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Coupled Meteorological-Electricity Behavior Analysis and Multi-Energy Load Forecasting Based on a Combined Model

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ABSTRACT: User electricity consumption behavior analysis and multi-load forecasting in integrated energy systems are crucial for system operation and scheduling. Traditional user electricity consumption behavior analysis fails to adequately incorporate meteorological factors, limiting the accuracy of characterizing user electricity consumption patterns. Traditional multi-load forecasting models do not consider the differentiated coupling relationships with meteorological factors across different seasons, which restricts the improvement of forecasting accuracy. To address the above issues, a method integrating data cleaning and meteorological correlation for electricity consumption behavior and multi-dimensional forecasting analysis is proposed. First, the Akima interpolation method is used to repair anomalous points in the load data. Second, the BK-Means algorithm is employed to determine the optimal number of clusters and initial centers, achieving a coupled analysis of wind-solar power output, load-meteorology clustering, and user electricity consumption behavior. Subsequently, the Kendall rank correlation coefficient method is applied to analyze the correlation between multi-dimensional loads and meteorological factors, constructing differentiated input feature sets for various loads tailored to different seasons. Finally, a combined model is used to generate multi-load forecasting results. The results demonstrate that compared to single forecasting methods, the proposed method achieves higher forecasting accuracy for electricity, cool, and heating loads across different seasons.

KEYWORDS: NRBO algorithm; BK-means algorithm; LSTM algorithm; XGBoost algorithm; multivariate load forecasting

1 Introduction

Electricity Consumption Behavior Analysis in Multi-Energy Coupled Power Systems: A Dual-Dimensional Decomposition of Explicit and Implicit Patterns. Under the paradigm of new-type power system development with multi-energy coupling, user electricity consumption behavior analysis has emerged as a critical technical enabler for demand-side refined management [1]. The behavioral characteristics can be decomposed into dual dimensions: explicit behavior characterized by load profiles from smart meter measurements, and implicit patterns requiring in-depth analysis through integrating environmental variables with data mining techniques [2].

With the large-scale deployment of Advanced Metering Infrastructure (AMI), user-side systems have generated massive data resources with minute-level sampling rates [3]. However, the extraction of effective features from high-noise, multi-dimensional heterogeneous data remains a central challenge in enhancing



demand response efficiency [4]. While significant progress has been achieved in data mining-based electricity consumption behavior analysis [5], several critical limitations persist in existing technical frameworks. Current approaches face three fundamental challenges in electricity consumption behavior analysis. First, existing clustering methods exhibit sensitivity to anomalous data and dependence on empirical assumptions. While Ref. [6] proposes an aggregated reward metric to optimize K-Means cluster number selection, it fails to address feature distortion caused by anomalous data. Similarly, Refs. [7,8] employ hierarchical clustering and mutual information-based dimensionality reduction but remain constrained by heuristic parameter initialization mechanisms. Second, despite introducing deep learning and fuzzy clustering to enhance algorithmic robustness [9], existing methodologies systematically overlook the dynamic modulation effects of meteorological factors on electricity consumption patterns. Third, current frameworks suffer from weaknesses in data preprocessing, where mean imputation methods induce load profile distortions through erroneous variance suppression, and non-adaptive selection of clustering parameters compromises interpretability in consumption pattern classification.

Parallel challenges exist in multi-energy load forecasting, which serves as the fundamental basis for achieving efficient energy utilization and optimized scheduling in integrated multi-energy scenarios [10,11]. The increasing diversity of energy structures and growing complexity of user demands have led to more prominent dynamic coupling and nonlinear characteristics of electricity, heat, cool, and other multi-energy loads, exceeding the effective processing capabilities of traditional load forecasting methods [12]. Traditional approaches primarily focus on independent prediction for single load types using statistical models (AR [13], ARIMA [14]) and machine learning techniques (RF [15], SVM [16]), but exhibit limited capability in capturing nonlinear responses and complex coupling relationships.

Deep learning models (TCN [17], GRU [18], CNN, LSTM [19]) have shown promise in characterizing complex coupling relationships, gradually developing into core technological models for high-accuracy multi-energy load forecasting. For instance, Ref. [20] proposed a hybrid CNN-BiLSTM model with attention mechanism, while Ref. [21] introduced multi-scale spatiotemporal graph convolutional networks combined with Transformer. However, most existing methods still focus on independent forecasting of single load types and fail to adequately interpret the nonlinear coupling physical mechanisms among multiple energy flows, resulting in limited cross-scenario generalization capability. Current research on multi-energy load forecasting primarily involves feature construction and selection [22] and forecasting model development. Existing studies focus on two types of inputs: basic external features (extreme weather [23], meteorological conditions, historical load data) and coupled internal features. While signal de-composition techniques like Improved Variational Mode Decomposition (IVMD) [24] and feature construction methods such as Synthesis Correlation Analysis (SCA) [25] and Load Participation Factor (LPF) have been developed, they still face challenges in fully capturing the complex coupling characteristics under seasonal and climatic influences.

To address these research gaps—specifically, the inadequate integration of meteorological behavioral analysis in multi-energy scenarios and insufficient consideration of seasonally varying external influences on multi-energy loads—this study proposes an integrated approach combining data cleaning with meteorological factor optimization for electricity load clustering, along with a combined model for short-term multi-energy load forecasting. The main contributions of this paper are threefold:

- (1) To tackle weaknesses in data preprocessing and non-adaptive clustering parameter selection, we employ Akima interpolation for outlier imputation and adopt BIRCH pre-clustering to achieve adaptive determination of optimal cluster numbers and initial centers.

- (2) To enhance initial population quality and maintain population diversity, we introduce a stochastic retraction mechanism that expands the generation region of opposition-based solutions from a fixed mirror point to a continuous probability space between the individual and the center.
- (3) Based on an improved XGBoost algorithm, we establish a feature variable screening method under multi-dimensional input conditions by directly computing feature importance from the tree structure via weights and gains, thereby improving the accuracy and efficiency of multi-energy load forecasting.

These contributions are organically integrated into a coherent framework: the refined data and meteorology-coupled feature sets obtained from the first two steps are directly fed into the forecasting model developed in the third step. This ensures that the final load predictions are not only data-driven but also physically interpretable, significantly enhancing accuracy and generalization.

2 Improved K-Means Algorithm Based on BIRCH Preclustering

2.1 Principles and Analysis of Akima Interpolation Filling Method

In the domain of data interpolation, the Akima interpolation method has emerged as a computationally efficient and precise technique, notably suitable for scenarios requiring the construction of smooth curves from sparse data points. The Akima interpolant aims to create a continuously differentiable curve $y = f(x)$ that strictly passes through all given data points. This is achieved by employing piecewise cubic polynomials for local approximation within each interval $[x_i, x_{i+1}]$. The polynomial coefficients are determined through systematic consideration of slope variations between adjacent data points and their neighbors, effectively circumventing undesirable oscillations typically associated with conventional interpolation methods. Particularly in cases of limited or irregularly distributed data points, this approach demonstrates superior capability in mitigating interpolation-induced errors, ensuring results that align with the underlying physical processes or authentic data evolution patterns.

For experimental validation, the daily electric load profile of a specific user was extracted from Dataset 1. To simulate realistic abnormal data scenarios, significant outliers were artificially introduced at strategic positions of the data sequence specifically at the 30th, 60th, and 90th data points. The restoration process not only effectively eliminated these anomalous perturbations but also preserved the intrinsic trend characteristics and localized fluctuations of the original dataset. A comparative visualization of the raw data, corrupted data, and restored data is presented in [Fig. 1](#).

The figure clearly reveals that before the outliers are introduced, the original data shows a steady and continuous trend of change; and after the outliers are artificially set, the data curve fluctuates suddenly at specific points, seriously affecting the overall continuity and authenticity of the data. After the outlier value repair, the error values dropped from 87.7% and 53.3% to 3.28% and 8.19%, respectively. After repairing by Akima interpolation filling method, the repaired data curve coincides with the original data trend, and a smooth transition is achieved at the exception points. The effectiveness of this method in dealing with such data exceptions is fully verified.

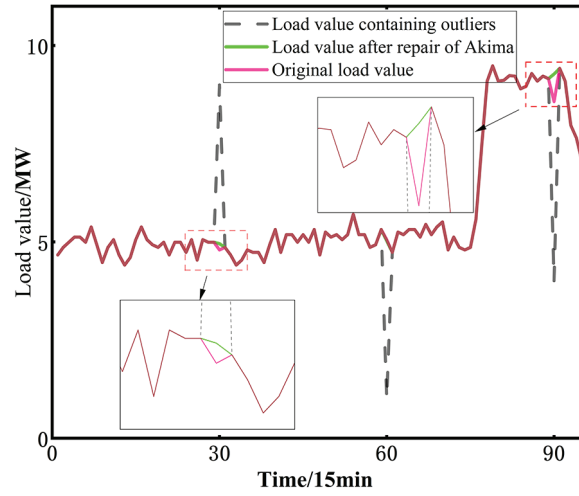


Figure 1: Comparison chart with original load curve before and after repair

2.2 Analysis of Cluster Validity Index

The clustering process aims to maximize intra-cluster similarity while minimizing inter-cluster dissimilarity, thereby establishing distinct and insightful data partitions. Cluster validity metrics effectively quantify both the compactness of data points within clusters and the separation between different clusters. This study employs three internal evaluation indices: the Silhouette Coefficient (SC), Calinski-Harabasz Index (CHI), and Davies-Bouldin Index (DBI), which are mathematically defined as follows.

- (1) **Silhouette Coefficient (SC):** The Silhouette Coefficient is a distance-based internal evaluation metric that quantifies both the compactness of data points within their assigned clusters and their separation from neighboring clusters. The mathematical formulations are specified in Eqs. (1) and (2).

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (1)$$

$$a(i) = \frac{1}{n-1} \sum_{j \neq i}^n \text{distance}(i, j) \quad (2)$$

where $a(i)$ represents the cohesion degree of the sample point, j represents other sample points in the same class as sample i , and distance represents the distance between j and i . The value range of the contour coefficient is between -1 and 1 . The larger the value, the better the clustering effect.

- (2) **Davies-Bouldin Index (DBI):** The Davies-Bouldin Index holistically evaluates clustering validity by integrating intra-cluster similarity and inter-cluster dissimilarity, where lower index values indicate superior clustering performance. For a dataset comprising m data points algorithmically partitioned into n clusters, the DBI method is employed to assess clustering efficacy. The mathematical formulation is defined in Eq. (3).

$$DBI = \frac{1}{n} \sum_{i=1}^n \max_{j \neq i} \frac{S_i - S_j}{\|w_i - w_j\|^2} \quad (3)$$

where: S_i is the average Euclidean distance from the i sample to its class center; $\|w_i - w_j\|^2$ is the Euclidean distance from the i and j class centers.

- (3) Calinski-Harabasz Index (CHI): The CHI holistically evaluates clustering validity by integrating inter-cluster dispersion (denoted as D and computed via Eq. (4)) and intra-cluster compactness (denoted as C and formulated in Eq. (5)), with its computational framework defined in Eq. (6).

$$D = \sum_{k=1}^K \sum_{i=1}^N w_{k,i} \|c_k - \bar{x}\|^2 \quad (4)$$

$$C = \sum_{k=1}^K \sum_{i=1}^N w_{k,i} \|x_i - c_k\|^2 \quad (5)$$

$$CHI = \frac{D/(K-1)}{C/(N-K)} \quad (6)$$

where $\bar{x}$ is the mean of all objects; $w_{k,i}$ represents the membership between the i object and the k class cluster. It can be seen that the larger the CHI , the better the dispersion between the class clusters and the compactness within the class clusters.

2.3 Improved Division Algorithm Based on BIRCH Preclustering

BIRCH clustering, as an efficient distance-based hierarchical clustering algorithm, skillfully organizes datasets and performs clustering by constructing a Clustering Feature (CF) tree. Its basic structure is shown in Fig. 2. This method allows users to flexibly shape the structure of the CF tree through parameter adjustments, thereby generating diverse clustering results. By requiring only a single pass through the dataset to achieve high clustering quality, BIRCH demonstrates remarkable speed and efficiency when handling large-scale datasets. This preprocessing step not only enhances clustering accuracy but also establishes a solid foundation for subsequent data analysis tasks [26].

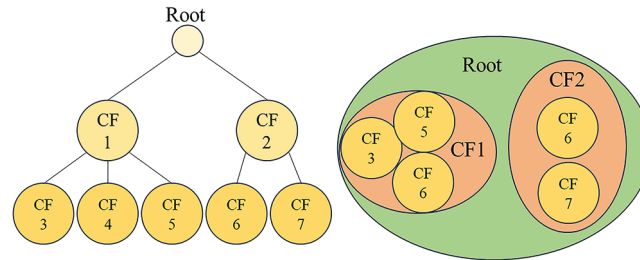


Figure 2: CF tree structure diagram

Partitional clustering algorithms demonstrate exceptional capability in exploring the intrinsic structure of data, enabling in-depth processing of complex datasets. By eliminating the requirement for predefined class labels, these methods exhibit remarkable flexibility and adaptability across diverse application scenarios.

Within the broad domain of partitional clustering, the K-Means algorithm stands as a prominent representative of hard partitioning methods, renowned for its computational efficiency and conceptual simplicity. Through an iterative optimization process, it categorizes data points into k distinct clusters, with each datum exclusively assigned to a single cluster, thereby explicitly revealing the underlying cluster structure. The objective function governing this process is mathematically formulated in Eq. (7).

$$\min \sum_{i=1}^N \sum_{x \in X_i} \|x - m_i\|^2 \quad (7)$$

Fuzzy partitioning algorithms, with the Fuzzy C-Means (FCM) algorithm as a prominent representative, offer an alternative perspective for data clustering. The FCM algorithm enables data points to belong to multiple clusters through probabilistic membership degrees, a soft partitioning approach that better aligns with real-world scenarios involving ambiguous or overlapping categorical boundaries. This methodology provides granular and comprehensive insights for cluster analysis. The governing objective function is mathematically defined in Eq. (8).

$$\min \sum_{i=1}^N \sum_{j=1}^K u_{ij}^p \|x_i - m_j\|^2 \quad (8)$$

By employing BIRCH clustering as a preprocessing step to enhance the K-Means clustering algorithm specifically as a pre-clustering method the K-Means algorithm operates on a refined and structurally organized subset of data. The BIRCH preprocessing stage generates preliminary cluster centroids and determines the optimal number of clusters, which are subsequently utilized as initialization parameters for K-Means. This hierarchical approach significantly improves clustering performance and accelerates convergence by leveraging BIRCH's noise-filtering capability and K-Means' iterative refinement mechanism. By employing BIRCH clustering as a preprocessing step to enhance the K-Means clustering algorithm specifically as a pre-clustering method the K-Means algorithm operates on a refined and structurally organized subset of data. The BIRCH preprocessing stage generates preliminary cluster centroids and determines the optimal number of clusters, which are subsequently utilized as initialization parameters for K-Means. This hierarchical approach significantly improves clustering performance and accelerates convergence by leveraging BIRCH's noise-filtering capability and K-Means' iterative refinement mechanism.

3 Analysis of Electricity Consumption Behavior of Coupled Meteorology

3.1 Data Collection

The user dataset was obtained from the Electricity Load-Diagrams in the UCI Machine Learning Repository, comprising 2011 electricity load data [27], recorded at 15-min intervals. Since electricity consumption characteristics are closely related to ambient temperature, localized temperature variations for 2011 were referenced from literature [28], as illustrated in Fig. 3. The datasets were partitioned into three subsets: Dataset 1 (01 January, representing low-temperature conditions), Dataset 2 (01 May, representing normal-temperature conditions), and Dataset 3 (15 July, representing high-temperature conditions), corresponding to the green line positions in the figure. All analyses in this study were conducted using these established datasets.

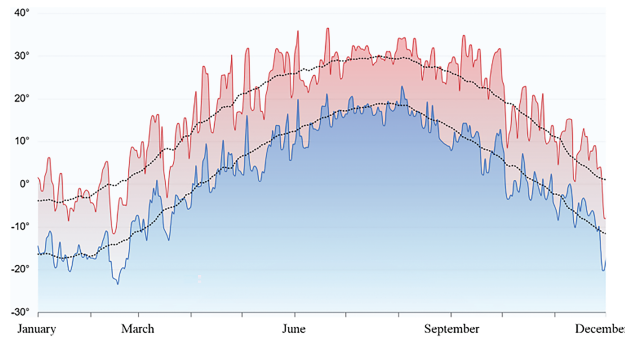


Figure 3: Temperature changes in the user's local area in 2011

3.2 Correlation Analysis

Existing studies have preliminarily demonstrated coupling relationships between meteorological factors and power load as well as wind and photovoltaic (PV) power output, where their variations directly influence user electricity consumption behavior. Fig. 4 illustrates the correlations between common meteorological parameters (atmospheric pressure, temperature, humidity, and wind speed) and power load as well as wind-PV power output. The analysis employs Pearson correlation coefficients calculated using Eq. (9). The Pearson correlation coefficient values were calculated using Eq. (9), as detailed in Table 1.

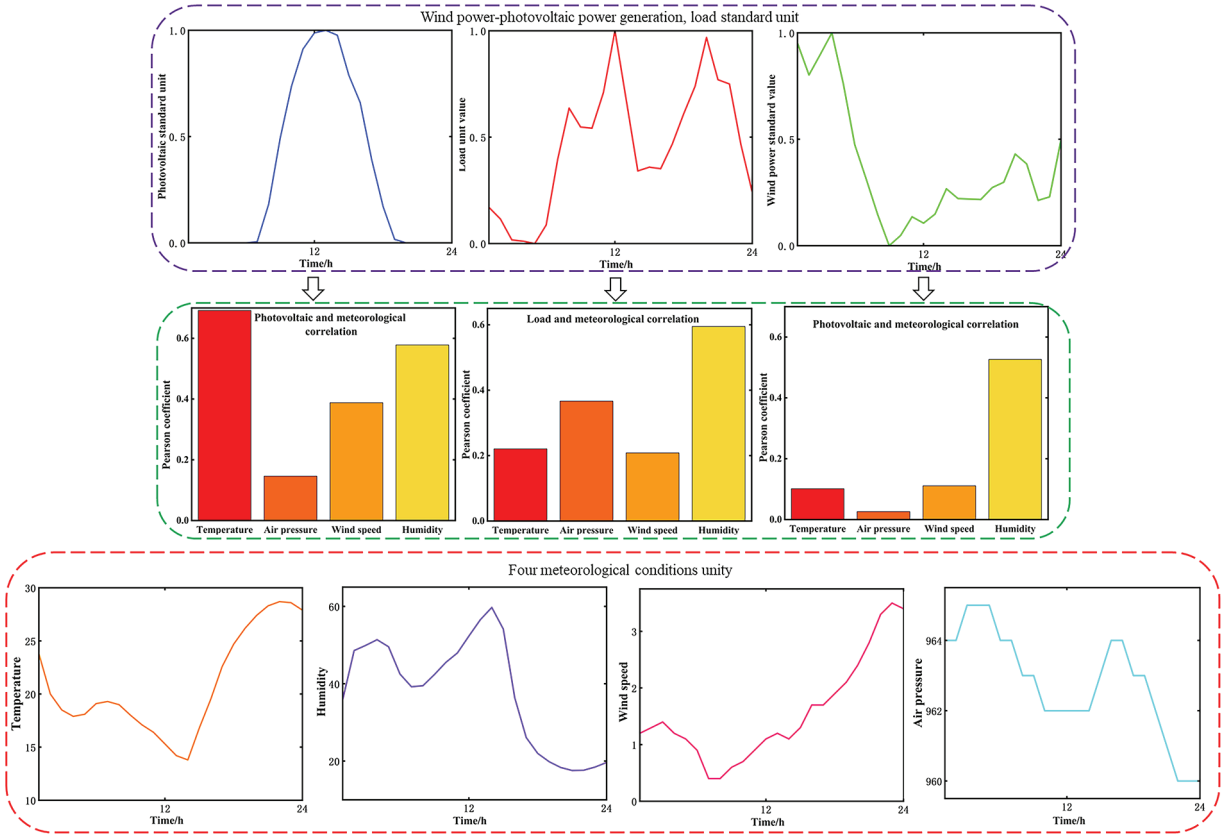


Figure 4: Correlation between meteorological factors and load, wind-light output

Table 1: Correlation between wind-light output, load and meteorological factors

Meteorological factors	Pearson coefficient		
	Wind power	Wind power	Photovoltaic
Temperature	0.10127	0.22072	0.69174
Air pressure	0.02606	0.36660	0.14610
Wind speed	0.11093	0.20847	0.38807
Humidity	0.52632	0.59494	0.57833

$$\rho_{x,y} = \frac{\text{cov}(x,y)}{\sigma_x \sigma_y} \quad (9)$$

in the equation: $\text{cov}(x,y)$ denotes the covariance between x and y ; σ_x and σ_y represent the standard deviations of x and y , respectively.

As shown in Fig. 4 and Table 1, meteorological factors exhibit strong correlations with wind-PV power output, where wind speed, humidity, and temperature serve as foundational factors for renewable energy generation. Simultaneously, these factors also demonstrate significant correlations with power load. Therefore, meteorological parameters such as atmospheric pressure, temperature, humidity, and wind speed can be employed to construct a meteorology-coupled electricity consumption behavior feature set.

3.3 Feature Clustering Based on Meteorological Historical Data

The user dataset was first partitioned based on temperature, followed by a comparative analysis using multiple clustering validity indices and clustering methods. The BK-Means clustering algorithm was employed to classify historical meteorological scenarios, thereby enabling electricity consumption behavior analysis and the construction of a meteorology-coupled feature set. The implementation workflow is depicted in Fig. 5. As shown on the following page.

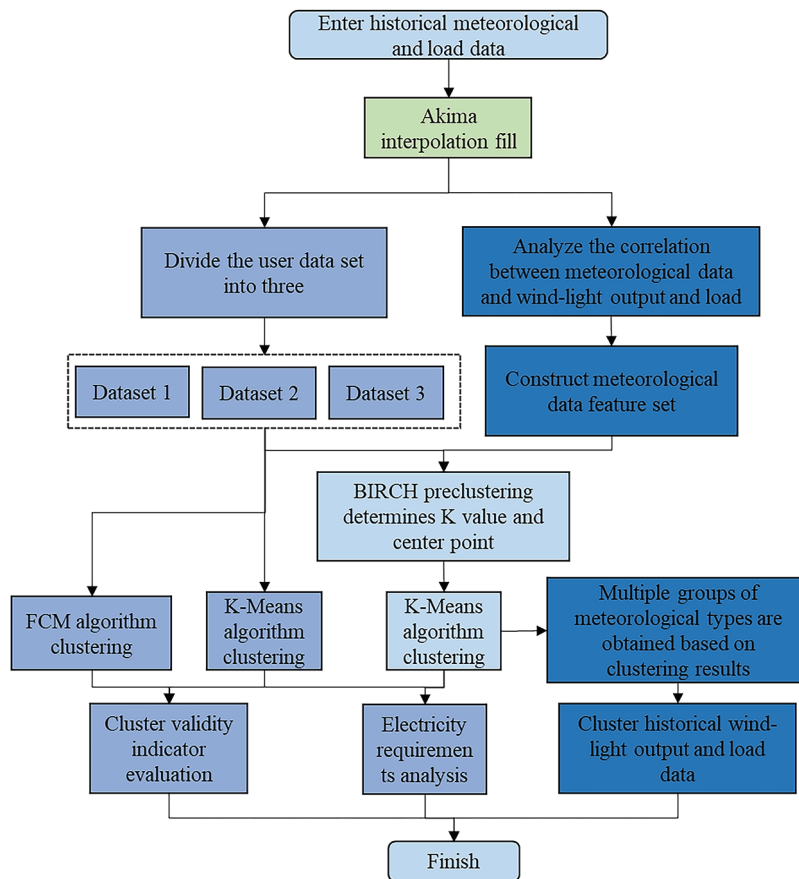


Figure 5: Coupled meteorological electricity behavior analysis and feature set construction flow chart

The number of clusters for meteorological factors, power load, and wind-PV power output was determined as three through BIRCH pre-clustering. Cluster analysis was conducted on meteorological data, power load, and wind-PV power output. Figs. 6 and 7 employ boxplots to illustrate the intraclass diurnal distributions of meteorological data after clustering, where blue solid lines denote cluster centers and red dots indicate outliers. As shown in Fig. 6, distinct meteorological characteristics emerge across clusters: Cluster 1 exhibits relatively humid conditions with significant diurnal temperature variation, lower daytime wind speeds, higher nighttime wind speeds accompanied by intense fluctuations, and the most stable atmospheric pressure with minimal variability. Cluster 2 demonstrates drier daytime conditions, higher wind speeds, lower average temperatures, and colder nighttime humidity. It features predominantly elevated atmospheric pressure with notable pressure differences, along with significantly lower temperature and humidity compared to Cluster 1. Cluster 3 shows slightly higher humidity than Cluster 1 but lower than Cluster 2, with overall lower and less variable wind speeds. Temperatures remain high during daytime but gradually decline from afternoon, exhibiting a high-to-low diurnal pattern, while atmospheric pressure remains relatively stable with moderate fluctuations. The distinct inter-cluster distribution patterns validate the effectiveness of the clustering results.

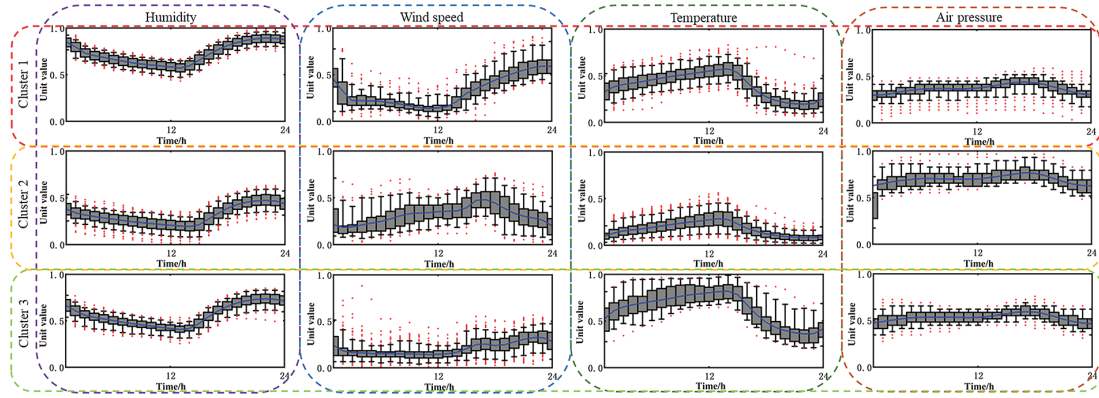


Figure 6: Coupled meteorological feature clustering

Following the construction of the meteorology-coupled feature set clusters, the characteristic distributions of wind-PV power output and power load data relative to cluster centers are illustrated in Fig. 7. Cluster 1 displays higher average wind power generation with significant volatility, substantial photovoltaic output showing notable incremental gains over time, and a dual-peak and dual-valley load pattern with moderate fluctuations. Cluster 2 demonstrates stable wind power generation with limited variation, smaller incremental photovoltaic output accompanied by supply gaps, and lower-load consumption with minimal fluctuations. Cluster 3, corresponding to low-wind meteorological features, shows the least wind power generation with low volatility, higher photovoltaic output marked by numerous outliers and substantial fluctuations without distinct supply gaps, coupled with high-load consumption featuring pronounced volatility and an ascending-descending temporal pattern. The wind-PV power output and load characteristics in Fig. 7 align coherently with the meteorology-coupled features presented in Fig. 6.

In summary, the proposed meteorology-coupled feature clustering effectively characterizes the intra-class correlations and inter-class differences of meteorological influences on wind-PV power output and power load.

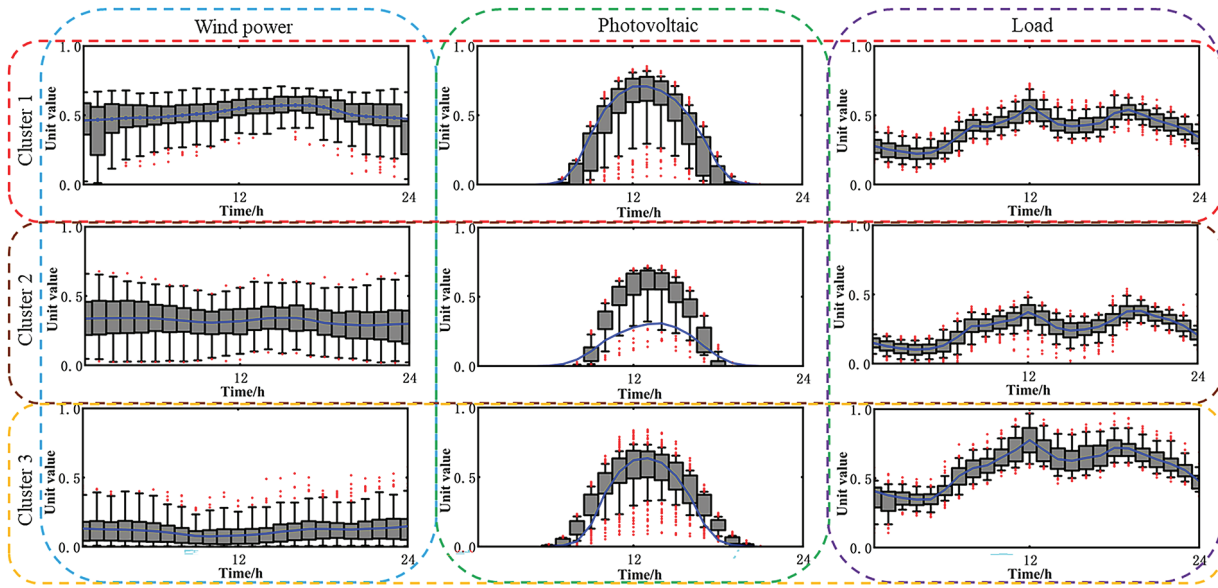


Figure 7: Wind-light output and load data feature clustering

In this study, the core purpose of performing cluster analysis on wind and photovoltaic (PV) output data is not to independently predict them, but to deeply reveal the coupling mechanism whereby meteorological conditions indirectly influence power load through their impact on renewable energy generation. As shown in Fig. 6, different weather patterns create specific climate scenarios that directly determine the output characteristics of wind and PV power. Moreover, the output of renewable energy—particularly the diurnal characteristics of PV generation—further affects the net load curve of the grid as well as user electricity consumption behavior. By conducting synchronized and parallel cluster analysis of meteorology, wind and PV output, and load, we can verify whether a consistent and interpretable coupling relationship exists among the three. This analysis ensures that the subsequently constructed ‘meteorological coupling feature set’ not only contains the original meteorological data but also includes patterns of renewable energy output driven by the weather, identified through pattern recognition. Consequently, it provides input features for load forecasting models with greater physical significance and discriminative power.

3.4 Clustering Algorithm Analysis

Dataset 1 was clustered using the proposed BK-Means algorithm alongside FCM and K-Means algorithms, with all methods configured for 1000 iterations and cluster numbers ranging from 3 to 15. The violin plots in Fig. 8 compare the three evaluation metrics across methods. The results indicate that the FCM algorithm underperforms in CHI and SC metrics, showing consistently lower average values. Additionally, it exhibits elevated DBI values, which reflect insufficient robustness and suboptimal clustering performance when processing heterogeneous data characteristics. The BK-Means algorithm achieved significant improvements: SC increased to 0.4679 (24.04% enhancement over conventional methods), CHI rose to 114.515 (17.98% improvement), and DBI decreased to 0.9265 (20.02% reduction). These results demonstrate that BK-Means effectively enhances intra-cluster cohesion while maximizing inter-cluster separation, thereby improving clustering validity and accuracy.

Comprehensive analysis of the three evaluation metrics confirms that the proposed BK-Means algorithm outperforms traditional partitioning clustering methods across all criteria, offering a more efficient and accurate solution for data clustering applications.

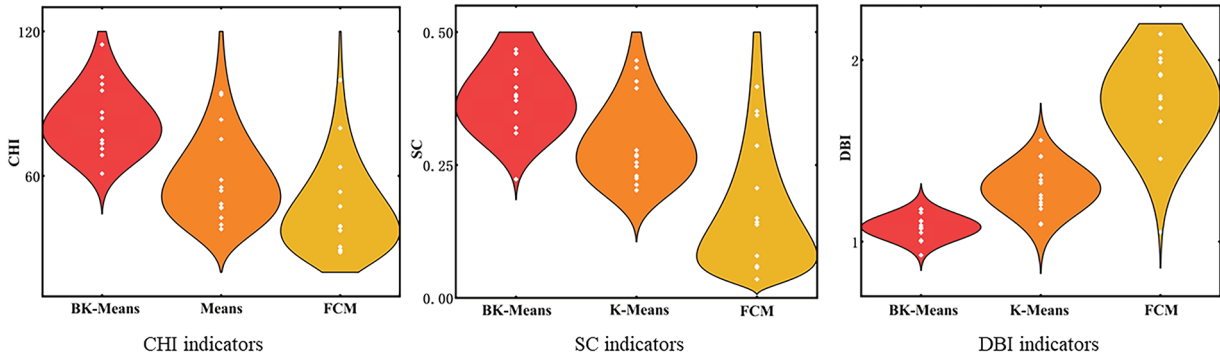


Figure 8: Comparison chart of three indicators

3.5 Analysis of Electricity Usage Behavior of Coupled Meteorology

The proposed BK-Means algorithm was applied to Datasets 1, 2, and 3, with optimal cluster numbers determined as 5, 3, and 3 through pre-clustering. Cluster centroids for the three datasets were temporally aligned using the averaging method to standardize data hourly intervals, facilitating subsequent analysis. Pearson correlation analysis was then conducted between the aligned centroids and daily meteorological parameters average temperature (Temp), dew point (DP), relative humidity (RH), and wind speed (WS) where meteorological data were retrieved from the NSRDB database [28]. The resultant user cluster characteristics and their meteorological correlations are illustrated in Figs. 9–11, with red solid lines representing cluster centers. The coupled meteorological correlation heat maps at the centers of the three datasets are shown in Fig. 12.

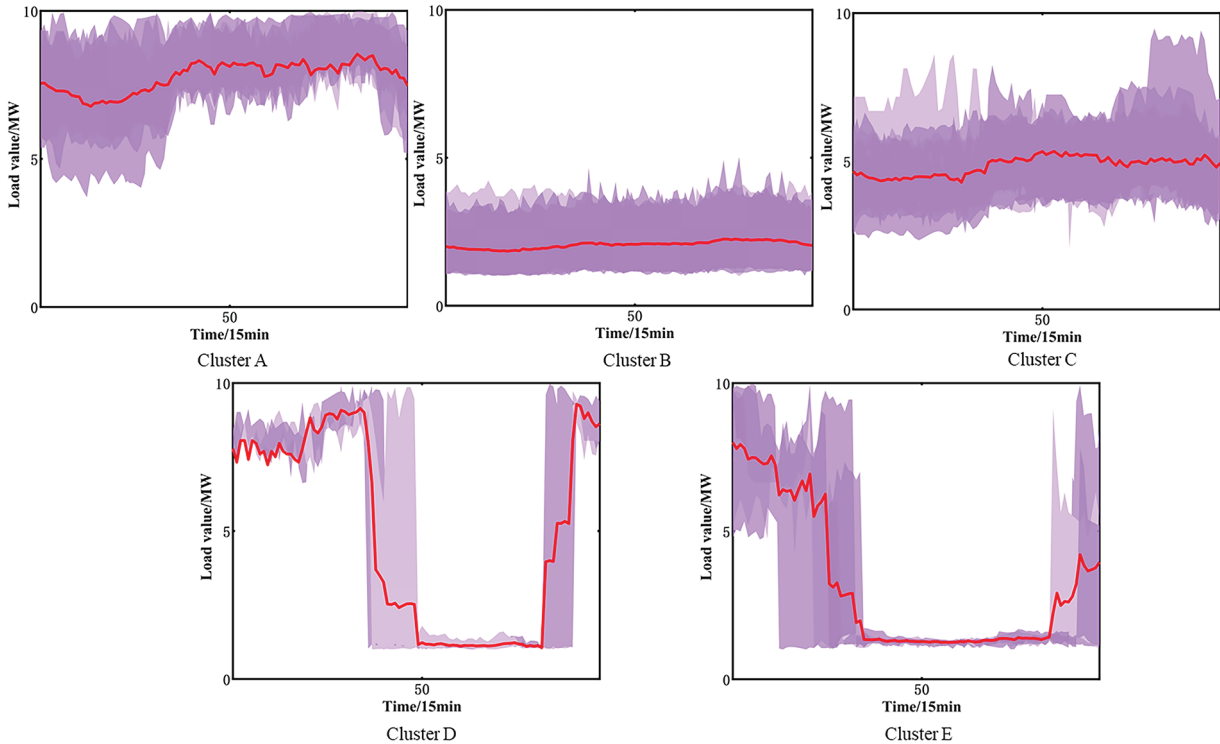


Figure 9: Dataset 1 user clustering characteristics

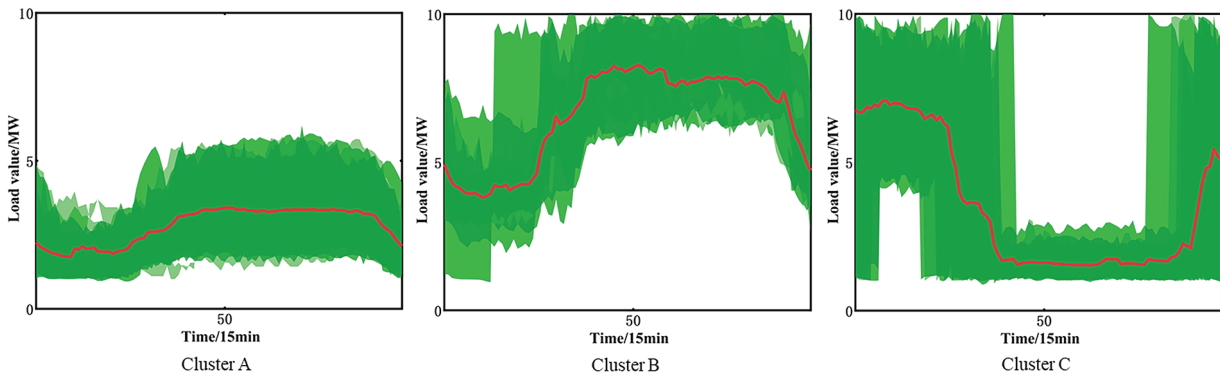


Figure 10: Dataset 2 user clustering characteristics

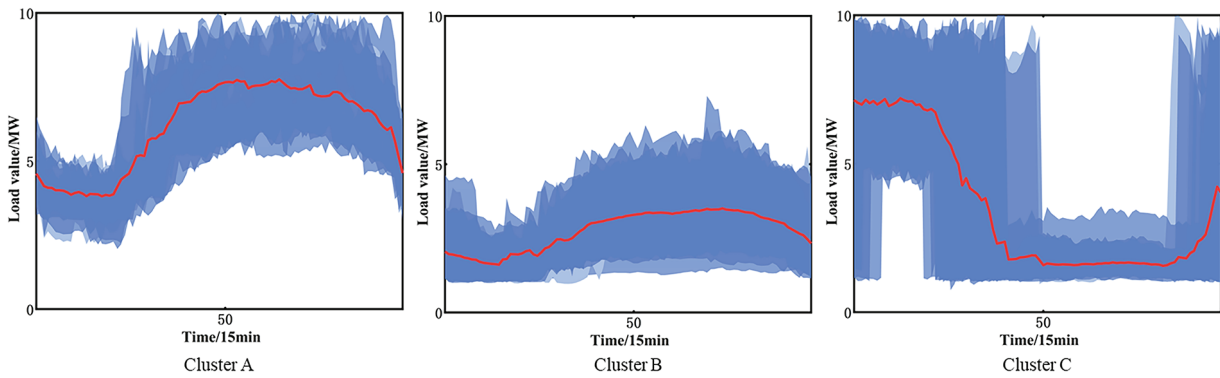


Figure 11: Dataset 3 user clustering characteristics

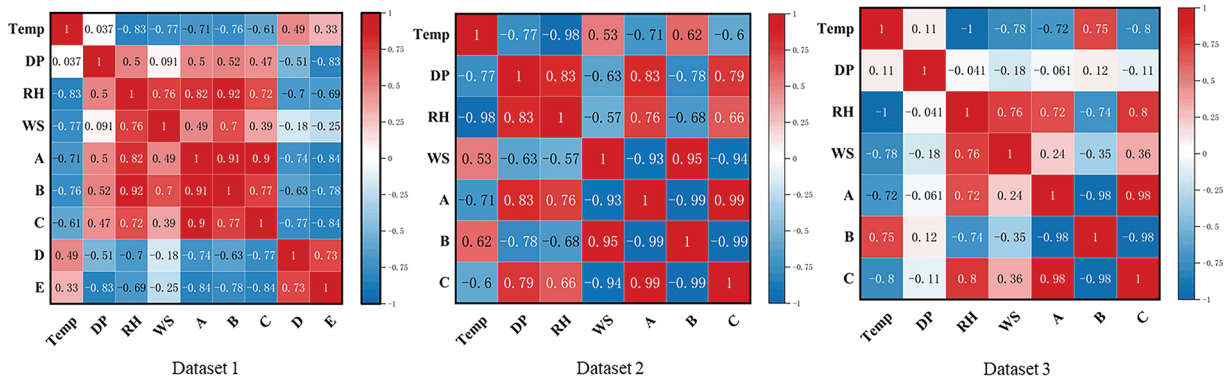


Figure 12: Coupled meteorological correlation heat map in the center of the data set

Dataset 1 (Figs. 9 and 12): Cluster A exhibits high load consumption characteristics, while Cluster B demonstrates low-load patterns. Cluster C displays a unique profile where consumption peaks align with Cluster A troughs and troughs approach Cluster B peaks, classifying it as a typical user group. Cluster D shows a distinct “dual-peak and single-valley” pattern, with peak consumption concentrated between 20:00 and 08:00, featuring significant peak-valley differences. Cluster E shares similarities with Cluster D but exhibits smaller peak-valley differences and smoother load curves. Clusters A and B display strong correlations with meteorological factors (temperature, humidity, dew point, and wind speed), indicating their behavioral patterns are heavily influenced by these parameters. Clusters C and D exhibit moderate meteorological

correlations but remain less sensitive to wind speed variations. Cluster E shows the weakest meteorological correlation, highlighting its behavioral stability.

Dataset 2 (Figs. 10 and 12): Cluster A follows a typical daily consumption pattern. Cluster B presents a unique bimodal profile: a primary peak occurs between 00:00 and 05:00, followed by a secondary peak from 22:30 to midnight, with low consumption otherwise. Cluster C exhibits an inverse pattern to Cluster B, with low consumption during late-night to early-morning hours and high-load usage during daytime. All three clusters maintain strong correlations with meteorological factors, underscoring the pervasive influence of weather conditions on user behavior in this dataset.

Dataset 3 (Figs. 11 and 12): Cluster A reaches its consumption peak at midday, declining gradually after-noon, with minimal usage from late night to early morning. Cluster B shows a trough between 10:30 and 20:00, followed by a secondary peak and a primary peak in the latter half of the night. Cluster C exhibits relatively stable consumption with minor peak-valley differences. Across all clusters, user behavior is predominantly influenced by temperature and wind speed variations, with lower sensitivity to humidity.

These findings demonstrate that user clusters across datasets exhibit distinct load patterns and varying degrees of meteorological dependency, reinforcing the utility of the proposed methodology in characterizing weather-coupled electricity consumption behaviors.

4 Analysis of Multi-Load Forecasting Based on Fusion of Generalized Reverse Learning NRBO-LSTM-XGBoost

Building upon the meteorology-coupled feature sets constructed, which provide a refined understanding of how seasonal and climatic factors influence user behavior and energy patterns, this section proceeds to develop a high-precision forecasting model. The insights and, more importantly, the differentiated input features derived from the previous behavioral analysis directly inform and enable the multi-load forecasting model proposed in this section. This section proceeds to develop a high-precision forecasting model. It is crucial to explicitly elucidate the intrinsic relationships that underpin our forecasting framework, which directly addresses the core of multi-energy load forecasting in Integrated Energy Systems (IES).

Firstly, the cooling and heating loads exhibit a direct and physically deterministic relationship with meteorological conditions, particularly ambient temperature and solar radiation. The cooling load primarily arises from the need to remove heat from buildings to maintain thermal comfort. It is positively correlated with ambient temperature and solar irradiance; as these factors increase, the demand for space cooling and refrigeration escalates. Conversely, the heating load is driven by the need to compensate for heat loss to the colder external environment. It demonstrates a strong negative correlation with ambient temperature, meaning heating demand significantly increases as the temperature drops.

Secondly, within an IES, electricity, cooling, and heating loads are not independent but are tightly coupled through energy conversion devices. This interdependence creates a complex web where meteorological factors influence not only the final demand for cooling and heating but also the intermediate electrical load required to satisfy that demand. Key coupling mechanisms include: Electricity-to-Cooling: Devices like electric chillers and heat pumps (in cooling mode) consume electrical energy to generate cooling. Electricity/Gas-to-Heating: Devices such as electric heaters, heat pumps (in heating mode), or gas boilers consume electrical or chemical energy to produce heat. Combined Systems: Combined Heat and Power (CHP) systems or complex heat pumps can simultaneously or sequentially produce both electricity and thermal energy (heating/cooling).

Therefore, the total 'electrical' load in an IES is an aggregation of the base electricity consumption and the parasitic electrical load from cooling/heating equipment. This creates a complex, non-linear coupling

among the multi-energy loads, which is both driven by external weather and constrained by internal system efficiency and conversion relationships. The differentiated input feature sets constructed, which incorporate these coupled meteorological and renewable energy patterns, are designed to capture these very physical mechanisms to inform the forecasting model proposed below.

4.1 N-Raphson Optimization Algorithm with a Fused Quasi-Inverse Learning Mechanism

The Newton-Raphson Optimization Algorithm is a derivative-driven metaheuristic algorithm. It synergistically drives the search process using the Newton-Raphson Search Rule (NRSR) and a Trap Avoidance Operator (TAO) based on gradient information for directed optimization. The procedure employs perturbation strategies to evade local optima and enhances global exploration capabilities through a multi-matrix cooperative evolution mechanism. The implementation framework follows the paradigm of swarm intelligence optimization: initializing a population of candidate solutions, iteratively refining them via NRSR and TAO, and incorporating matrix-based operations to enable efficient hyperparameter space search, ultimately yielding a neural network optimizer with global convergence properties.

NRBO employs a conventional random initialization strategy, which fails to effectively utilize the spatial structural characteristics of the problem, resulting in an uneven initial population distribution. This uneven distribution not only reduces the algorithm's probability of finding the global optimum but also increases the risk of premature convergence. The quality of the initial population directly affects the convergence properties. When iteratively updating parameters, the algorithm's update amount depends simultaneously on the individual's current position, the best position, and the worst position, and involves finite-difference approximations of the first and second derivatives of the objective function. This update mechanism has two potential issues. First is the sensitivity to initial positions: when the initial population is far from the global optimum, the optimization process is prone to becoming trapped in local optima, achieving only incremental improvements. Second is the ill-conditioning of the second derivative: when the second derivative of the objective function approaches zero in a local region, the denominator term in the update formula drastically decreases, causing excessively large gradient steps that severely slow convergence or lead to algorithmic instability.

To address the aforementioned initialization and diversity issues (which aligns with our second contribution), this paper adopts a fitness-weighted quasi-oppositional learning initialization strategy aimed at improving initial population quality and maintaining population diversity. Compared to traditional oppositional learning, quasi-oppositional learning introduces a random scaling mechanism via [Eq. \(14\)](#), expanding the generation region of oppositional solutions from a fixed mirror point to a continuous probabilistic space between the individual and the population center, thereby significantly broadening the coverage of candidate solutions. Furthermore, this strategy incorporates a fitness-weighted selection mechanism: solutions with better fitness values have a higher probability of being selected. This mechanism effectively preserves high-quality solutions while maintaining population diversity. Applying this strategy to the initialization process of NRBO organically integrates fitness information with randomness, significantly enhancing the algorithm's initial search efficiency and population diversity. The improvement mechanism of this strategy is illustrated in [Fig. 13](#). As shown on the following page.

To use the quasi-inverse learning to generate adversarial solutions, the formula for calculating the midpoint Z_j is as follows:

$$Z_j = \frac{L_j + H_j}{2} \quad (10)$$

where: L_j and H_j represent the lower and upper bounds of the definition range of the j -th dimension, respectively.

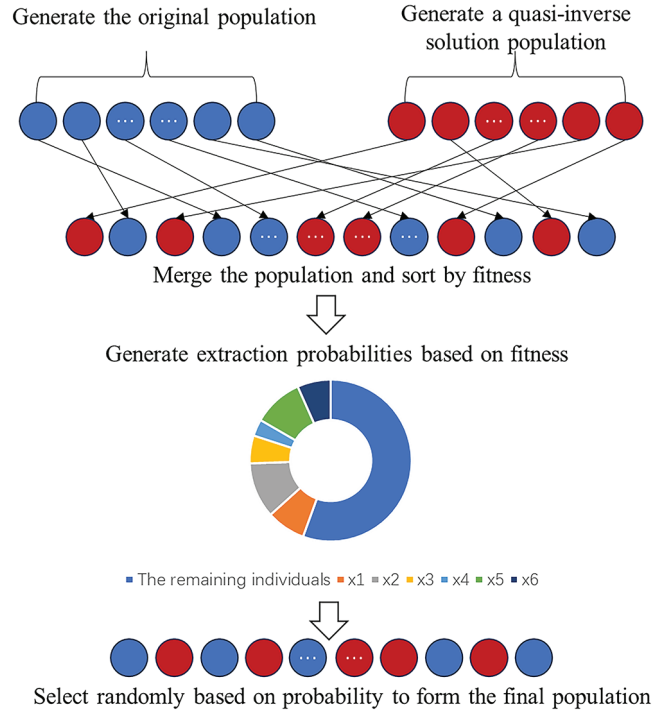


Figure 13: Schematic diagram of the fitness-weighted quasi-inverse learning initialization principle

The opposing solution can be calculated using the following equation:

$$\begin{cases} X_j^p = Z_j + (X_j - Z_j) \times r, & \text{if } X_j < Z_j \\ X_j^p = X_j + (Z_j - X_j) \times r, & \text{otherwise} \end{cases} \quad (11)$$

where: $j = 1, 2, \dots, D$; D is the dimensionality of the problem. The original population and opposing solutions are combined to form a larger population. The selection probability P is calculated using the following equation:

$$P = \frac{AllFitness}{\sum AllFitness} \quad (12)$$

where: $AllFitness$ is the reciprocal of the fitness of the individuals in the population; $\sum AllFitness$ is the cumulative sum of the reciprocal of the population's fitness; P is the probability of an individual being selected.

4.2 Improved Feature Selection Model of the XGBoost Algorithm

XGBoost is an efficient supervised learning algorithm that builds a strong predictive model for predicting target variables by aggregating multiple weak classifiers (decision trees). Its core lies in the iterative training of the additive model: in each iteration, XGBoost constructs a new weak learner in the direction of gradient descent along the loss function. The algorithm utilizes a second-order Taylor expansion to approximate the loss function and explicitly includes a regularization term in the objective function to optimize both prediction accuracy and control model complexity, seeking a global optimal solution. Thanks

to its regularization mechanism, efficient algorithm design, and support for parallel computing, XGBoost effectively prevents overfitting, has a fast training speed, and has become one of the most widely successful machine learning methods.

Converting the original input data into features and selecting effective features to better describe potential issues helps improve the accuracy of predictive models. In short-term multi-load forecasting, effectively screening out the set of features that significantly influence the load is of great importance for subsequent prediction work. The improved XGBoost algorithm can directly calculate feature importance based on the tree structure itself after creating trees, completing effective feature selection. Its core indicators include weight and gain. The former indicates the total number of times this feature is used as a split node across all trees. The latter indicates the weighted average of the information gain brought by this feature each time it is used as a split node in all trees. The calculation of gain is shown in Eqs. (13) and (14):

$$G_{ain} = 0.5 \left(\frac{G_{Li}^2}{H_{Li} + \lambda} + \frac{G_{Ri}^2}{H_{Ri} + \lambda} - \frac{G_i^2}{H_i + \lambda} \right) - \lambda \quad (13)$$

$$G_i = \sum_{i \in I_j} g_i, H_i = \sum_{i \in I_j} h_i \quad (14)$$

where: the subscript R and L represent the right subtree and left subtree after the split, respectively.

4.3 LSTM Model

Long Short-Term Memory networks (LSTM) are a variant of Recurrent Neural Networks (RNN) developed to address the issues of vanishing and exploding gradients that RNNs face when processing long sequences. Compared to standard RNNs, the core of LSTM lies in its internal structure, which introduces input gates, forget gates, output gates, and memory cells (often associated with information transmission functions). These gating mechanisms work together, allowing LSTMs to selectively remember, update, and transmit key information during the processing of sequential data. The typical structure of LSTM is shown in Fig. 14.

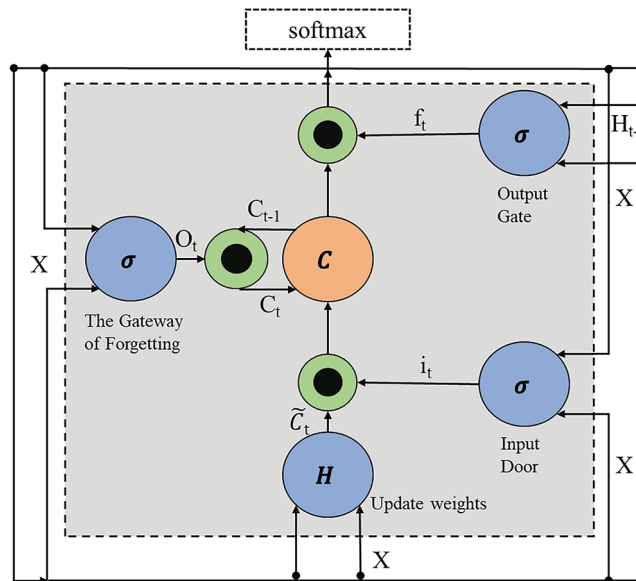


Figure 14: LSTM internal structure schematic diagram

The working principle of the LSTM neural network is as follows. The forget gate determines the retention and forgetting of information in the cell at time $t - 1$. The input gate is used to determine which new information can be input into the memory cell to update the cell state. The output gate is used to filter the information in the memory cell and output the most necessary information to predict future values.

4.4 Combination Model

The integrated energy system has overcome the bottlenecks of traditional independent operation of energy supply systems and the shortcomings of multi-energy complementarity. However, its multi-source load forecasting faces challenges such as complex internal and external coupling, difficulty in feature construction, and limitations in forecasting accuracy. To address these issues, this paper proposes a NRBO-LSTM-XGBoost ensemble model, which enhances forecasting performance through a three-level collaborative mechanism: (1) The NRBO optimizer improves the quality and diversity of the initial population by introducing a fitness-weighted quasi-inverse learning mechanism, thereby enhancing convergence efficiency and solving parameter sensitivity issues. (2) The improved XGBoost algorithm's feature selection model efficiently integrates multi-source data, filtering differentiated key features suitable for seasonal and load type variations. (3) The LSTM time series modeler uses the filtered features as input, leveraging its long-term dependency modeling and multi-variable collaborative capabilities to accurately capture load dynamics. This model significantly improves time series forecasting accuracy under complex internal and external features and provides support for intelligent scheduling of integrated energy systems. The forecasting process within a single iteration of the algorithm is illustrated in Fig. 15.

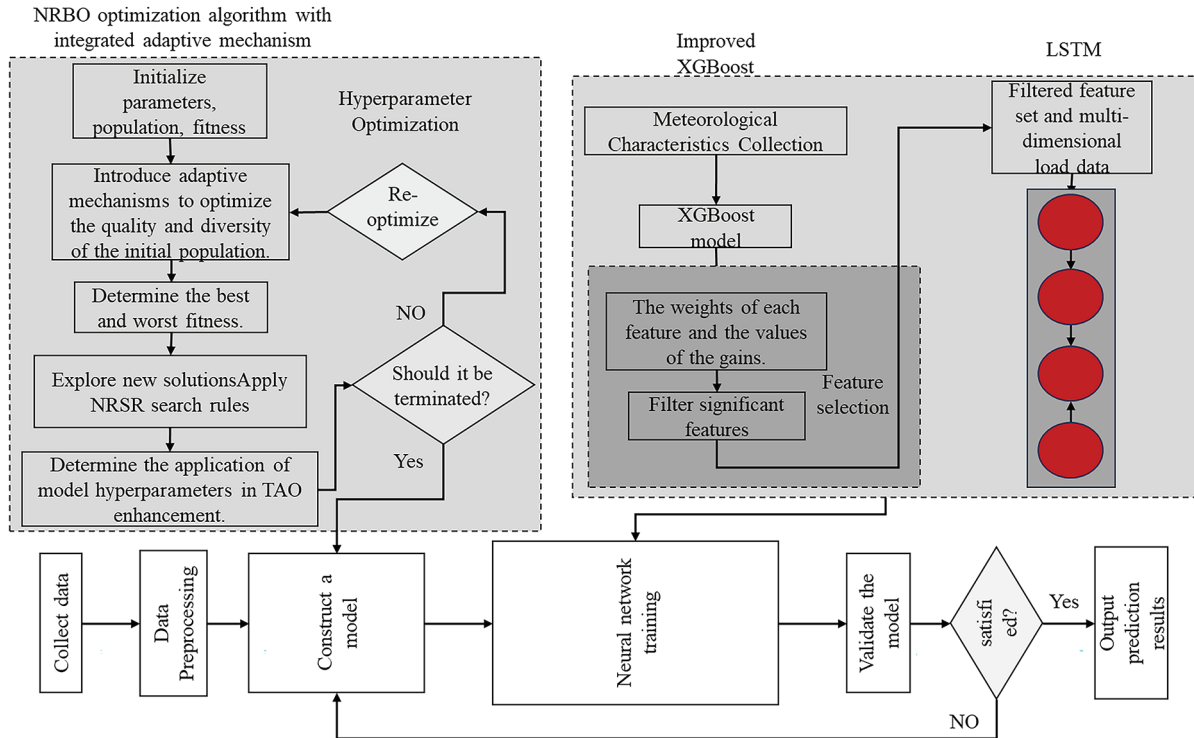


Figure 15: Flowchart of the combined model multi-load forecasting process

5 Example Analysis

5.1 Data Collection and Preprocessing

The diverse load forecasting part of the integrated energy system uses the IES electricity, cooling, and heating load data from Arizona State University Tempe campus from 00:00 on 01 March 2020 to 23:00 on 28 February 2021 (with a sampling interval of 1 h) and meteorological data from the National Solar Radiation Database of the United States. To fully consider seasonal load variations, the diverse load data is divided by season. The data for each quarter is further split into training and testing sets at a ratio of 7:3.

The feature data attributes vary, mainly categorized into numerical attributes (such as load values, temperature values, etc.), nominal attributes (such as weather conditions, wind direction parameters, etc.), and ordinal attributes (such as time parameters). Among them, outlier detection and missing value filling for numerical attributes can be directly performed through numerical operations, while nominal data needs to be transformed into binary attributes before further processing. During the data processing, anomalous data in historical loads is filtered based on certain criteria and treated as missing values. The missing values are filled using the Akima interpolation method. Additionally, to eliminate the influence of dimensional differences in input features on prediction results, Min-Max normalization is uniformly applied after data preprocessing, ensuring that the input data falls within the range of [0, 1], as shown in Eq. (15):

$$\tilde{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (15)$$

where: x is a certain sequence in the input data; $x_{\max}$ and $x_{\min}$ are the maximum and minimum values in that sequence, respectively.

5.2 Model Parameter Settings and Evaluation Metrics

The construction and training of a multi-dimensional load forecasting model is based on the Pytorch deep learning framework, with the hardware configuration of the experimental platform being an Intel(R) Core (TM) i5-13500HX CPU, accelerated by an NVIDIA GeForce RTX 4050 GPU. This paper selects Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) as evaluation metrics, with their calculation formulas shown in Eqs. (16)–(18).

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - y_j| \quad (16)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - y_j)^2} \quad (17)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - y_j}{y_i} \right| \times 100\% \quad (18)$$

where: n it indicates the sample size; y_i it represents the true load value; y_j it represents the predicted load value. The smaller the values of MAE , $MAPE$, and $RMSE$, the more accurate the predictions of the model.

Table 2 shows the hyperparameter settings of the algorithms involved in this paper.

Table 2: Parameters of each algorithm

Algorithm	Parameter name	Parameter value
XGBoost	Learning_rate	0.1
	Max_depth	6
	N_estimators	100
LSTM	LSTM units	[32, 64]
	Num_layers	2
	Learning_rate	0.001
	Epochs	100
	Batch size	16
	Optimizer	Adam
CNN	Out channels	16
	Kernel size	2
	Learning_rate	0.01
	In features	64
NRBO	DF	0.6
	Epochs	100

5.3 Multivariate Load Seasonal Coupling Meteorological Analysis

The seasonal differences in meteorological conditions significantly affect the energy consumption behavior patterns of IES users. This change in energy consumption behavior further impacts the energy conversion strategies within the IES, resulting in multi-energy flow loads such as electricity, cooling, and heating presenting typical seasonal and periodic characteristics. Therefore, deeply exploring the coupling mechanisms between diverse loads across different seasons and quantifying the correlation between diverse loads and meteorological factors has dual significance for constructing high-precision load forecasting models: on one hand, it can reveal the inherent laws of system operation, and on the other hand, it can provide key variable selection criteria for feature engineering in forecasting models. This paper selects the Kendall rank correlation coefficient, which is suitable for continuous sequential variables and robust against outliers, to conduct a correlation analysis on the historical data of diverse loads across different seasons. The calculation formula for Kendall rank correlation analysis is shown in Eq. (19).

$$\tau = \frac{n_c - n_d}{\sqrt{(n_c + n_d + t_x)(n_c + n_d + t_y)}} \quad (19)$$

where: n_c represents the number of consistent pairs, n_d represents the number of inconsistent pairs, and n is the total number of observation samples. t_x and t_y indicate the number of ties for variables x and y . The value of τ ranges from $[-1, 1]$; the larger its absolute value, the stronger the correlation.

Fig. 16 shows the results of the Kendall correlation analysis between seasonal multi-load and meteorological factors. The coupling analysis between meteorological factors and multi-load indicates that cloud type and wind speed have Kendall correlation coefficients with electrical, cooling, and heating loads of less than 0.2 in absolute value throughout the four seasons, showing the weakest correlation. Additionally, the correlation of wind speed, wind direction, clearsky DHI, and clearsky GHI with seasonal electrical load is similarly at a minimal level. In contrast, the other meteorological factors show significant impacts on

electrical, cooling, and heating loads ($|\tau| > 0.35$). This reveals a differentiated coupling mechanism between loads in different seasons and between loads and meteorological factors. Based on this finding, this study employs a seasonally differentiated feature selection strategy, including meteorological factors with absolute Kendall correlation coefficients greater than 0.35 into the input feature set for multi-load forecasting in each season (Fig. 16). As shown on the following page.

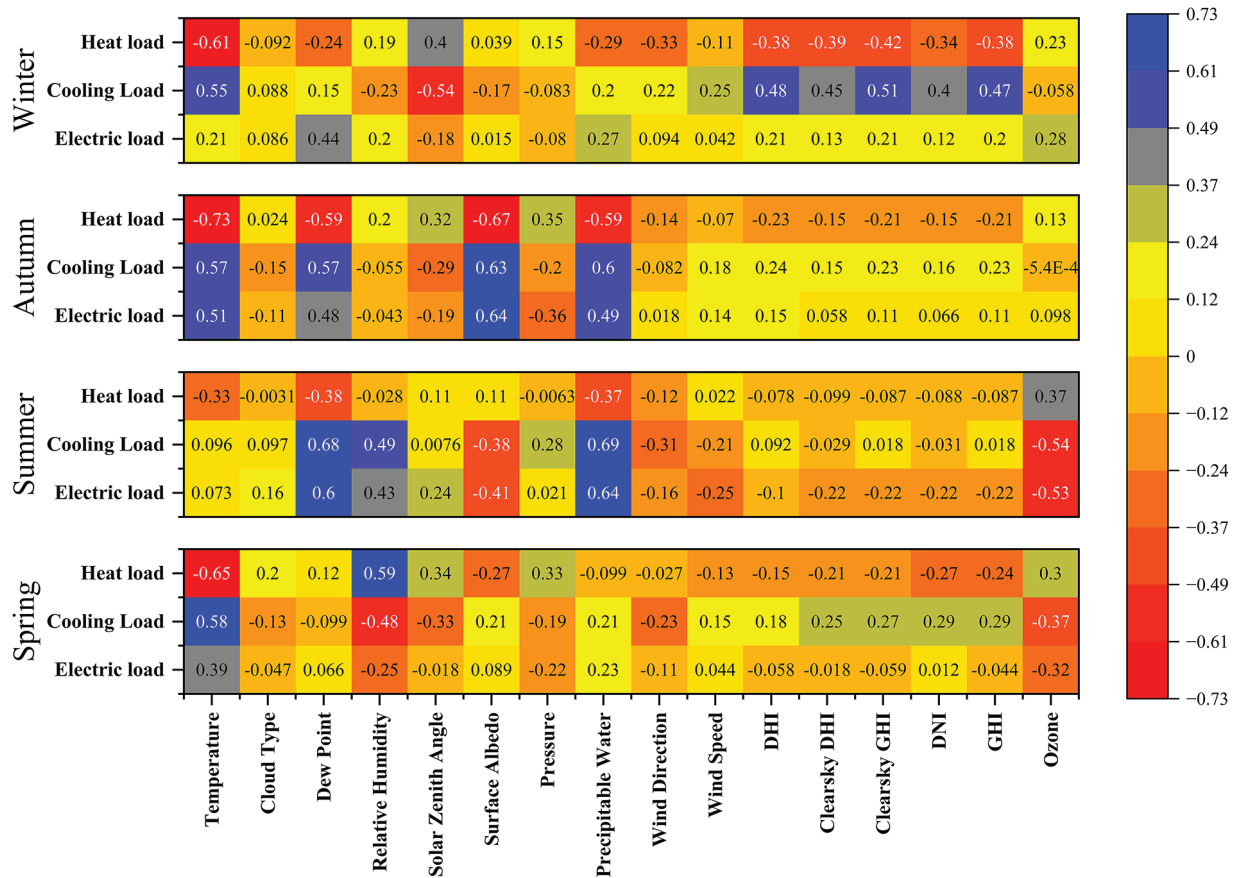


Figure 16: Correlation analysis of Kendall heat maps of multi-load coupling meteorological with four seasons

5.4 Comparative Analysis of Multi-Dimensional Load Forecasting

To verify the effectiveness of the multivariate load short-term forecasting method proposed in this paper, which is based on a fusion quasi-backward learning mechanism of NRBO-LSTM-XGBOOST coupled meteorological differentiated characteristics, comparative experiments were designed. These involved using a single algorithm (CNN, LSTM, XGBoost) for single-input load forecasting and using the LSTM-XGBoost algorithm coupled to extract the feature set for multi-input independent forecasting of each load. The evaluation indicators for electricity, cooling, and heating loads in different seasons are shown in Tables 3–6. The forecasting results for electricity, cooling, and heating loads in different seasons are illustrated in Figs. 17–20.

From Figs. 17–20 and Tables 3–6, it can be seen that the generality and significance analysis of the improvement in prediction accuracy of the proposed combined model shows that in comparison to the second-best performing LSTM-XGBoost combined model, the method in this paper significantly reduces the MAPE for all seasons and all load types. Taking MAPE as an example, the average improvement ranges

from 65% to 82% (for instance, in spring, the heating load MAPE decreased from 2.74% to 0.98%, a reduction of 64.2%; in autumn, the heating load MAPE decreased from 2.47% to 0.87%, a reduction of 64.8%). The prediction accuracy surpasses that of a single model overall, where compared to the best-performing single model (typically LSTM or XGBoost, depending on the specific load and season), the MAPE improvement for the method proposed in this paper generally exceeds 70%–85% (for example, for summer cooling load, the optimal single model LSTM has a MAPE of 4.55%, while the method in this paper achieves 0.92%, a reduction of 79.8%; for winter heating load, the optimal single model LSTM has a MAPE of 4.58%, while the method in this paper achieves 1.22%, a reduction of 73.4%).

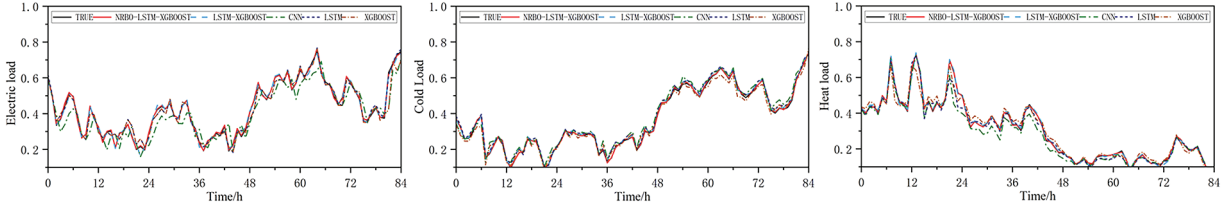


Figure 17: Spring multi-dimensional load forecasting results

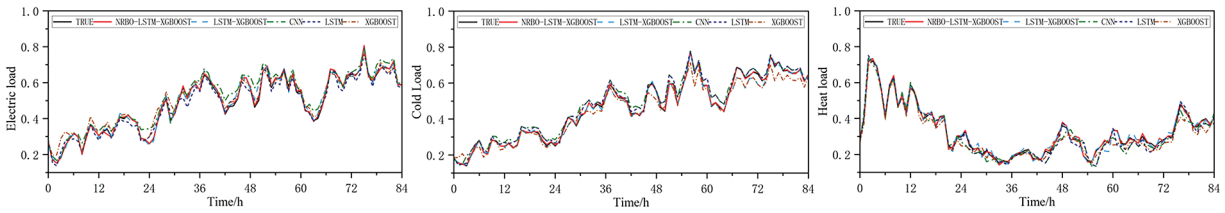


Figure 18: Summer multi-dimensional load forecasting results

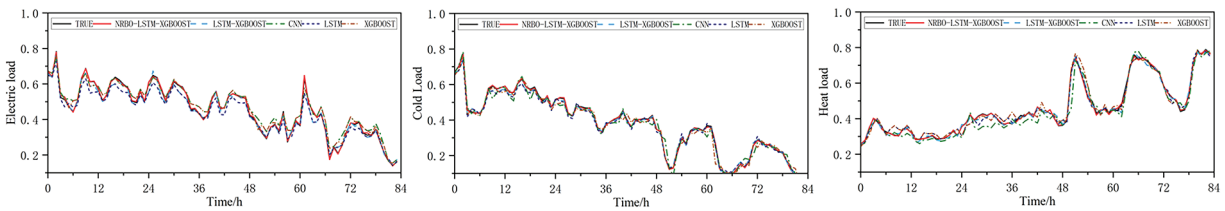


Figure 19: Autumn multi-dimensional load forecasting results

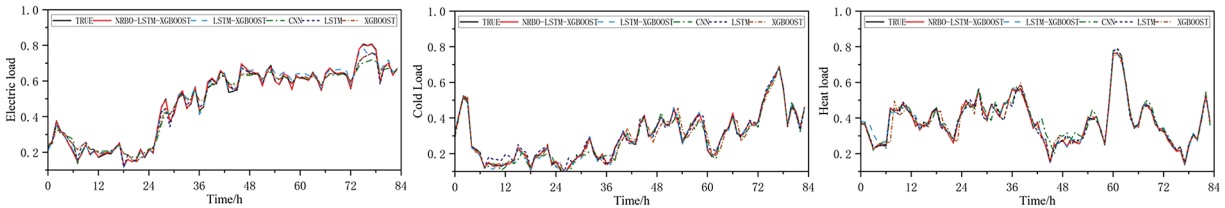


Figure 20: Winter multi-dimensional load forecasting results

Table 3: Spring multi-dimensional load evaluation indicators

Load type	Algorithm	MAE	RMSE	MAPE
Electric load	NRBO-LSTM-XGBoost	0.0050	0.0062	1.2579%
	LSTM-XGBoost	0.0126	0.0161	3.6246%
	CNN	0.0212	0.026	7.6115%
	LSTM	0.0208	0.0244	5.7837%
	XGBoost	0.0254	0.0361	6.6542%
Cooling load	NRBO-LSTM-XGBoost	0.0032	0.0044	1.1124%
	LSTM-XGBoost	0.0105	0.0127	3.4769%
	CNN	0.0211	0.025	7.5873%
	LSTM	0.012	0.016	4.5351%
	XGBoost	0.0176	0.0221	5.8886%
Heating load	NRBO-LSTM-XGBoost	0.0022	0.0025	0.9761%
	LSTM-XGBoost	0.0072	0.0092	2.7393%
	CNN	0.0233	0.0373	7.4232%
	LSTM	0.016	0.024	5.1434%
	XGBoost	0.0211	0.0289	7.3586%

Table 4: Summer multi-dimensional load evaluation indicators

Load type	Algorithm	MAE	RMSE	MAPE
Electric load	NRBO-LSTM-XGBoost	0.0048	0.0064	0.9873%
	LSTM-XGBoost	0.0132	0.0183	2.8858%
	CNN	0.0291	0.0373	6.8241%
	LSTM	0.020	0.0244	4.5686%
	XGBoost	0.0206	0.0292	5.6157%
Cooling load	NRBO-LSTM-XGBoost	0.0038	0.0046	0.9249%
	LSTM-XGBoost	0.0126	0.0182	2.7083%
	CNN	0.0245	0.0282	6.3812%
	LSTM	0.017	0.023	4.5492%
	XGBoost	0.0246	0.032	5.6521%
Heating load	NRBO-LSTM-XGBoost	0.0041	0.0058	1.5223%
	LSTM-XGBoost	0.0122	0.0165	4.3572%
	CNN	0.024	0.0321	8.5533%
	LSTM	0.0194	0.0264	7.1429%
	XGBoost	0.0259	0.0331	8.4825%

Table 5: Autumn multi-dimensional load evaluation indicators

Load type	Algorithm	MAE	RMSE	MAPE
Electric load	NRBO-LSTM-XGBoost	0.0044	0.0051	1.0453%
	LSTM-XGBoost	0.0143	0.0205	3.2068%
	CNN	0.0235	0.0292	6.4189%
	LSTM	0.0235	0.0295	4.9157%
	XGBoost	0.0204	0.0261	5.5386%
Cooling load	NRBO-LSTM-XGBoost	0.0032	0.004	1.0527%
	LSTM-XGBoost	0.0091	0.0118	3.2065%
	CNN	0.0188	0.0258	6.9824%
	LSTM	0.0142	0.0157	4.4123%
	XGBoost	0.0162	0.0219	5.9576%
Heating load	NRBO-LSTM-XGBoost	0.004	0.0052	0.8723%
	LSTM-XGBoost	0.0104	0.0135	2.4667%
	CNN	0.028	0.0393	6.0714%
	LSTM	0.0178	0.0211	4.34784%
	XGBoost	0.0216	0.028	5.20015%

Table 6: Winter multi-dimensional load evaluation indicators

Load type	Algorithm	MAE	RMSE	MAPE
Electric load	NRBO-LSTM-XGBoost	0.0048	0.0065	1.1956%
	LSTM-XGBoost	0.0166	0.0217	3.6534%
	CNN	0.0273	0.0366	7.1117%
	LSTM	0.0186	0.0244	4.9346%
	XGBoost	0.0245	0.032	6.7829%
Cooling load	NRBO-LSTM-XGBoost	0.0038	0.0047	1.6973%
	LSTM-XGBoost	0.0094	0.0115	4.3228%
	CNN	0.0203	0.0267	8.6749%
	LSTM	0.0144	0.0187	7.2339%
	XGBoost	0.0221	0.0295	8.3021%
Heating load	NRBO-LSTM-XGBoost	0.0042	0.0048	1.2218%
	LSTM-XGBoost	0.013	0.0182	3.5346%
	CNN	0.0237	0.0317	7.2757%
	LSTM	0.0166	0.0246	4.5782%
	XGBoost	0.0235	0.0466	6.2414%

Analysis of seasonal differences in the improvement of prediction accuracy. The highest accuracy is achieved in autumn, especially with the heating load reaching 0.872% MAPE. This is due to the strongest

differentiated coupling features in autumn: the correlation between autumn meteorological factors, such as temperature fluctuations, and load is also the most pronounced. The accuracy of electric and cooling loads is prominent in summer, with summer electric load MAPE at 0.98% and cooling load MAPE at 0.92%, which are second only to autumn heating load. The combined model effectively integrates highly correlated meteorological factors (such as temperature and GHI) through feature engineering. However, the summer heating load MAPE of 1.52% is the lowest prediction accuracy for heating loads throughout the year, but it still significantly outperforms the comparative model. This corresponds to the characteristic of very low and steady summer heating load demand, which is weakly coupled with external factors. The model achieves an excellent performance of 0.98% MAPE on spring heating load, while electric and cooling load MAPEs are as low as 1.26% and 1.11%, respectively. This is due to the effective capture of spring's mild meteorological condition features by the combined model. The winter heating load MAPE of 1.22% shows high prediction accuracy, reflecting the combined model's ability to learn the high-demand and highly fluctuating heating load patterns in winter. The electric load MAPE is stable at 1.19%. In contrast, the winter cooling load MAPE of 1.70% is the lowest prediction accuracy for load types throughout the year. This mainly results from the sporadic and non-periodic nature of winter cooling load demand, which is low in value and does not have significant fluctuations, with a low coupling degree with external factors, primarily relying on historical trend predictions, making it more challenging. Nonetheless, the combined model reduced MAPE significantly from the LSTM-XGBoost model's 4.32% to 1.70%, a decrease of 60.6%, proving the model's robustness in weak feature scenarios.

Analysis of the differences in load types and coupling mechanisms for improved accuracy. Highly coupled loads exhibit autumn heat and summer cold, which demonstrate a strong coupling relationship with external meteorological factors. The method in this paper precisely identifies these key driving factors by selecting high-weight features through seasonal differentiation using XGBoost. These strongly correlated features are then input into an LSTM for time series modeling and combined with the NRBO optimization mechanism of quasi-inverse learning to maximize the prediction accuracy (e.g., autumn heat MAPE of 0.8723%). This validates the decisive role of external differentiated features in highly coupled scenarios. Weakly coupled and internally dominant loads, such as winter cold and summer heat: these loads show weak external coupling or internal characteristics in specific seasons (e.g., the episodic nature of winter cold, the low demand stability of summer heat). Although the contribution of external features is limited, this method retains the most important features through XGBoost and effectively models their intrinsic temporal patterns using LSTM. The NRBO optimization of the quasi-inverse learning mechanism ensures that the model can best fit these relatively 'simple' but noise-sensitive patterns. Therefore, even in weakly coupled scenarios, the model can still achieve significant accuracy improvements (e.g., winter cold MAPE of 1.70%, summer heat MAPE of 1.52%), significantly outperforming single models that neglect internal dominant characteristics or fail to effectively denoise, as well as basic combination models with unoptimized parameters. This enhances the overall accuracy and robustness of the model in multi-load forecasting.

The proposed hybrid model significantly outperforms the comparison models in prediction accuracy. To comprehensively evaluate its performance, the average training time of each model was compared. Although the training time of this method is longer than that of a single model due to higher model complexity, the improvement in accuracy it brings is worthwhile in most practical application scenarios, fully meeting the real-time requirements of short-term load forecasting. To statistically validate the superiority of the proposed model, we conducted a paired *t*-test on the MAPE errors of the NRBO-LSTM-XGBoost model and the LSTM-XGBoost model across all test samples. The test results ($p < 0.001$) provide strong evidence that the observed improvement in prediction accuracy is statistically significant at the 0.01 level.

6 Conclusion

In response to the analysis of electricity consumption behavior characteristics and multi-load forecasting in multi-energy coupling scenarios, an integrated analysis method combining data cleaning, clustering optimization, and meteorological correlation is proposed. By improving the data preprocessing process and using the Akima interpolation method, the reliability of abnormal data repair is effectively enhanced; in conjunction with an adaptive clustering algorithm, the BK-means algorithm achieves refined classification of user electricity consumption behavior; and a multi-load forecasting model based on a fused quasi-inverse learning NRBO-LSTM-XGBoost coupled with meteorological data is constructed, significantly improving the accuracy of load forecasting. The study verifies the dynamic impact of meteorological factors on electricity demand, providing a new technological pathway for demand-side management in power systems. The reliance on a dataset from a single region and a single year, which may affect the model's generalizability to other geographical and climatic scenarios. The focus on meteorological factors without incorporating other potential influences like electricity pricing, macroeconomic factors, or social behaviors. Furthermore, we have highlighted promising avenues for future research to address these limitations, primarily through the application of transfer learning to enhance generalization and the integration with real-time demand response programs to demonstrate practical utility. Future research can further explore the deep integration mechanism of multi-source heterogeneous data, taking into account external factors such as economy and region, balancing the optimization algorithm's real-time performance and generalization, and expanding the model's application in complex energy interaction scenarios to promote flexible scheduling and energy efficiency improvements in smart grids.

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Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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