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Green Electricity Product Solution in the Background of Electricity Market

Maoqing Shi

Business School, University of Shanghai for Science and Technology, Shanghai, China
Email: 879076379@qq.com

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Abstract

In the development of a new power system dominated by green energy, green electricity has become a standardized commodity circulating nationwide through market mechanisms. The role of green electricity has evolved from being a dependent entity reliant on grid-guaranteed procurement to becoming a value-driven competitor driven by price signals and electricity demand. This paper proposes a green electricity product solution designed to provide reliable value assessment models and feasible implementation plans for users with diverse renewable energy needs. By modeling current internal power generation and consumption data within enterprises, the solution enables efficient communication between both parties during preliminary discussions. Based on digitalized models, green electricity service providers can deliver comprehensive solutions that are environmentally sustainable, economically viable, and highly efficient through policy analysis and technical evaluation.

Keywords

Green Electricity, Electricity Market, Load Clustering, Photovoltaic Power Generation Forecasting, Value-Driven Solutions

1. Introduction

Against the backdrop of deepening power market reforms, the new energy industry is transitioning from a subsidy-dependent phase to a market-driven competition phase, with fundamental changes in its development logic and profit models. China, in response to the global temperature control targets of the Paris Agreement and the international consensus on accelerating energy transition, as well as the trend of new energy becoming a core alternative energy in global carbon reduction efforts, issued over 10 policy documents in 2025 alone, either independently or jointly with the National Energy Administration, addressing issues such as new energy development and carbon reduction investments. This demonstrates China's firm commitment to advancing energy transition and fulfilling its global carbon reduction pledges. Among these, there are significant documents that reshape the industry's development logic and lead market reforms in new energy, such as the "Notice on Deepening the Market-oriented Reform of New Energy Feed-in Tariffs to Promote High-quality Development of New Energy" (hereinafter referred to as "Document No.136"), which explicitly promotes the full market entry of new energy electricity. The core function of Document No.136 lies in bridging the transition period from "policy-backed" to "market-driven" for new energy [1]: on one hand, it breaks the path dependence of the traditional guaranteed purchase model, and on the other hand, it mitigates significant profit fluctuations for new energy enterprises caused by imperfect rules in the early stages of marketization, providing institutional safeguards for a smooth industry transition. The new trends in the power industry are driving exploration of new business models on both the generation and consumption sides, with green, economical, and efficient power supply solutions becoming a key factor for long-term competitiveness of power generation enterprises.

The limited understanding of the power industry among industrial and commercial users has compelled power generation companies to proactively develop solutions, helping clients establish green, cost-effective, and efficient energy utilization plans. Current negotiations between power producers and consumers are primarily centered around electricity markets, which can be categorized into medium-to-long-term markets and spot markets. The medium-to-long-term market helps businesses mitigate price risks by enabling controlled transactions of electricity commodities. However, industrial and commercial users still face persistently high electricity costs, mainly due to insufficient digitalization capabilities in power usage and poor alignment between supply plans and policy requirements. Key challenges include inadequate data exchange during initial coordination between renewable energy producers and power users [2], as well as insufficient consideration of policy changes when evaluating supply solutions. These issues highlight the need for green energy products to establish accurate rules based on mutual understanding of power generation and consumption data. This requires not only digital tools and precise algorithms but also dynamic adjustments to implementation strategies for green energy products.

After the operation of the electricity market, research on generation forecasting models and green electricity product solutions has significantly increased. Generation forecasting is considered the most critical step in discovering price signals. When enterprises connect with electricity users, precise control of future generation curves can improve the efficiency of negotiations between both parties. The adoption of menu pricing allows users to autonomously choose electricity pricing models, guiding users to independently schedule their electricity loads while helping new energy enterprises clearly understand the overall electricity consumption of users [3]. With the increase in distributed photovoltaic installations, establishing private databases can enhance users' awareness of their own electricity consumption [4]. However, the current establishment of the electricity market has driven new energy enterprises to shift their competitive focus from cost control to value competitiveness. In recent years, China's new energy enterprises have built large-scale new energy power stations, leading to an oversupply of electricity commodities. Enterprises need to obtain power supply contracts through low-price bidding in the electricity market, which has resulted in consecutive losses for most enterprises in the industry and significant resource waste. Meanwhile, the current cooperation model is mostly characterized by enterprises formulating a static plan, under which all users sign electricity contracts [5] [6].

In conclusion, this paper combines the new rules of the electricity market to deeply study the solution of the power demand differentiation of the new energy enterprises, and based on the research conclusions, proposes the design of the medium and long-term forecast model of the photovoltaic under the electricity market environment and the solution of the differentiation of the new energy demand.

2. Value-Driven Green Electricity Solutions

To better address users' electricity demand, this study tackles the cost escalation caused by power consumption deviations by designing an effective value exchange solution between power generation and consumption entities. The solution involves modeling annual and monthly output curves of renewable energy. First, DTW-spectral clustering algorithm is applied to group electricity consumption curves of all users under bilateral negotiation contracts. Second, long-term power forecasting algorithms predict renewable energy generation scenarios. Finally, different time-of-use pricing schemes are automatically generated to provide differentiated digital contracts for various users. In the monthly trading market, historical data from all contracted users undergoes demand response capability evaluation. Power prediction results are updated based on real-time weather data, while the full lifecycle costs of renewable energy equipment are calculated for users. The study concludes by communicating demand response incentive mechanisms to proactively guide behavioral changes, thereby reducing market structure balancing costs caused by supply-demand imbalances.

The three core classification dimensions form the foundation for user stratification and product adaptation. Each dimension has clearly defined connotations and boundaries, explained as follows: The Green Electricity Demand Dimension categorizes users based on actual needs into three types: no demand, passive demand driven by government low-carbon emission requirements, and export-driven demand resulting from reduced carbon tariffs for EU exports. The Load Characteristics Dimension analyzes historical electricity consumption data, combining load fluctuation patterns with future trends to classify users into four groups: high-load fluctuation with upward trend, low-load fluctuation without upward trend, stable-load fluctuation with upward trend, and stable-load fluctuation without upward trend. The Revenue Preference Dimension focuses on core benefits of new energy partnerships, dividing users into environmental expectation-oriented and long-term investment-oriented types. Environmental expectation-oriented users prioritize short-term electricity cost reductions and are sensitive to policy changes and supply chain risks in new energy. Long-term investment-oriented users are willing to proactively invest in new energy facilities during initial phases, owning partial equity, and focus on long-term investment returns.

2.1. User Classification Method Based on DTW-Spectral Clustering

Considering *n* users, the dataset records their power consumption at *m* time points. For the *i*-th user, its power consumption curve is denoted as X_i, where $X_i = [x_{i1}, x_{i2}, \cdots, x_{im}]$ (x_{ik} represents the power consumption of the *i*-th user at the *k*-th time point, $i = 1, 2, \cdots, n$, $k = 1, 2, \cdots, m$). Due to potential inconsistencies in data standards across users, dynamic time warping (DTW) is employed to calculate the shape similarity between two load curves; the DTW distance between the *i*-th and *j*-th user's power consumption curves X_i and X_j is denoted as $\mathrm{DTW}(X_i, X_j)$, which quantifies the dissimilarity between the two curves (the larger the value, the lower the similarity). To map the DTW distance (dissimilarity) to similarity, the Gaussian kernel function is used to construct the similarity matrix $K \in \mathbb{R}^{n \times n}$, where each element K_{ij} (representing the similarity between the *i*-th and *j*-th user) is calculated as follows:

$$K_{ij} = \exp\left(-\frac{\mathrm{DTW}(X_i, X_j)}{\sigma}\right)$$

In the formula above, σ is the bandwidth parameter of the Gaussian kernel, which is used to adjust the sensitivity of similarity to DTW distance (a larger σ makes the similarity less sensitive to distance changes, and vice versa; no additional normalization is performed here, and the similarity value ranges from (0, 1]). The definitions of all newly appearing symbols and matrices in this process are shown in the following table:

The similarity matrix K characterizes the connectivity between users, while the Laplacian matrix L further reflects the interconnectivity between users' power consumption curves [7] [8]. In this study, the RatioCut graph-cutting method is applied to minimize the RatioCut function; the specific implementation process involves identifying the *k* smallest eigenvalues of the Laplacian matrix L and their corresponding unit eigenvectors. These *k* unit eigenvectors form a new dataset of size $n \times k$, which is then clustered using the *k*-means clustering algorithm. The contour coefficient is used to assist in selecting the optimal number of categories (*k*) after clustering [9].

2.2. Power Generation Prediction Curve

Medium-and long-term photovoltaic power forecasting requires consideration of data and network model characteristics, making it a significant and worthy research topic in the medium-and long-term market. The data characteristics of phtovoltaic power show relatively small variations within short cycles, but medium-and long-term forecasting needs to capture long-term patterns such as seasonal and monthly solar radiation changes. However, the medium-and long-term time series of photovoltaic power belong to non-stationary sequences, and their long-term prediction is highly challenging due to the intertwined effects of periodicity and random fluctuations on prediction accuracy. To address this issue, deep learning has been proven effective in power forecasting [10] [11]. Deep learning-based photovoltaic power forecasting models can be categorized into two types: Transformer models based on encoder-decoder architectures and recurrent neural network models. Among them, the RUL prediction model proposed in [12] encodes and decodes time series models at different scales, solving the error accumulation problem caused by multi-step forecasting. According to the periodic characteristics of photovoltaic power generation, [13] introduced a periodic attention mechanism during decoding to enhance certain time series features, thereby improving prediction accuracy. Recurrent neural network models have various variants and hybrid models. The bidirectional structure of BiLSTM can simultaneously learn the impact of historical data on current conditions and the reverse correlation of future trends on the present, adapting to the characteristics of photovoltaic power influenced by both medium-and long-term periodic factors (e.g., solar radiation and seasons) and random fluctuations [14]. GRU, as a variant of LSTM, retains the ability to capture long-range dependencies while improving computational efficiency. However, the aforementioned models exhibit limited generalization capabilities, and recurrent neural networks face performance bottlenecks due to the vanishing gradient problem. To address this, this study proposes an attention mechanism integrated into the hybrid GRU-BiLSTM model. This mechanism enhances the nonlinear temporal characteristics of photovoltaic power generation, thereby improving the model's ability to capture critical temporal patterns and ultimately boosting prediction accuracy.

2.3. Differentiated New Energy Demand Solutions

The core strategy centers on "matching policies to demand, products to load profiles, and cooperation models to user preferences", aiming to build value-driven differentiated solutions. This paper reviews changes in the current energy landscape and identifies characteristics of electricity users, laying a solid foundation for delivering green, cost-effective, and efficient energy solutions.

Some export-oriented enterprises are required to account for carbon emissions in their products. For instance, the EU's Carbon Border Adjustment Mechanism (CBAM) mandates physical traceability of green electricity, leading to strong demand for renewable power among such enterprises. As wind and solar power are characterized by high uncertainty, a user's load profile directly determines its electricity costs. Enterprises with a high proportion of adjustable loads can adopt strategies to achieve more economical power costs.

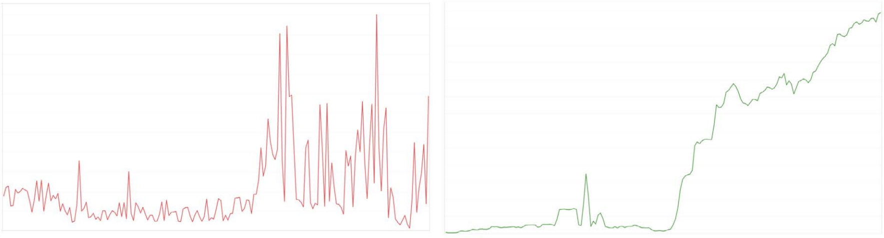
In the new-type power system with a high share of new energy, forward-looking enterprises have recognized the importance of a reliable and integrated power supply solution. As professional providers of power supply technical solutions, power generation enterprises should provide an investment evaluation model in the early project stage. The model should dissect the intrinsic value of user needs, select the most reliable solution that best meets user requirements, and present the results to users in a digital form [15] [16].

3. Case Analysis

3.1. User Power Consumption Curve Clustering

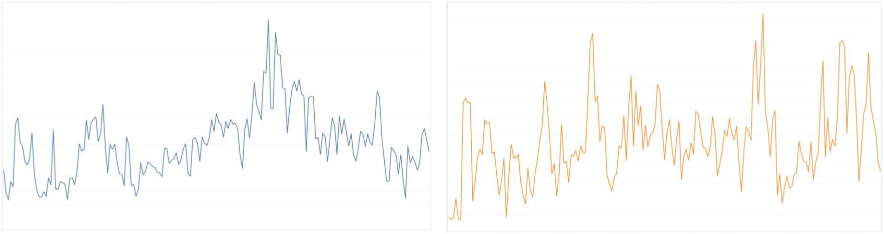
The electricity data in this paper are from the public dataset on the github website, which includes the power consumption data of 83 electricity users in a typical province of China in 2020 over a half-year period, with daily electricity consumption curves measured at a time scale of 15 minutes.

The DTW-spectral clustering method was used to classify users' electricity consumption behaviors in the data. The number of cluster centers was determined by the contour coefficient. The experiment revealed that when the number of centers was 4, the clusters with higher than average contour coefficients first reached saturation. Therefore, 4 was selected as the number of cluster centers. The user curves closest to the cluster centers were chosen as typical curves. The four subgraphs in **Figure 1** correspond to four types of users respectively.



Volatility-driven production increase

Steady growth type



Volatility Fixed Type

Steady Fixed Type

Figure 1. Diagram of power feature clustering.

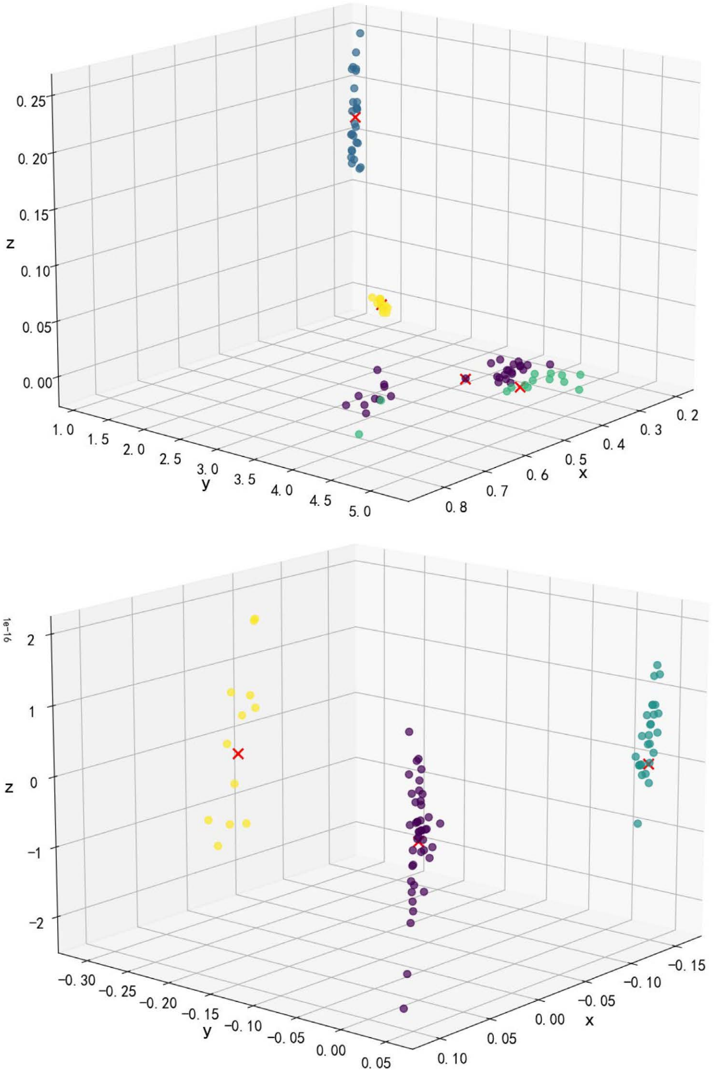
To demonstrate the practical value of the proposed method, this study compares it with DTW-spectrum clustering, using power feature clustering and cosine distance-spectrum clustering as benchmark methods. Power feature clustering, a common engineering approach for user electricity behavior analysis, calculates statistically significant features with domain-specific knowledge to cluster consumption patterns. The following features are employed to describe user electricity consumption behavior:

1) Daily load fluctuation $CV = \frac{\sigma_{daily}}{\mu_{daily}} \sigma_{daily} \mu_{daily}$ rate: where is the daily load standard deviation and is the daily load mean.

2) Monthly load peak-to $\frac{P_{peak} - P_{vally}}{\mu_{monthly}} P_{peak} \mu_{monthly}$ -valley ratio: (monthly maximum load, monthly average load).

3) Linear regression coefficient: The linear regression is used to fit the load curve of a single user, and the growth trend of a user is judged by the regression coefficient.

The three subgraphs in **Figure 2**, from left to right, show the clustering results of DTW-spectral clustering, power feature clustering, and cosine distance-spectral clustering. The differences among these methods can be evaluated by calculating their closeness and separation metrics, with the comparison of results presented in **Table 1**.



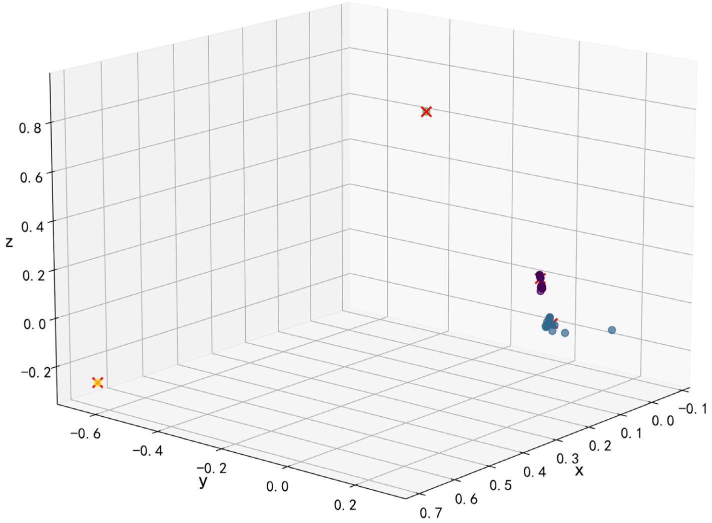


Figure 2. User clustering result diagrams of different clustering methods.

Table 1. Table type styles (Table caption is indispensable).

Algorithm	Cluster labels	Number of samples within class	Compactedness	Resolution
DTW-spectral Clustering	1	30	0.211	0.463
	2	27	0.045	0.495
	3	14	0.185	0.463
	4	12	0.089	0.495
Power Feature Clustering	1	44	0.008	0.244
	2	27	0.005	0.244
	3	12	0.019	0.325
Cosine Distance-spectral Clustering	1	56	0.020	0.233
	2	25	0.027	0.233
	3	1	0	1
	4	1	0	1

Quantitative analysis of clustering results demonstrates that spectral clustering outperforms power feature clustering, as evidenced by three key metrics: 1) In intra-class distribution, spectral clustering achieves more balanced sample allocation across categories, effectively addressing the over-concentration or sparsity issues in power feature clustering while better aligning with real-world user distribution patterns; 2) In terms of intra-class proximity, spectral clustering exhibits significantly smaller average distances than power feature clustering, indicating superior ability to group samples with similar consumption patterns and higher consistency in intra-class behavior; 3) Regarding inter-class separation, spectral clustering maintains greater minimum distances between categories compared to power feature clustering, demonstrating clearer boundaries between distinct categories and enhanced differentiation of samples with different consumption behavior patterns.

The user classification results show that these four categories correspond to users in four different industries.

- Volatility-driven production increase: enterprises with high energy-intensive application scenarios such as steel, petrochemicals, building materials, and non-ferrous metals.
- Steady growth type: Enterprises providing computing power facilities, such as data centers.
- Volatility Fixed Type: Enterprises with flexible application scenarios in machinery, light industry, textiles, automotive, battery manufacturing, etc.
- Steady Fixed Type: Enterprises with scalable and adjustable loads, such as electrolytic aluminum, polysilicon, and hydrogen production through water electrolysis.

When providing power supply technical solutions, new energy power generation companies develop customized product strategies for different user categories. By analyzing collected electricity load data through classification methods, companies identify user segments and design contingency plans during initial planning phases to accommodate future expansion. For users with strong demand flexibility, investing in energy storage systems becomes a strategic option. This integrated solution not only enhances grid resilience and reduces electricity price risks post-project delivery, but also enables peak-valley arbitrage during power trading to further optimize energy consumption costs.

3.2. Annual and Monthly Power Generation Forecast

This section specifies reproducible forecasting model architecture and training settings. Annual forecasting uses 4 years of historical data and a 6-month test set; monthly forecasting adopts rolling prediction for the first 6 months of the test period.

In data preprocessing, missing photovoltaic power data were filled by periodic interpolation. A sensitivity check (5% data masked) showed 3.2% MAE, with the rule applied to 4.8% of the dataset; interpolated data were only used in the training set to avoid test deviation. Power measurement was standardized by 15-minute interval averages.

Model input features include historical transaction volume, seasonal/trend indicators (Min-Max normalized to [0, 1]); prediction horizon is 6 months and 1 month.

Feature engineering involves extracting characteristics, applying variance filtering, and selecting features from the data. The study revealed that the photovoltaic power curve approaches zero at night. To address this, the paper introduces sine and cosine encoding, mapping hours onto a unit circle to transform the 24-hour periodicity into continuous numerical features, enabling the model to capture temporal cyclic patterns. Two fields in the original data showed minimal variance and were removed prior to fitting. During feature selection using the embedding method, three fields were identified as explaining over 95% of the photovoltaic power variations. The importance scores of all features are as follows (**Figure 3**):

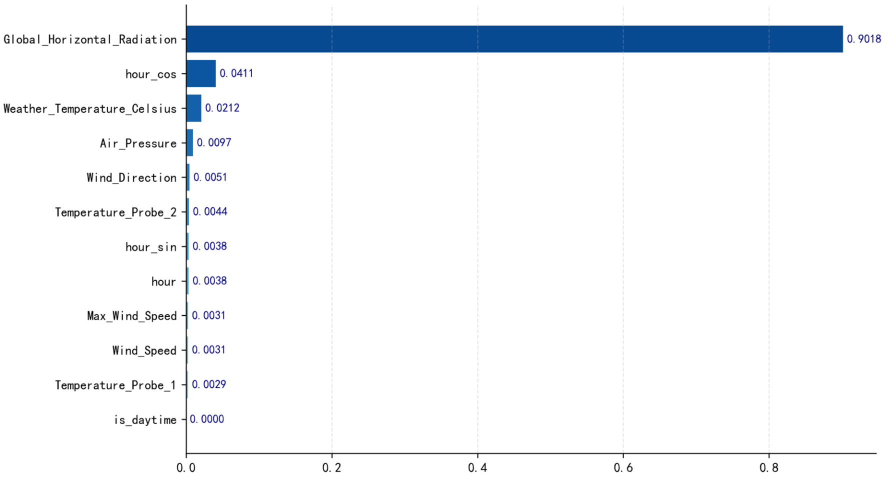


Figure 3. Importance score of features.

Prediction Process and Results

This section details the forecasting model architecture and training settings with reproducible parameters. Annual and monthly transaction forecasting differ slightly in dataset partitioning but share core training settings. For annual forecasting, the training set uses 4 years of historical data, and the test set uses the subsequent 6 months of data. For monthly forecasting, rolling prediction is adopted for the first 6 months of the test period: e.g., to forecast a target month, the training set uses the preceding 12 months of historical data, with the target month as the test set, repeated for each target month.

The input features of the forecasting model are strictly defined to ensure reproducibility, including historical transaction volume (daily/weekly aggregated values corresponding to annual/monthly forecasts), seasonal indicators, and trend indicators; all input features are normalized using the Min-Max normalization method to eliminate the impact of dimension differences. The prediction horizon is set according to the forecasting type: the annual forecast adopts a fixed prediction horizon of 6 months, while the monthly forecast adopts a prediction horizon of 1 month.

For model training details, the mean squared error (MSE) is selected as the loss function to measure the deviation between the predicted value and the actual transaction volume, and its calculation formula is as follows:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2$$

where N is the number of samples in the training/validation subset, y_i is the actual transaction volume, and $\hat{y}_i$ is the predicted transaction volume. The Adam optimizer is used to minimize the loss function, with the initial learning rate set to 0.001, the momentum parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$, and the weight decay set to 10^{-5} to prevent overfitting. The batch size is fixed at 32 for both annual and monthly forecasts, and the model is trained for a maximum of 200 epochs; an early stopping strategy is adopted to avoid overfitting, where the validation loss is monitored every epoch, and if the validation loss does not decrease for 15 consecutive epochs (with a tolerance of 10^{-4}), the training process is terminated early, and the model parameters corresponding to the minimum validation loss are saved as the optimal parameters.

To ensure optimal model parameters, this study employs a grid search strategy to optimize hyperparameters (e.g., the number of hidden layer neurons, dropout rate, and learning rate decay factor), and the following are the finally determined optimal model parameters after grid search validation, which are used for both annual and monthly transaction forecasting (Table 2).

Table 2. Training parameters.

Parameter	Annual Forecast	Monthly Forecast
Time step	8	12
Number of Neurons	32/48	64/96
Regularization Parameter	0.1	0.2

This study employs BiLSTM, GRU-BiLSTM, and GRU-BiLSTM-Attention models for power forecasting, with evaluation metrics including RMSE, MAE, R2, and MAPE. In Table 3, comparative analysis demonstrates that the proposed model achieves lower RMSE, MAE, and R2 values, while maintaining consistent predictive performance across various trading cycles.

Table 3. Result of training.

Trading Cycle	Model	RMSE	MAE	R^2	MAPE (%)
Annual Trading Market	BiLSTM	1.323	9.634	0.924	7.193
	GRU-BiLSTM	7.112	5.268	0.949	3.325
	GRU-BiLSTM-Attention	6.699	3.961	0.955	6.233
Monthly Trading Market	BiLSTM	1.323	9.634	0.934	7.237
	GRU-BiLSTM	6.946	3.858	0.951	4.711
	GRU-BiLSTM-Attention	2.686	1.715	0.993	8.336

This study employs BiLSTM, GRU-BiLSTM, and GRU-BiLSTM-Attention models for power forecasting, with evaluation metrics including RMSE, MAE, R2, and MAPE. Figure 4 Comparative analysis demonstrates that the proposed model achieves lower RMSE, MAE, and R2 values, while maintaining consistent predictive performance across various trading cycles.

4. Green Electricity Product Solution

This paper presents a green, cost-effective, and efficient solution for green power products, overcoming the historical challenge of data-driven constraints in traditional industrial enterprises. The solution delivers comprehensive service packages to power users throughout the entire product lifecycle. This section details the implementation workflow, employing the methodology outlined earlier to conduct data analysis and economic evaluation.

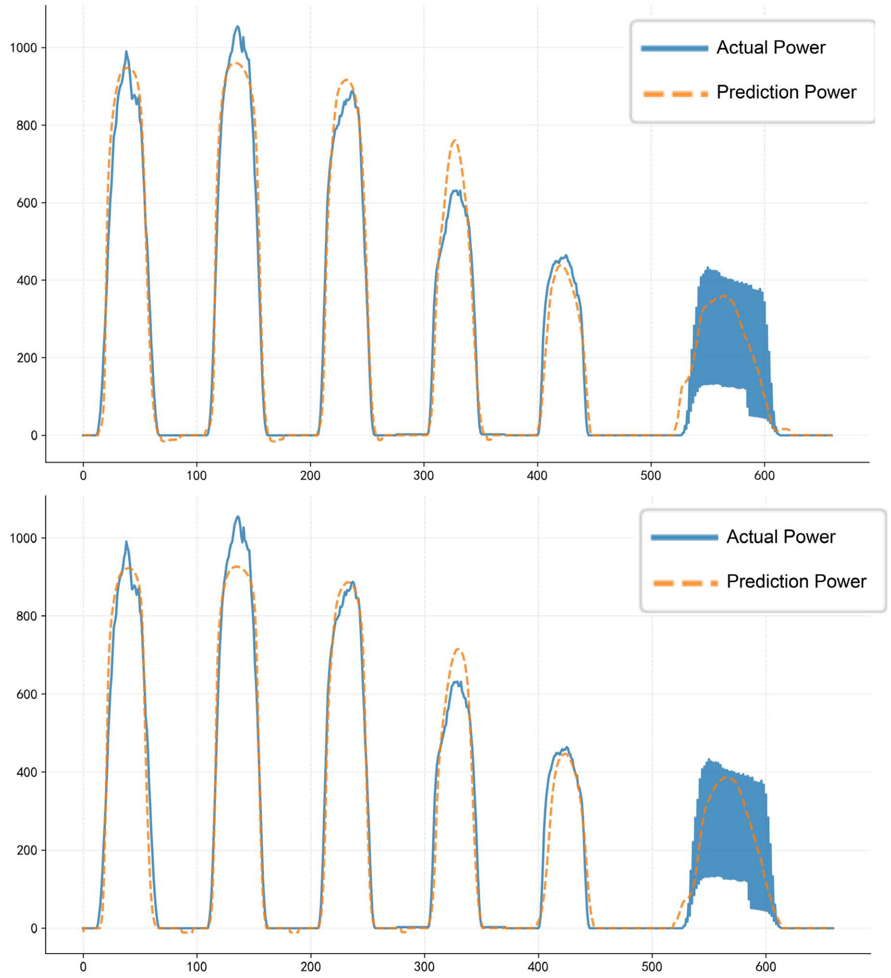


Figure 4. Comparison of predicted output with actual output for the model in this paper across different trading cycles.

4.1. Preliminary Proposal

In the initial phase of the implementation plan, we first collect users' load data, gathering their electricity consumption patterns from the past year up to the current day. Using the method described in Section 3.1, we extract core load characteristics and categorize them. Next, we develop tailored adaptation strategies based on each user's load profile to achieve precise alignment between power supply and demand. Through analysis of electricity bills from centralized data, two key characteristics were identified:

Characteristic 1: Export-oriented enterprises demonstrate a strong demand for green electricity, likely because when exporting to Europe, they must bear the carbon costs under the Carbon Border Adjustment Mechanism (CBAM). CBAM stipulates that such costs can only be offset when enterprises use physically traceable green electricity.

Characteristic 2: When a company's load profile demonstrates high stability and robust growth momentum, it actively considers investing in green power direct connection projects. This stems from their long-term financial planning philosophy and urgent need to mitigate electricity risks. Therefore, integrated wind-solar-storage systems and dedicated green power transmission lines become their preferred solutions.

Based on these characteristics, we identified four primary categories of electricity users in the dataset, with Table 4 also presenting preliminary proposals from earlier stages.

Table 4. Preliminary proposals.

Order Number	Export Oriented	Load characteristics	Power Supply Willingness	Scheme
Scenario 1	×	Volatility-driven production increase	not have	Annual Green Power PPA Contract and Energy Storage Lease
Scenario 2	√	Steady growth type	have	Joint Venture Project for Integrated Wind-Solar-Storage System and Direct Power Transmission Line
Scenario 3	×	Steady Fixed Type	not have	Annual Green Power PPA Contract and Green Certificate Accompanying
Scenario 4	√	Volatility-driven production increase	not have	Annual Green Power PPA Contract, Short-term Green Power Procurement

4.2. Construction of Optimization Model

The study establishes mathematical models for the proposed products to determine optimal power consumption and investment allocation ratios. In practical operations, our solution integrates three complementary services: electricity trading, green power procurement, and investment assessment. By collecting user data, we provide professional recommendations for electricity consumption and investment decisions. First, we utilize power quality analyzers, wind speed sensors, and solar radiation sensors to collect cumulative output values of functional parameters, wind speed, ambient temperature, and global horizontal radiation. Using the annual and monthly power generation forecasting methods proposed in Section 3.2, we predict the power generation capacity of power stations. These results determine market-based electricity purchase volumes, enabling dynamic trading services for users. Second, during the trading process, we analyze users' electricity consumption patterns and carbon costs to determine green power combination schemes and equipment capacity. If users intend to hold power sources, our model considers the net revenue over the equipment's entire lifecycle. Table 5 is the symbolic definitions of the model.

4.2.1. Objective Function

The objective function focuses on maximizing the users' comprehensive annual income, integrating green power income and net income of the full life cycle of power sources (only for power source holding users), deducting total electricity costs, and realizing the coordinated optimization of "green, economic, and efficient". The expression is as follows:

$$\max \quad J = J_1 + \delta_{own} \cdot J_2 - J_3$$

Table 5. Symbolic definitions.

Symbol	Definition	Description
δ_{exp}	Export-oriented enterprise identifier	$\delta_{exp} \in \{0,1\}$ 1 = Export-oriented, 0 = Non-export-oriented
δ_{own}	Power source ownership willingness identifier	$\delta_{own} \in \{0,1\}$ 1 = Willing to own, 0 = Purchase only
L_{type}	User load type	$L_{type} \in \{1,2,3,4\}$ 1 = Fluctuating and increasing, 2 = Stable and increasing, 3 = Stable and fixed, 4 = Fluctuating and fixed
P_{pv}	PV direct connection installed capacity (kW)	$P_{pv} \geq 0$ (Continuous variable)
P_{wt}	Wind turbine installed capacity (kW)	$P_{wt} \geq 0$ (Continuous variable)
P_{ess}	Energy storage installed capacity (kW)	$P_{ess} \geq 0$ (Continuous variable)
E_{ess}	Energy storage energy capacity (kWh)	$E_{ess} \geq 0$ (Continuous variable)
α	Wind-PV ratio	$0 \leq \alpha \leq 1$ (Continuous variable), $\alpha = P_{pv} / (P_{pv} + P_{wt})$
E_{green}	Annual green electricity (kWh)	$E_{green} \geq 0$ (Continuous variable)
R_{cbam}	Marginal reduction benefit of CBAM	$R_{cbam} \geq 0$ (Constant)
R_{cert}	Unit benefit of green certificate	$R_{cert} \geq 0$ (Constant)
T	Full life cycle years (year)	$T \in \mathbb{N}^+$ (Constant)
Rev_t^{gen}	Power generation revenue in year t	$Rev_t^{gen} \geq 0$ (Constant)
$Cost_t^{inv}$	Investment cost in year t (RMB)	$Cost_t^{inv} \geq 0$ (Constant)
$Cost_t^{om}$	Operation and maintenance cost in year t (RMB)	$Cost_t^{om} \geq 0$ (Constant)
r	Benchmark rate of return	$0 < r < 1$ (Constant)
$w(T_{const})$	Weight of construction period impact	$0 < w(T_{const}) \leq 1$ (Constant, the shorter the period, the higher the weight)
T_{const}	Construction period	$T_{const} \in \mathbb{N}^+$ (Constant)
τ	Time granularity identifier (15 minutes/unit)	$\tau = 1, 2, \cdots, N$, $N = 35040$ (Total number of annual time granularities)
N	Total number of annual time granularities	$N = 35040$ (Constant, 8760 h × 4)

Continued

$C_{ppa}(\tau)$	PPA electricity price at the τ-th granularity	$C_{ppa}(\tau) \geq 0$ (Constant)
$P_{pre}(\tau)$	Predicted green power output at the τ-th granularity (kW)	$P_{pre}(\tau) \geq 0$ (Constant)
$C_{market}(\tau)$	Time-of-use electricity price in power market at the τ-th granularity	$C_{market}(\tau) \geq 0$ (Constant)
$L(\tau)$	User load at the τ-th granularity (kW)	$L(\tau) \geq 0$
$P_{market}(\tau)$	Power purchased from power market at the τ-th granularity (kW)	$P_{market}(\tau) \geq 0$ (Continuous variable)
$\underline{P}_{pv}, \overline{P}_{pv}$	Upper and lower limits of PV installed capacity (kW)	$\underline{P}_{pv} \geq 0$, $\overline{P}_{pv} \geq \underline{P}_{pv}$ (Constant)
$\underline{P}_{wt}, \overline{P}_{wt}$	Upper and lower limits of wind installed capacity (kW)	$\underline{P}_{wt} \geq 0$, $\overline{P}_{wt} \geq \underline{P}_{wt}$ (Constant)
$\alpha_{min}, \alpha_{max}$	Upper and lower limits of Wind-PV ratio	$0 \leq \alpha_{min} \leq \alpha_{max} \leq 1$ (Constant)
β_{req}	Policy requirement for green power consumption ratio	$0 < \beta_{req} \leq 1$ (Constant)
$\overline{E}_{ess}$	Upper limit of energy storage energy capacity (kWh)	$\overline{E}_{ess} \geq 0$ (Constant)

Among them, the meaning of each item is as follows:

1) Green power revenue (J_1): Enjoyed by all users. According to whether the user is an export-oriented enterprise, it distinguishes between CBAM reduction revenue and green certificate revenue. The expression is:

$$J_1 = \begin{cases} R_{cbam} \cdot E_{green} & \delta_{exp} = 1 \\ R_{cert} \cdot E_{green} & \delta_{exp} = 0 \end{cases}$$

In the formula, $E_{green} = \sum_{\tau=1}^{N} P_{pre}(\tau) \times 0.25$, (0.25 is the number of hours corresponding to 15 minutes, *i.e.*, the duration of time granularity), which represents the annual actual green power consumption of users and reflects the "green" goal of the model.

2) Net revenue of the full life cycle of power sources (J_2): Enjoyed only by users willing to hold power sources ($\delta_{own} = 1$), considering the time value of funds and the impact of construction period. The expression is:

$$J_2 = \sum_{t=1}^{T} \frac{Rev_t^{gen} - Cost_t^{inv} - Cost_t^{om}}{(1+r)^t} \cdot w(T_{const})$$

In the formula, $\frac{1}{(1+r)^t}$ is the discount factor of the time value of funds, and $w(T_{const})$ is the weight of the impact of the construction period (the shorter the construction period, the closer the weight is to 1, and the higher the net income), reflecting the "economic" goal of the model and the efficiency of project implementation.

3) Total electricity cost (J_3): Calculated based on 15-minute time granularity,

including green power PPA purchase cost and power market purchase cost. The expression is:

$$J_3=\sum_{\tau=1}^{N}\left[C_{ppa}(\tau)\cdot P_{pre}(\tau)\times 0.25+C_{market}(\tau)\cdot \max\left\{L(\tau)-P_{pre}(\tau),0\right\}\times 0.25\right]$$

In the formula, $\max\left\{L(\tau)-P_{pre}(\tau),0\right\}$ represents the electricity that users need to purchase from the power market when the green power output is insufficient, reflecting the "efficient" goal of the model (accurately matching supply and demand and reducing purchase costs); 0.25 is the duration of the time granularity, ensuring that the cost calculation unit is uniformly RMB.

4.2.2. Constraints

Combined with practical constraints such as green power supply, user load, and policy requirements, convex constraints are constructed to ensure the feasibility and engineering applicability of the model solution. The constraints are as follows:

1) Green power predicted output constraint: The predicted green power output shall not be negative and shall not exceed the total installed capacity of wind and PV, ensuring the rationality of power generation output:

$$0\le P_{pre}(\tau)\le P_{pv}+P_{wt},\quad \forall\tau\in\{1,2,\cdots,N\}$$

2) Energy storage capacity constraint: The real-time energy capacity of energy storage shall not exceed the reasonable range, ensuring the safe and stable operation of the energy storage system:

$$0\le E_{ess}(\tau)\le \bar{E}_{ess},\quad \forall\tau\in\{1,2,\cdots,N\}$$

3) Load balance constraint: At any time granularity, the sum of the user's predicted green power output and the power purchased from the power market is equal to the user's real-time load, ensuring that the power demand is fully met:

$$P_{pre}(\tau)+P_{market}(\tau)=L(\tau),\quad \forall\tau\in\{1,2,\cdots,N\}$$

4) Wind and PV installed capacity constraints: The installed capacity of PV and wind turbines shall not exceed the reasonable upper and lower limits of the industry, adapting to the user's actual power consumption scale and site conditions:

$$\underline{P}_{pv}\le P_{pv}\le \bar{P}_{pv}$$

$$\underline{P}_{wt}\le P_{wt}\le \bar{P}_{wt}$$

5) Wind-PV ratio constraint: The wind-PV ratio shall be within a reasonable range to ensure the stability of green power supply and adapt to the wind and PV resource conditions in different regions:

$$\alpha_{min}\le\alpha\le\alpha_{max}$$

6) Green power consumption ratio constraint: The user's annual green power consumption ratio shall meet the local policy requirements, ensuring the compliance of green power use and reflecting the "green" goal of the model:

$$\frac{\sum_{\tau=1}^{N}P_{pre}(\tau)\times 0.25}{\sum_{\tau=1}^{N}L(\tau)\times 0.25}\ge\beta_{req}$$

After simplification, it can be obtained:

$$\frac{\sum_{\tau=1}^{N} P_{pre}(\tau)}{\sum_{\tau=1}^{N} L(\tau)} \geq \beta_{req}$$

which eliminates the impact of the duration of time granularity and makes the calculation more concise.

7) Non-negativity constraint: All decision variables are non-negative, which conforms to engineering practice and economic logic:

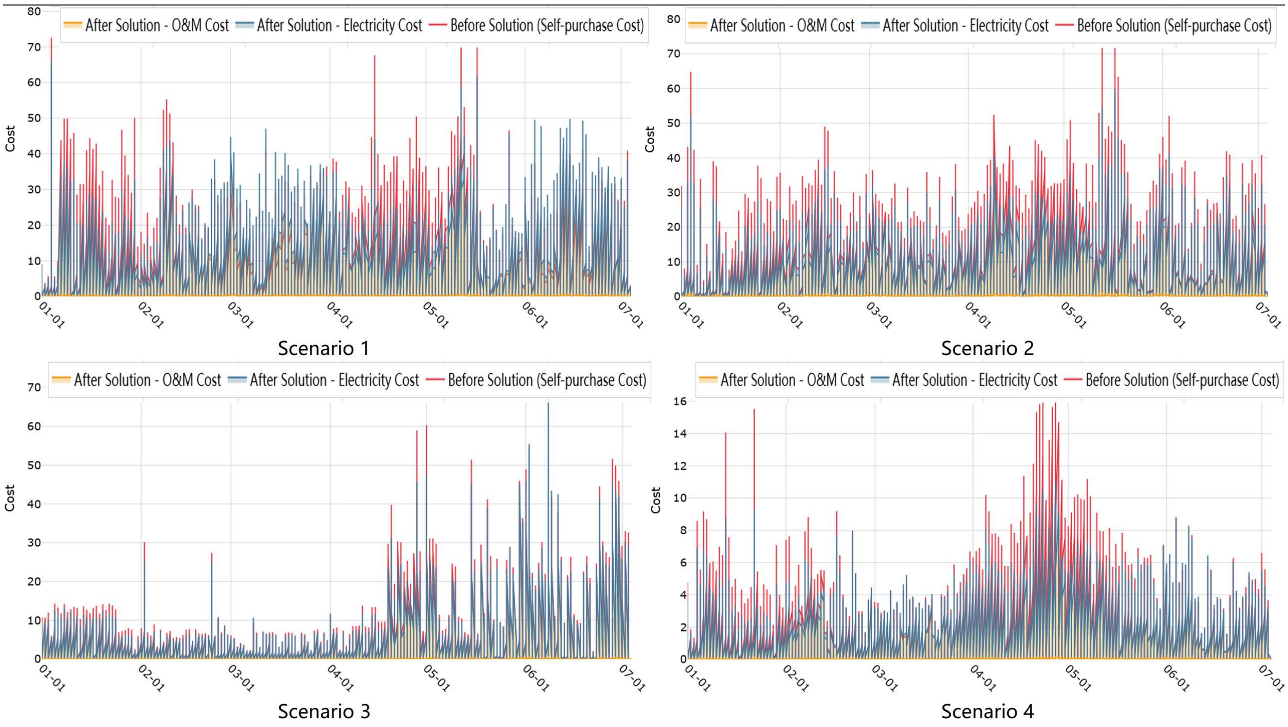
$$P_{pv} \geq 0, \quad P_{wt} \geq 0, \quad P_{ess} \geq 0, \quad E_{ess} \geq 0, \quad P_{market}(\tau) \geq 0$$

4.3. Cost Comparison of Solutions in Typical Scenarios

We utilize user data for financial projections. By analyzing variations across multiple dimensions under four typical scenarios, we found that the cost of electricity procurement decreased in each scenario. Details of the reduction are presented in **Table 6** and **Figure 5**.

Table 6. Cost comparison and saving rate.

User Type	Electricity Cost Before	Electricity Cost After	Saving Rate
Scenario 1	415814.47	393456.73	5.38%
Scenario 2	396719.18	313563.49	20.96%
Scenario 3	158461.61	144395.3	8.88%
Scenario 4	78452.09	63642.8	18.88%



Scenario 1

Scenario 2

Scenario 3

Scenario 4

Figure 5. Comparison of time-of-use integrated electricity costs by user type before and after the implementation of the solution.

The four cost comparison charts demonstrate that after implementing the green electricity scheme, the total electricity costs (sum of electricity fees and operation costs) for all user types have decreased compared to pre-scheme self-purchased electricity costs, with particularly notable cost control during peak electricity price periods. Notably, stable export users with property rights achieved the most significant cost reduction, reaching an annual savings rate of 21%, while non-export fluctuating users without property rights exhibited more pronounced cost volatility, with an annual savings rate of only 5%.

This disparity stems from multiple factors. Firstly, export-oriented enterprises can benefit from carbon tariff reductions through green electricity usage, directly enhancing the economic viability of the scheme. Secondly, users with stable loads can more efficiently match green electricity supply, reducing the impact of market fluctuations in power purchases and achieving more significant cost savings. Lastly, users holding power generation rights can further enhance the long-term economic value of the scheme by discounting lifecycle benefits, while non-ownership users lack this additional revenue stream. Overall, the economic performance of green electricity schemes is closely tied to user load stability, export attributes, and ownership status, with these factors collectively determining the effectiveness of cost savings.

4.4. Revenue of the Plan

The solution proposed in this article can bring actual benefits to all types of users. For ordinary enterprises, they can better plan their electricity usage time through the power generation forecast curve and multi-year green power contracts, thereby preventing price risks. Export-oriented enterprises can obtain carbon tariff reduction benefits through the use of green power, which directly enhances the economic viability of the solution. Users with stable loads can more efficiently match green power supply, reducing the impact of fluctuations in market power purchases and achieving more significant cost savings. Users with power source property rights can further enhance the long-term economic value of the solution through the discounted cash flow of the entire life cycle, while users without property rights lack this additional benefit. Overall, the economic viability of the green power solution is highly correlated with the load stability, export attributes, and property rights holding status of users, and these factors jointly determine the effect of cost savings.

5. Conclusion

The user clustering method, generation forecasting approach, and financial modeling framework developed in this study form an integrated green energy solution that combines value orientation with multidimensional efficiency. This system provides systematic technical support for precise user-side services in the renewable energy market. Centered on value-driven logic, the solution achieves accurate user profiling through clustering, integrates time-accurate generation forecasts with full-cycle quantification capabilities of financial models, and maximizes comprehensive user benefits as its core optimization goal. This creates deep integration between green energy allocation and user value demands. The solution's environmental attributes are demonstrated through precise green energy coverage expansion and systematic carbon emission reduction, offering quantifiable pathways for corporate carbon compliance and industrial green transformation. Economically, it leverages long-term PPA pricing locks and dynamic green energy coverage strategies to effectively hedge against market price fluctuations. By aligning generation-load matching with user load characteristics, it significantly reduces overall electricity costs. Efficiency is highlighted through precise user stratification and generation forecasting, enabling rapid alignment of green energy resources with demand. This effectively addresses core pain points like high electricity costs and volatile pricing. The solution validates the compatibility between technical models and market demands, providing theoretical foundations and practical paradigms for large-scale deployment of green energy products and user-side energy transition.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

[1] Wang, D., Tian, H., Luo, Z., *et al.* (2025) Practices and Reflections on Renewable Energy Participating in Electricity Market. *Automation of Electric Power Systems*, **49**, 1-7.

[2] Jiang, X., Cui, Y. and Ma, Y. (2025) Recommendation Method for Retail Electricity Packages Based on Weighted Interval-Valued Intuitionistic Hesitant Fuzzy Sets. 2025 5*th IEEE International Conference on Energy Engineering and Power Systems* (*EEPS*), Shenzhen, 31 October 2025-2 November 2025, 1047-1053. https://doi.org/10.1109/eeps68057.2025.11351882

[3] Xu, L., Zhou, C., Sheng, J., Li, J. and Xu, Y. (2025) Analysis of Distributed PV Harmonic Characteristics Based on Harmonic Coupling Admittance Matrix Model. 2025 8*th Asia Conference on Energy and Electrical Engineering* (*ACEEE*), Qingdao, 25-27 July 2025, 478-482. https://doi.org/10.1109/aceee66257.2025.11148731

[4] Li, D., Xu, J., Liu, S. and AL-Wesabi, I. (2025) Impacts of Government Subsidies and Risk Aversion on an Electricity Plant's Energy Transition and the Optimal Electricity Sales Decisions under Renewable Electricity Production Uncertainty. *Energy Economics*, **152**, Article 109041. https://doi.org/10.1016/j.eneco.2025.109041

[5] Mantilla, N., Oviedo-Cepeda, J.C., Toquica, D., Agbossou, K. and Henao, N. (2025) A Market-Clearing Mechanism Based on Hierarchical-Spectral Clustering with Multiple Similarity Measures for Flexibility Spot Markets. *Sustainable Energy*, *Grids and Networks*, **44**, Article 101983. https://doi.org/10.1016/j.segan.2025.101983

[6] Wang, L., Cao, Z. and Li, P. (2024) Research on the Mechanism of Leader-Follower Product Sales Competition Based on Market Access Restrictions and Forward Contract Considerations. *Heliyon*, **10**, e32372. https://doi.org/10.1016/j.heliyon.2024.e32372

[7] Tian, X., Yuan, B., Zheng, P., Mei, Y. and Zhang, C. (2026) Standardized Modeling

and Prediction of Multi-Type Loads for Shared Energy Storage Scheduling in Customized Park Applications. *Electric Power Systems Research*, **250**, Article 112180. https://doi.org/10.1016/j.epsr.2025.112180

[8] Priya, E. and Preetha Roselyn, J. (2024) A Multi-Layer Constrained Spectral K-Embedded Clustering Methodology Approach for Intelligent Partitioning of Power Grid to Enhance Resiliency in Transmission Networks. *E-Prime—Advances in Electrical Engineering, Electronics and Energy*, **10**, Article 100813.

[9] Huang, Y., Yao, Z. and Xu, Q. (2024) Classification Model of Electricity Consumption Behavior Based on Sparse Denoising Autoencoder Feature Dimensionality Reduction and Spectral Clustering. *International Journal of Electrical Power & Energy Systems*, **158**, Article 109960. https://doi.org/10.1016/j.ijepes.2024.109960

[10] Yang, M., Zhang, H., Yu, X., Seklouli, A.S., Bouras, A. and Ouzrout, Y. (2025) A Composite Photovoltaic Power Prediction Optimization Model Based on Nonlinear Meteorological Factors Analysis and Hybrid Deep Learning Framework. *International Journal of Electrical Power & Energy Systems*, **169**, Article 110660. https://doi.org/10.1016/j.ijepes.2025.110660

[11] Chandel, S.S., Gupta, A., Chandel, R. and Tajjour, S. (2023) Review of Deep Learning Techniques for Power Generation Prediction of Industrial Solar Photovoltaic Plants. *Solar Compass*, **8**, Article 100061. https://doi.org/10.1016/j.solcom.2023.100061

[12] Chen, W., Wu, Y., Pei, T., Lin, J. and Yuan, G. (2026) Predictive Maintenance Strategy for Photovoltaic Power Systems: Collaborative Optimization of Transformer-Based Lifetime Prediction and Opposition-Based Learning HHO Algorithm. *Energy Engineering*, **123**, 1-10. https://doi.org/10.32604/ee.2025.070905

[13] Yu, H., Chen, S., Chu, Y., Li, M., Ding, Y., Cui, R., *et al.* (2024) Self-Attention Mechanism to Enhance the Generalizability of Data-Driven Time-Series Prediction: A Case Study of Intra-Hour Power Forecasting of Urban Distributed Photovoltaic Systems. *Applied Energy*, **374**, Article 124007. https://doi.org/10.1016/j.apenergy.2024.124007

[14] Michael, N.E., Bansal, R.C., Ismail, A.A.A., Elnady, A. and Hasan, S. (2024) A Cohesive Structure of Bi-Directional Long-Short-Term Memory (BiLSTM) -GRU for Predicting Hourly Solar Radiation. *Renewable Energy*, **222**, Article 119943. https://doi.org/10.1016/j.renene.2024.119943

[15] Feng, J. and Li, Z. (2026) Distributed Multi-Community-Collaborative Method for Multi-Site Behind-the-Meter Solar Disaggregation for Heterogeneous Communities. *IEEE Transactions on Smart Grid*, 1. https://doi.org/10.1109/TSG.2026.3660316

[16] Di Piazza, M.C., Luna, M., Tona, G.L. and Di Piazza, A. (2017) Energy Management of Hybrid PV-Storage Systems for Improved Grid Integration. 2017 *IEEE International Conference on Environment and Electrical Engineering and* 2017 *IEEE Industrial and Commercial Power Systems Europe* (*EEEIC*/*I&CPS Europe*), Milan, 6-9 June 2017, 1-5. https://doi.org/10.1109/eeeic.2017.7977539