to sample j. Furthermore, n represents the number of samples that adequately cover the sample space of prediction errors.

In each sampling process, after obtaining the prediction error as shown in equation (12), overlaying it onto the original forecast values enables the simulation of actual data for production purposes.

$$\Delta p^t = f_h^t(x)|_{x=rand(\Delta p_{\min}, \Delta p_{\max})} \tag{11}$$

$$\mathbf{P} = \mathbf{P}^{'} + \mathbf{\Delta P} \tag{12}$$

where $\mathbf{P}$ represents the generated power sequence considering prediction errors, $\mathbf{P}^{'}$ represents the initial power prediction sequence, and $\mathbf{\Delta P}$ represents the prediction error sequence after probabilistic sampling at each time point.

5.2 Energy management model used for production simulation

An energy management strategy suitable for residential photovoltaic energy storage systems has been proposed. In this strategy, the residential users of the photovoltaic energy storage system adopt an economically optimized dispatch way to manage their household energy. As shown in Fig. 4, based on predicted data and real-time transmitted data of photovoltaic generation and load power, the objective is to minimize the cost of coordinated operation of daily energy storage in the household, taking into account the long-term constraint of monthly demand charges.

5.2.1 Objective function: Household energy management strategies typically prioritize energy cost as the objective

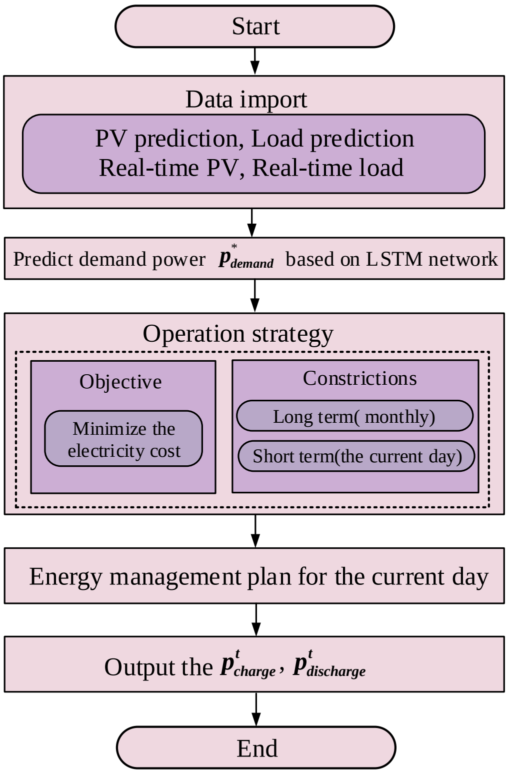

Fig. 4: Energy management strategy for residential photovoltaic energy storage systems based on prediction.

function[33-35]. To minimize the the cost of electricity consumption, the objective function of the model can be expressed as:

$$minf(x,u) = \sum_{t\in L_T} (c_{buy}^t {P_b}^t - c_{sell}^t {P_s}^t)\Delta t + \lambda_m \Delta ess \quad (13)$$

where c_{buy}^t represents unit price per kilowatt-hour (kWh) of electricity bought from the grid during time period t, c_{sell}^t represents unit price per kilowatt-hour (kWh) of feeding electricity to the grid during time period t, L_T represents the remaining time periods of the day, ${P_b}^t$ represents the power imported from the grid during time period t, ${P_s}^t$ represents the power fed to the grid during time period t. Δess represents the value of the maximum power imported from the grid on the current day exceeding the predicted monthly demand power, λ_m represents punishment factor.

5.2.2 Constraints: It is necessary to maintain a balance in the transmitted power:

$$P_{\mathrm{b}}^t + P_{\mathrm{pv}}^t + P_{\mathrm{dh}}^t = P_{\mathrm{load}}^t + P_{\mathrm{s}}^t + P_{\mathrm{ch}}^t + P_{\mathrm{a}}^t \quad (14)$$

where P_{pv}^t represents the predicted photovoltaic power during time period t, P_{load}^t represents the predicted load power during time period t, P_{dh}^t represents the discharging power of the energy storage during time period t, P_{ch}^t represents the charging power of the energy storage during time period t, P_{a}^t represents the discarded PV power during time period t.

Energy storage needs to consider constraints such as charging and discharging power, state of charge (SOC), and ramp rate:

$$0 \le P_{\mathrm{ch}}^t \le U_{\mathrm{ch}}^t \cdot P_{\mathrm{chmax}} \quad (15)$$

$$0 \le P_{\mathrm{dh}}^t \le U_{\mathrm{dh}}^t \cdot P_{\mathrm{dhmax}} \quad (16)$$

$$U_{\mathrm{ch}}^t + U_{\mathrm{dh}}^t \le 1 \quad (17)$$

$$\begin{aligned} &E_{BESS}(SOC^t - SOC^{t-1}) \\ &= (\eta_{ch} P_{\mathrm{ch}}^t - P_{\mathrm{dh}}^t/\eta_{dh})\Delta t \end{aligned} \quad (18)$$

$$SOC_{min} \le SOC^t \le SOC_{\max} \quad (19)$$

$$\Delta t \cdot \Delta P_{\mathrm{ch\_max}} \le P_{\mathrm{ch}}^{t+1} - P_{\mathrm{ch}}^t \le \Delta t \cdot \Delta P_{\mathrm{ch\_max}} \quad (20)$$

$$-\Delta t \cdot \Delta P_{\mathrm{dh\_max}} \le P_{\mathrm{dh}}^{t+1} - P_{\mathrm{dh}}^t \le \Delta t \cdot \Delta P_{\mathrm{dh\_max}} \quad (21)$$

where U_{dh}^t and U_{ch}^t represent binary variables ensuring that energy storage does not discharge and charge at the same time. P_{chmax} and P_{dhmax} represent maximum charging power and maximum discharging power of energy storage. E_{BESS} represents capacity of energy storage, SOC^t represents SOC of energy storage. η_{ch} and η_{dh} represent charging and discharging efficiency of energy storage. SOC_{min} and SOC_{max} represent minimum value and maximum value of SOC. $\Delta P_{\mathrm{ch\_max}}$ and $\Delta P_{\mathrm{dh\_max}}$ represent maximum charging and discharging ramp rate.

The whole system needs to consider constraints of buying and selling electricity:

$$0 \le P_{\mathrm{b}}^t \le U_{\mathrm{b}}^t \cdot P_{\mathrm{bmax}} \quad (22)$$

$$0 \le P_{\mathrm{s}}^t \le U_{\mathrm{s}}^t \cdot P_{\mathrm{re}} \quad (23)$$

$$U_{\mathrm{b}}^t + U_{\mathrm{s}}^t \le 1 \quad (24)$$

$$P_{\mathrm{pv}}^t - P_{\mathrm{ch}}^t + P_{\mathrm{dh}}^t - P_{\mathrm{a}}^t \le P_{\mathrm{vt}} \quad (25)$$

where U_{b}^t and U_{s}^t represent binary variables ensuring that the system does not import electricity from the grid and feed electricity to the grid at the same time. P_{bmax} represents maximum power that can be imported from the grid, P_{re} represents maximum power that can be fed to the grid (some European countries set it at 50-70 percent of the inverter's maximum power). P_{vt} represents the inverter's maximum power.

After forecasting the demand power for the current month, it is necessary to ensure that the purchased power from the grid during operation does not exceed this value.

$$0 \le P_{\mathrm{b}}^t - \Delta ess^t \le p_{\mathrm{demand}}^m \quad (26)$$

$$\Delta ess^t \le \Delta ess \quad (27)$$

where p_{demand}^m is the maximum predicted demand for this month on the current day m, Δess^t represents the penalty variable for exceeding limits.

5.3 *Charge comparison and electricity tariff selection*

By generating a large number of operational scenarios based on Monte Carlo simulations and employing an energy management model that takes demand charges into account, production simulations can yield the electricity costs for users considering source-load prediction uncertainties under different electricity tariffs as shown in Fig. 5.

Furthermore, by analyzing the extensive electricity cost results generated across multiple scenarios using KDE once again, it is possible to obtain the probability distribution of electricity costs under different electricity tariffs.

Under each electricity tariff, further analysis can yield diversified references for household users' tariff selection, including the average electricity cost under probabilistic scenarios, electricity costs under optimistic estimates, and the maximum potential cost that may be reached in low-probability scenarios.

6 Case study

An analysis was conducted on a number of real-world residential users with photovoltaic energy storage systems. The study compared

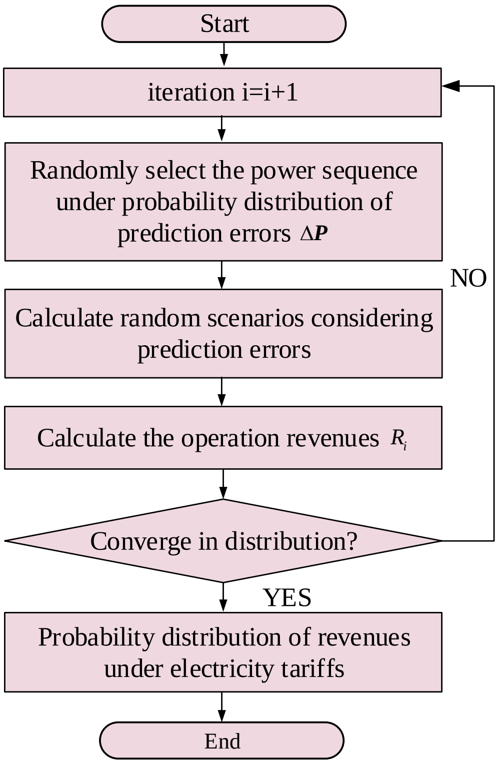

Fig. 5: Monte Carlo simulation process.

Table 1 Electricity tariff A (peak time from 4pm to 7pm)

Electricity price	Summer	Winter	
Basic service charge	$ 0.400	$ 0.400	per day
Demand charge	$ 16.875	$ 11.845	per kW
Energy charge (On-peak)	$ 0.12414	$ 0.08711	per kW
Energy charge (Off-peak)	$ 0.05267	$ 0.05267	per kWh
Energy charge (Super Off-peak)		$ 0.03166	per kWh

Table 2 Electricity tariff B (peak time from 3pm to 8pm)

Electricity price	Summer	Winter	
Basic service charge	$ 0.400	$ 0.400	per day
Demand charge	$ 16.870	$ 11.842	per kW
Energy charge (On-peak)	$ 0.08615	$ 0.06323	per kW
Energy charge (Off-peak)	$ 0.05146	$ 0.05137	per kWh
Energy charge (Super Off-peak)		$ 0.03166	per kWh

Table 3 Electricity tariff C (peak time from 3pm to 8pm)

Electricity price	Summer	Winter	
Basic service charge	$ 0.400	$ 0.400	per day
Demand charge (On-peak)	$ 19.434	$ 13.676	per kW
Demand charge (Off-peak)*	$ 6.239	$ 6.239	per kW
Energy charge (On-peak)	$ 0.08615	$ 0.06323	per kW
Energy charge (Off-peak)	$ 0.05146	$ 0.05137	per kWh

∗ During Off-peak hours, demand charges are only applied to the portion exceeding 5kW of maximum power.

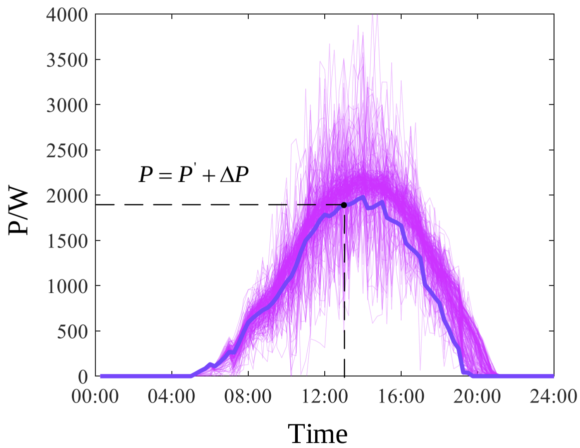

Fig. 6: The PV forecast and the randomly generated scenarios taking into account the prediction errors for a typical day.

the control strategy of the photovoltaic energy storage system proposed in this article with a control method that does not involve forecasting. The data used in the analysis and the photovoltaic energy storage system utilized were provided in Arizona. The user's household is equipped with a 5 kWh energy storage system, capable of accommodating a maximum charge/discharge power of 2.5 kW.

The reference electricity price tariff, as shown in Tab 1, Tab 2 and Tab 3, including energy charge pricing and demand charge pricing, is from a power utility in Arizona. The energy-based pricing is divided into two levels: Peak, Off-peak and Super Off-peak. The defined time periods are as follows: May to October is designated as the summer season, while November to April is classified as the winter season. During winter weekdays, an extended Super Off-Peak period is observed from 10 AM to 3 PM, allowing for electricity consumption at a reduced tariff.

Analyze the accuracy of dynamic prediction for the maximum imported power in the current month; comprehensively compare the advantages of the strategies proposed in this paper for two electricity pricing tariffs provided by the company; simultaneously consider the scale of the deployed energy storage and evaluate the applicability of different storage sizes to the strategies outlined in this paper.

6.1 *Prediction error and demand power forecast*

This section focuses on characterizing the user's source-load prediction errors and forecasting the maximum monthly power consumption.

6.1.1 Prediction error characterizing: In addition to deterministic profit analysis results, probabilistic analysis methods considering prediction errors can be used to compare the electricity costs of different packages and calculate the electricity costs under different probabilities.

Based on the historical photovoltaic power, actual load values, and power values for each month, KDE is used to transform the prediction errors at different time intervals within a day into probability distribution functions. When combined with the original source-load prediction data, this process yields the distribution of uncertainties in photovoltaic and load power. A number of scenarios can be generated using the prediction error distribution to simulate the desired electricity costs. Taking photovoltaics as an example, Fig. 6 shows the photovoltaic forecast for a typical day and the randomly generated scenarios.

6.1.2 Demand power forecasting using LSTM netwok: Currently, the energy management strategy for demand charge is being taken into account, which involves predicting the peak power consumption. This prediction is typically based on the maximum electricity demand observed over a historical period of 15 or 30 days. However, as depicted in Fig. 7, there can be notable disparities between the maximum power recorded in the previous month or half a month ago and the actual electricity consumption patterns observed in the current month. During the LSTM prediction process, the training set consists of historical data spanning a period of nine months, while the testing set includes data from the subsequent two months. As depicted in in Fig. 8, the predictions exhibit

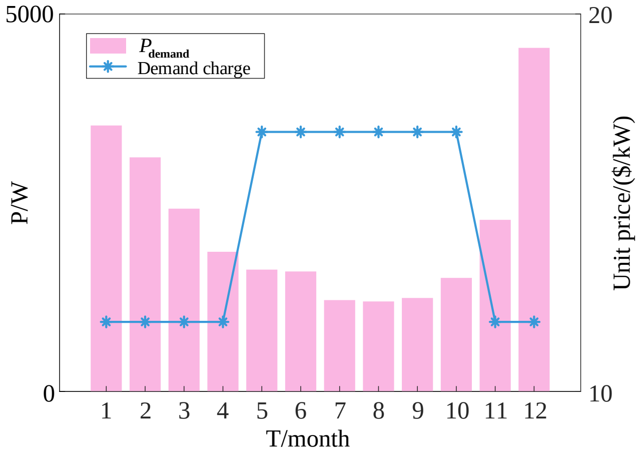

Fig. 7: Monthly highest consumption power in a year.

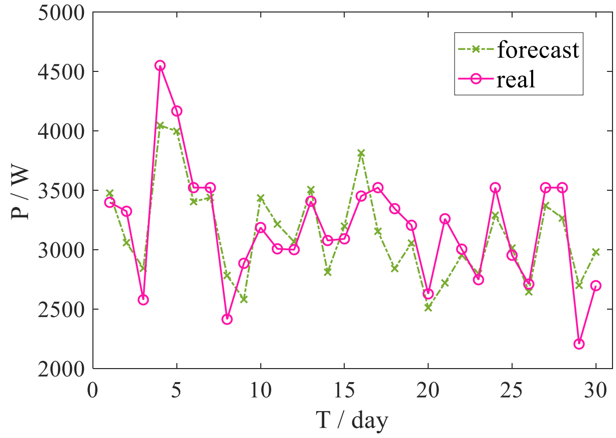

Fig. 8: Predicting the daily peak electricity consumption for the next 30 days.

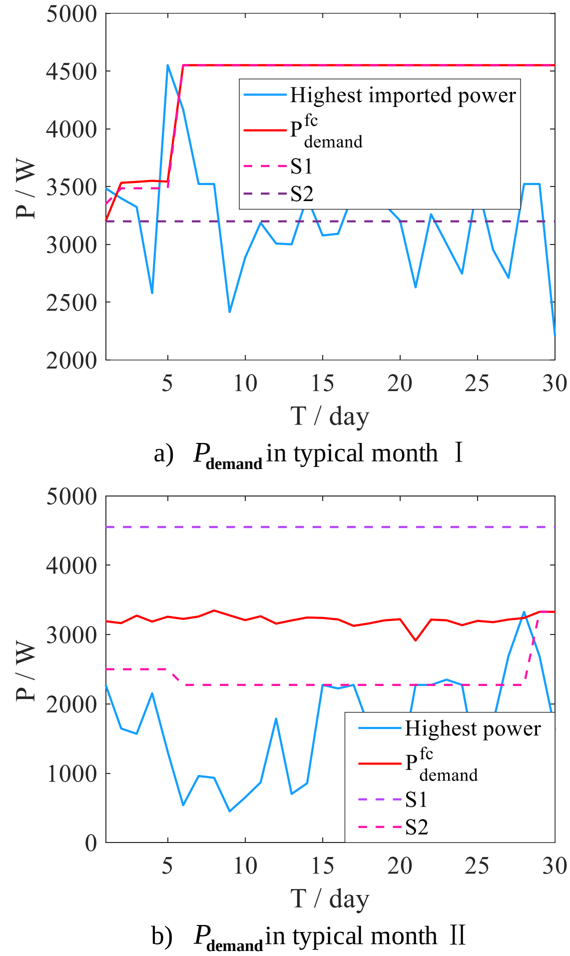

Fig. 9: Prediction the daily peak electricity consumption for the next 30 days.

a high degree of accuracy in capturing the variations of the daily maximum electricity demand for the next 30 days. These results effectively demonstrate the model's ability to reflect the underlying trend in power consumption dynamics.

6.1.3 Refining predictions based on historical peak consumption power: Based on historical data, the objective is to refine predictions and enhance their accuracy through adjustment. After optimization, we have determined the value of parameter $lamda$ to be 0.0057, aiming to maximize the overall predictive accuracy after adjustment. As depicted in Fig. 9, the household user employs a strategy of daily forecasting and updating in two typiacal months. Due to the seasonal nature of electricity tariff packages with demand charges, which are divided into summer and winter seasons, the typical Month I is selected from a month during the summer season, while the typical Month II is selected from a month during the winter season. The daily estimated maximum demand for this month, obtained through this approach, demonstrates an early convergence with the actual values. Consequently, these estimates are deemed reliable and are assimilated as enduring constraints within the control model of the photovoltaic storage system.

Two commonly used long-term constraint acquisition methods within a month S1 and S2 are selected for comparison. S1 represents: optimizing the overall system directly to obtain the highest power based on historical data or future predictions. In this paper, an operation of monthly updates is added for comparison. S2 represents: using the highest load power from the previous month as the maximum demand constraint for the next month, which is commonly applied in this scenario.

Furthermore, in a), the occurrence of peak demand for the month is observed at an earlier stage. The predictive method incorporating adjustments effectively captures this feature, allowing for the timely establishment of a long-term constraint based on the estimated value. This constraint remains applicable throughout the subsequent period of the same month.The method S1 and the proposed method in this paper yield similar results, while the method S2 clearly does not adapt well to the high load conditions of this month.

Conversely, in b), where the peak demand for the month manifests at a later stage, the augmented predictive method anticipates this scenario in advance, so it enables the precise setting of a long-term constraint at the commencement of the month, ensuring accurate integration within the control framework. The S2 method, which is based on the highest load of the past month, appears to be overestimated. On the other hand, the S1 method fails to predict the load peak in a timely manner, resulting in a long-term strict demand constraint that hinders the optimal energy management strategy for the photovoltaic and storage system.

As a result, the demand forecasting method that incorporates intra-month adjustments refines the prediction in terms of household electricity consumption using LSTM network. And it can provide more support for the subsequent energy management strategy.

6.2 Electricity tariff selection

6.2.1 Energy management strategy considering demand charge: A comparison was made on the household electricity usage of a specific day for a residential user under three different strategies, which are:

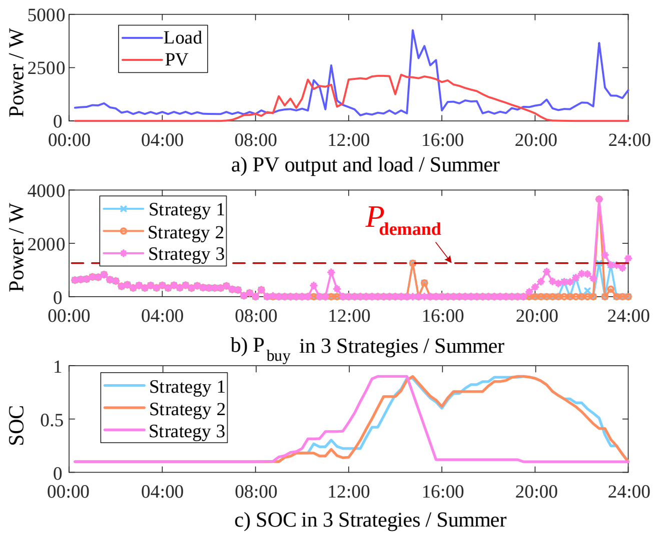

Fig. 10: Comparative analysis of the three strategies during winter.

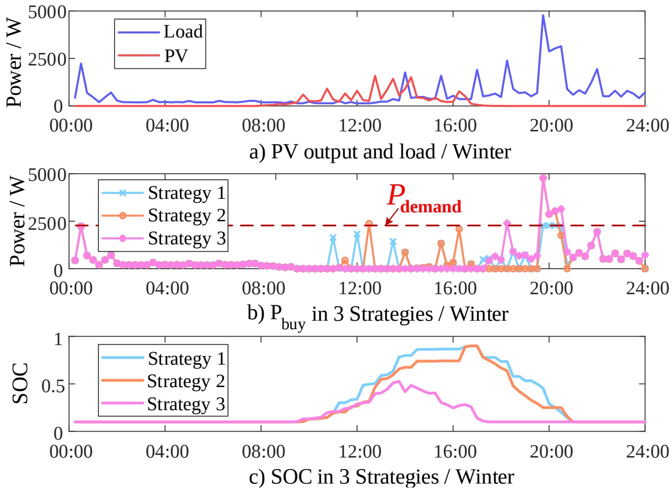

Fig. 11: Comparative analysis of the three strategies during summer.

Table 4 Comparison of charges for electricity tariffs under deterministic conditions

Electricity price	Summer	Winter	Total electricity charges
Tariff scheme A	\$ 174.38	\$ 228.97	\$ 403.36
Tariff scheme B	\$ 171.94	\$ 233.74	\$ 405.68
Tariff scheme C	\$ 116.46	\$ 259.65	\$ 376.12

Strategy 1: Daily forecasting of monthly demand power and incorporating demand constraints in the model with rolling operation, which is the energy management strategy proposed in this study.

Strategy 2: Energy management strategy without considering demand constraints.

Strategy 3: The commonly used strategy in residential photovoltaic energy storage systems. When the solar power generation exceeds the household load, the excess electricity is prioritized for charging the energy storage system, and any surplus electricity is fed back to the grid. Conversely, when the solar power generation is lower than the energy storage level, priority is given to using the stored energy to power the household, and if the energy storage capacity is insufficient, electricity is purchased from the grid.

As shown in Fig. 10, under the three energy management strategies, the highest input power for the daily load during the peak summer month of July exhibits significant variations. Strategy 1 effectively restricts the peak power below the anticipated highest power for that specific day in July, thereby reducing the demand charges for that month.

Furthermore, as shown in Fig. 11, the three energy management strategies demonstrate distinct effects on the highest input power for the daily load of the household during the peak winter month of November. Despite the introduction of an off-peak electricity price during the winter season, Strategy 1 still effectively manages to control the peak power below the projected highest power for that specific day in November, resulting in a reduction in demand charges for that month.

6.2.2 Electricity charge comparison and tariff selection: For the three different electricity tariffs listed in Table 1 to Table 3, we employ the proposed energy management strategies in this study to conduct operational simulations of actual photovoltaic and load outputs over the past year. Subsequently, we analyze the total electricity costs for the user under each tariff. Only for the electricity tariffs with demand charges, the demand power is predicted and incorporated into long-term constraints. The comparative analysis results for the entire year are shown in Table 4.

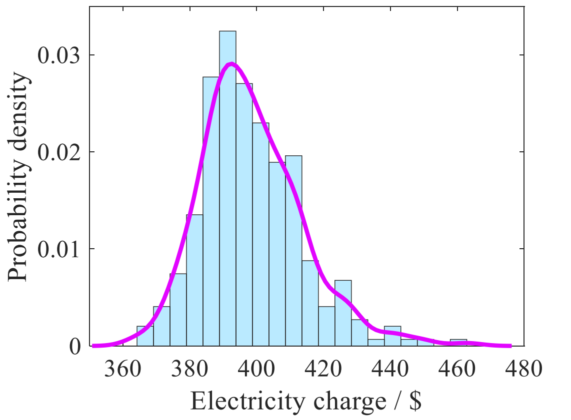

Fig. 12: Distribution of electricity costs under Tarrif scheme A.

In summer, the peak electricity demand throughout the day often occurs during off-peak hours of Tariff C. The peak charges during this period are relatively low, resulting in lower overall electricity costs compared to Tariffs A and B.

In winter, however, the peak electricity demand throughout the day often occurs during peak hours of Tariff C, which have high peak charges. As a result, the total charges during winter are higher compared to Tariff schemes A and B. Taking into account the electricity costs for the entire year, choosing Tariff scheme C remains the optimal choice for this residential user.

In addition to deterministic profit analysis results, probabilistic analysis methods considering prediction errors can also be used to compare the electricity costs of different packages and calculate the electricity costs under different probabilities.

The probability distribution of electricity costs for the year under electricity tariff A is shown in Fig. 12. Table 5 shows the maximum electricity costs that can be reached within each electricity tariff package under high, moderate, and low probabilities. It can be observed that under Tariff scheme A, a conservative estimate suggests that the electricity cost is approximately \$ 430, on average it is estimated to be around \$ 410, and in fewer cases, it may only require an electricity cost of \$ 370. Fig.13 depicts the probability distribution of electricity costs for the upcoming year under three different tariff schemes. Comparatively, the electricity cost distributions for Tariff A and Tariff B exhibit close similarity, owing to their approximate demand charges. Conversely, the electricity cost distribution under Tariff C demonstrates significant divergence, primarily due to its minimal demand charges in certain months. This finding aligns well with the results of deterministic electricity cost comparison, affirming that selecting Tariff C as the optimal tariff choice is consistent with the deterministic assessment of electricity costs.

Table 5 The potential maximum electricity costs for various tariffs under different probabilities

Probabilities	Low	Moderate	High
Tariff scheme A	$ 432.56	$ 399.42	$ 374.55
Tariff scheme B	$ 436.15	$ 402.87	$ 376.49
Tariff scheme C	$ 441.73	$ 382.13	$ 347.02

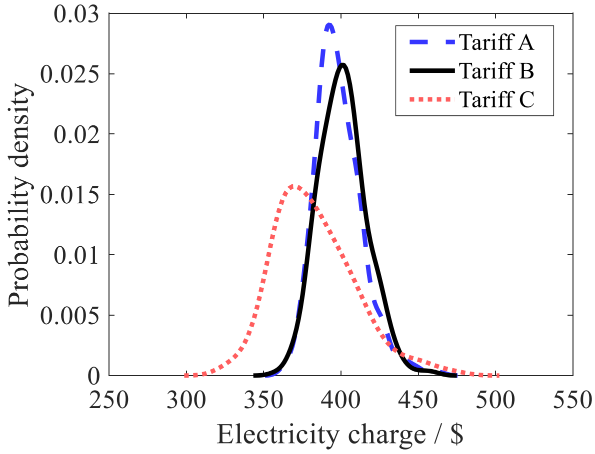

Fig. 13: Distribution of electricity costs under three tariffs.

7 Conclusion

Diversified pricing tariffs for electricity, including time-of-use rates and demand charges based on peak power demand, are increasingly being adopted. This study focuses on the pricing structure of electricity tariffs with demand charges in Arizona, North America, and analyzes an electricity tariff selection method considering uncertainty applicable to households equipped with solar PV and energy storage systems.

In this study, a dynamically updated monthly demand power forecasting method is proposed for production simulation, enabling energy management strategies to account for long-term scale constraints on a monthly basis and perform rolling optimizations. Additionally, considering prediction uncertainty, probabilistic electricity costs under different electricity tariff packages are obtained using Monte Carlo simulations, providing a richer set of references for electricity tariff selection.

In the case study presented in this paper, an analysis was conducted on a household user's annual energy usage for three electricity tariff schemes that include demand charge. Both deterministic and probabilistic analyses of electricity costs were performed. In both cases, the conclusion was that selecting Tariff scheme C would result in the lowest electricity costs. However, the tariff selection method that considers uncertainty could also provide insights into the best and worst-case scenarios for each package, particularly when dealing with lower prediction accuracy.

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