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An advanced Load Simulation Methodology Incorporating Dynamic Correlation Analysis for Diverse Electricity Users

Abstract: Real-time load simulation plays a pivotal role in power system dispatching and safety assessments. However, the heterogeneous composition of load groups complicates the trends of load changes. Traditional simulation methods often fall short in capturing the intricate patterns of load variations and fluctuations, as well as the interconnections among different load groups. To address these shortcomings, this paper enhances the granularity of load simulation by mapping the relationships between typical load processes and individual user loads. We introduce a clustering neural network specifically designed for the typical load processes of multiple users. This network utilizes a fluctuation attention mechanism and a deep embedding clustering algorithm to identify diverse typical fluctuation processes across different load types. Furthermore, we propose a causality analysis method for various load groups and processes, using a convergent cross mapping algorithm to detect potential causal links among different load users and their processes. Additionally, we establish a multi-task learning-based neural network model for simulating multiple loads, enabling parallel, high-precision simulations of typical multi-user load processes. The effectiveness of our proposed methods is validated using electricity data from a city in North China, demonstrating their capability to accurately capture typical output characteristics and the interrelations among different users, thereby enhancing the accuracy of load simulations.

Keywords: Load simulation; Causality analysis; Deep learning.

I. INTRODUCTION

With the continuous construction and development of smart grids, the power system has entered a new era of accelerated development [1,2]. The inherent randomness and volatility of renewable energy have affected the grid connection and consumption of renewable energy generation, posing challenges to ensuring real-time power dynamic balance and safety stability of the power grid. Power load simulation plays a crucial role in multiple aspects of the power system. It can not only provide important basis for the planning and design of the power system, helping optimize the grid layout and equipment configuration, but also evaluate the safety and economy of the system, providing strong support for enterprise decision-making [3,4]. In addition, by simulating loads, future electricity demand can be predicted, scheduling strategies can be optimized, and the stable operation of the power system can be ensured. In terms of renewable energy integration, power load simulation also plays an important role, providing strong technical support for the development of renewable energy. In summary, power load simulation plays a crucial role in the planning, design, operation, maintenance, and management of the power system, and is of great significance for ensuring the safety, stability, and sustainable development of the power system [5].

The selection and application of power load simulation methods is a complex problem involving multiple technologies and methods [6]. Currently, power load simulation methods mainly include methods based on statistics and artificial intelligence [7-9]. Statistical methods are suitable for situations where historical load data is rich and reliable. By fitting and analyzing historical data, relatively simple load models can be established. However, this method may not accurately reflect the dynamic characteristics and nonlinear relationships of loads. In contrast, methods based on artificial intelligence such as neural networks and support vector machines can more accurately predict power loads by simulating complex nonlinear relationships. These methods require a large amount of training data and computing resources, but exhibit high accuracy and flexibility in handling complex and dynamic load data [10]. Georgios et al. [11] directly predicted short-term net load based on machine learning methods and evaluated the predictive performance of linear regression, nearest neighbor, Bayesian neural network, and support vector machine methods. The results show that the Bayesian neural network model has stable and accurate predictive performance regardless of season and weather conditions. Due to the high uncertainty in urban load simulation and the difficulty in obtaining high-quality load data, Praaviera et al. [12] introduced uncertainty and sensitivity analysis of urban energy simulation results to improve energy demand and peak power calculation results. Dabirian et al. [13] proposed a framework for urban energy data simulation, which parameterizes urban

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energy simulation and improves simulation accuracy through data collection and integration. Battin et al. [14] proposed a "shoe box" algorithm that simplifies urban buildings into shoe boxes, further accelerating urban load simulation. Mohammadali et al. [15] proposed a net load prediction model that integrates deep neural networks and wavelet transform. The wavelet transform is applied to the input of the deep neural network model to achieve accurate net load prediction. Zhang et al. [16] proposed a mixed support vector machine regression method based on weather factors and electricity prices, using an improved adaptive genetic algorithm to establish a prediction model and achieve accurate prediction of electricity consumption. This method introduces various load influencing factors to achieve accurate prediction of electricity quantity, but ignores the compatibility between various factors and the prediction model, and cannot quantify the uncertainty of load changes.

In addition, methods such as constant impedance and static characteristic simulation of loads are suitable for some approximate calculations or preliminary analyses. Although these methods are simple and easy to use, their accuracy is relatively low and cannot fully meet the needs of some high-precision and complex scenarios [17]. For more accurate and complex load simulations, a typical comprehensive load dynamic characteristic model considering the mechanical and electromechanical transient processes of induction motors can be considered [18]. These models can more comprehensively reflect the dynamic characteristics and nonlinear relationships of loads, and are suitable for complex scenarios such as transient stability calculation and power flow calculation. In summary, the selection of power load simulation methods needs to be comprehensively considered based on specific needs and scenarios. In practical applications, multiple methods and techniques can be combined to improve the accuracy and reliability of simulation. Meanwhile, with the continuous development and application of new technologies, power load simulation methods will also be constantly updated and improved, providing more accurate and reliable support for the planning, operation, and management of the power system.

However, the above technologies mainly target single load changes or overall load trends in the power system, but there are still the following problems in response to the increasingly complex load composition. The diversified composition of load groups has led to increasingly complex trends in load changes. Traditional load calculation methods cannot fully consider the patterns of load changes and fluctuations, as well as the correlation between load groups. In different environments, there may be differences in the electricity consumption characteristics and patterns of different industries, which can have an impact on the calculation results of power load. Therefore, it is necessary to choose appropriate power load calculation methods based on the actual situation of different regions and industries, as well as the current environmental conditions.

Therefore, this article proposes a load simulation method that considers the dynamic correlation between multiple types of electricity users. As shown in Figure 1, its main contributions are as follows:

1) Firstly, a clustering neural network for typical load processes of multiple users is proposed, which identifies multiple typical fluctuation processes of different types of loads through the OPTICS clustering algorithm.

2) Then, a causal relationship-based identification method for multi-type load groups and multi-type load processes is proposed, which locates potential causal relationships between different load users and load processes through a convergent cross mapping algorithm.

3) Finally, a multi-task learning based multi-load simulation neural network model was established to achieve parallel high-precision simulation of typical multi-user load processes.

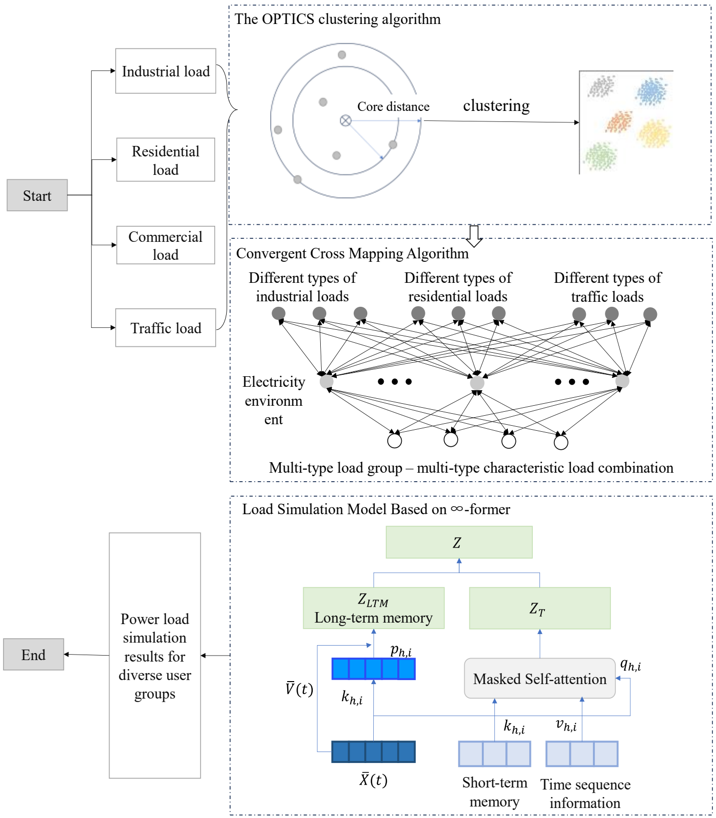

Figure 1: Overall flowchart of power load simulation model

II. METHODS

A. *Identification of Typical Load Fluctuation Processes Based on OPTICS Clustering Algorithm*

Ordering Points to Identify the Clustering Structure (OPTICS) is a density based clustering algorithm that can effectively identify data clusters with different densities [19,20]. It is an extension of the Density Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. Unlike DBSCAN, OPTICS does not require prior knowledge of the number of clusters. It works by generating a density-based reachability graph in the dataset, which can exhibit good performance when dealing with clusters with arbitrary shapes. OPTICS reveals the density structure of the dataset by calculating the reachable distance and core distance of each point, and generates a clustering order. Users can choose the appropriate number of clusters based on this order.

The process of the OPTICS clustering algorithm aims to reveal the density structure of the dataset and generate an output representing the clustering order of data points, as shown in Figure 2.

1) Initialization parameters: set the minimum density and domain radius, as well as the dataset to be clustered. This is a necessary setting before the algorithm starts, providing basic data for subsequent steps.

2) Calculate the core object: For each data point in the dataset, calculate the number of points contained within its neighborhood. If the number of points about the point is greater than or equal to the minimum density, then the point is the core object. This step is a crucial step in determining which points can become cluster centers.

3) Searching for direct density reachable points: For each core object, identify all points within its domain. If the point is also a core object, add it to the set of directly density reachable points of the core object. This step helps to determine the density reachable relationship between points, providing a basis for subsequent clustering.

4) Generate family order: Calculate the core distance and reachable distance of each sample object in the dataset to generate a family order. Family order is the order in which samples are expanded externally when processing a dataset. This step is an important feature of the OPTICS algorithm, allowing the algorithm to cluster based on different densities.

5) Cluster grouping: Using the generated family order information, select a core sample, and then expand outward to divide the cluster groups. This is the actual clustering process of the algorithm, which gradually divides different clusters based on the previously generated family order and core objects.

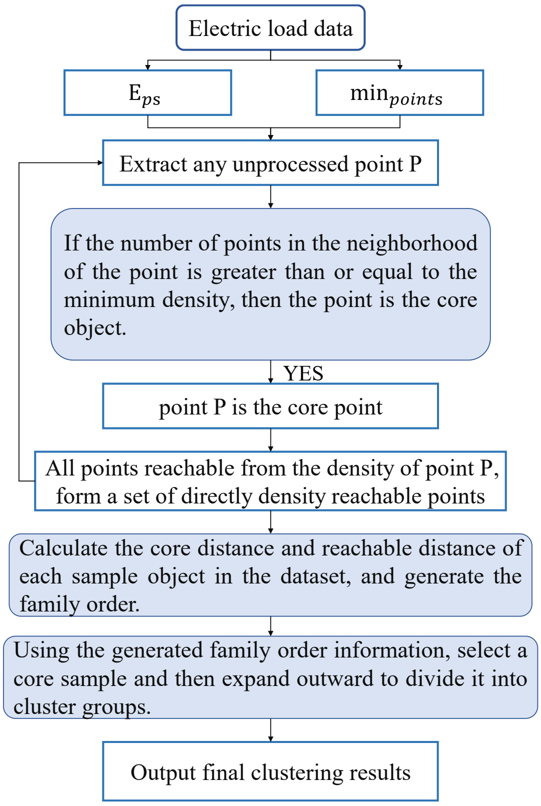

Figure 2: Flowchart of OPTICS clustering algorithm

The OPTICS clustering algorithm exhibits unique advantages in load analysis: it can accurately identify load patterns with different fluctuation intensities due to its density sensitive clustering characteristics. Its flexible output mode allows for personalized interpretation and processing based on actual needs. The insensitivity of algorithms to parameters reduces the complexity of adjusting parameters. These advantages collectively enhance the accuracy and practicality of load analysis.

B. Exploring Potential Causal Relationships between Different Load Users and Load Processes based on Convergent Cross Mapping Algorithm

The Convergent Cross Mapping (CCM) algorithm is an optimization algorithm that combines crossover and mapping operators and improves based on genetic algorithms [21]. It achieves convergence by continuously performing crossover and mapping operations, gradually leading individuals in the population towards the optimal solution. CCM can also serve as a method for analyzing causal relationships between time series variables in nonlinear systems. It obtains historical information of variables by reconstructing their state space, and infers causal relationships based on the "traces" that contain "causes" in the "results". This method can effectively solve the complex causal relationship problem between multiple variables in nonlinear ecosystems.

1) Determine the optimal embedding dimension.

For multi-type load groups and multi-type load processes, we first reconstruct the shadow manifold according to a specific embedding dimension E. Then, calculate its E+1 neighboring points and Euclidean distance, and use the calculated distance to obtain the weights of each neighboring point. Finally, the estimated value of the observed value is obtained through weighted averaging. This step is carried out through cross validation, which involves reconstructing the input data into a specific dimension E, and then calculating the error between the reconstructed data and the original data to determine the optimal embedding dimension, as shown in equations 1-6.

$$X = \{X(1), X(2), X(3), ..., X(L)\} \tag{1}$$

$$Y = \{Y(1), Y(2), Y(3), ..., Y(L)\} \tag{2}$$

where, X and Y are time series data, respectively.

$$MX = \{X(t), X(t-\tau), X(t-2\tau), ..., X(t-(E-1)\tau)\} \tag{3}$$

$$MY = \{Y(t), Y(t-\tau), Y(t-2\tau), ..., Y(t-(E-1)\tau)\} \tag{4}$$

where, MX and MY are shadow manifolds of X and Y, τ is time lag, E is the embedding dimension, with a minimum value of E+2 and a maximum value of L.

$$\hat{Y}(t) \mid M_X = \sum \omega_i Y(t_i), i = 1, ..., E+1 \tag{5}$$

$$\hat{X}(t) \mid M_Y = \sum \omega_i X(t_i), i = 1, ..., E+1 \tag{6}$$

where, $\hat{Y}(t)$ and $\hat{X}(t)$, are the Euclidean distances from each point in *MX* and *MY* to other points, and ω_i is the weight coefficient.

2) Multi type load groups and causal impact analysis of multi type load data based on dynamic system theory.

Based on Tarkens' embedding theorem, reconstruct attractor manifolds from multi-type load groups and time series data of multi-type loads. Applying dynamic system theory to the reconstructed shadow manifold, analyze whether the points on the reconstructed shadow manifold approach or move away from each other over time. If such a trend exists, it can be considered that there is a causal effect between the data.

3) To obtain more accurate results, the above steps can be iterated multiple times, using different embedding dimensions E for each iteration, and observing which dimension has the most obvious causal relationship between the data obtained.

4) Based on the convergence cross mapping algorithm, evaluate the causal relationship between multi-type load groups and multi-type load processes, and establish a real-time mathematical representation model of typical load characteristics of multi user groups that considers the dynamic correlation relationship of load groups, as shown in equation 7.

$$\forall e \in E, \forall t \in T, n \in N', L_e = \sum_{n}^{N'} L_n \tag{7}$$

where, *e* represents different "environmental" conditions, *t* represents time series, *n* represents different types of load processes in different load groups, and *N′* represents clustering results of different types of loads in different load groups.

C. *Maintaining the Integrity of the Specifications*

The infinity-former (∞-former) model is a Transformer model with infinite long-term memory (LTM), proposed by researchers from DeepMind and other institutions [22,23]. Its mathematical principles mainly involve the modeling of continuous spatial attention mechanism and infinite long-term memory, and the model structure is shown in Figure 3.

Firstly, in order to handle context of any length, ∞-former introduces a continuous LTM mechanism. This LTM stores the input embedding and hidden states from the previous steps, allowing the model to better capture long contexts without losing relevant information. Compared with traditional Transformer models, the LTM of ∞-former can reach an infinite degree, thus solving the memory capacity limitation problem encountered by traditional models when dealing with long-range contexts. Secondly, the ∞-former utilizes a continuous spatial attention framework to handle LTM. This framework balances the number of information units (basis functions) applicable to memory with the granularity of their representation. The input sequence is characterized as a continuous signal, represented as a linear combination of radial basis functions. ∞-former can model any length of context at a fixed computational cost and maintain sticky memory. This continuous spatial attention mechanism makes the attention complexity of the ∞-former independent of the context length, thereby improving the efficiency of the model. Finally, the ∞-former also considers the combination of long-term memory (LTM) and short-term memory (STM). Similar to the memory mechanism of Transformer XL, ∞-former uses both LTM and STM to process input sequences, allowing the model to capture important contextual information at different time scales. This combination helps to improve the representation and generalization performance of the model.

In summary, the ∞-former model introduces infinite long-term memory and continuous spatial attention mechanisms. This effectively solves the memory capacity limitation problem encountered by traditional Transformers when dealing with long-term contexts, improving the efficiency and performance of the model. In load simulation models based on ∞-former, the ∞-former algorithm is used to capture and model long-term dependencies and complex patterns in load data. By utilizing the continuous spatial attention mechanism and sticky memory mechanism of ∞-former, the model can more effectively process historical load data and capture time series dependencies and periodic patterns within it.

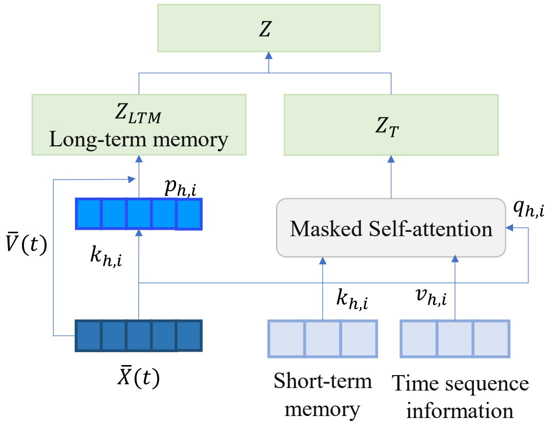

Figure 3: ∞-former structure diagram

III. Results and Discussion

A. Data Source

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In this paper, NRMSE, MAPE, and MAE, which are commonly used in the field of electricity forecasting, are used to evaluate each forecasting model.

The calculation method of the indicators are as follows.

$$\mathrm{MAPE}(Y_{\mathrm{pred}}, Y_{\mathrm{actual}}) = \frac{1}{T}\sum_{t=1}^{T}\frac{|y_{\mathrm{pred}}^{t} - y_{\mathrm{actual}}^{t}|}{|y_{\mathrm{actual}}^{t}|} \tag{8}$$

$$\mathrm{NRMSE}(Y_{\mathrm{pred}}, Y_{\mathrm{actual}}) = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{y_{\mathrm{pred}}^{t} - y_{\mathrm{actual}}^{t}}{y_{\mathrm{actual}}^{\max}}\right)^{2}} \tag{9}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{10}$$

Where y_{pred}^{t} is the predicted value of electricity consumption; y_{actual}^{t} is the actual value of electricity consumption at time t, $y_{\mathrm{actual}}^{\max}$ is the maximum value of electricity consumption in a cycle, $y_{\mathrm{actual}}^{\mathrm{ave}}$ is the average value of actual electricity consumption, and T is the length of the time series.

MAPE is used to evaluate the ratio of the forecast error for each sample to the actual value, which can indicate the relative size of the error for each sample compared to the actual value. NRMSE is used to evaluate the average proportion of the difference between the predicted results and the actual results, and it amplifies the larger part of the error by calculating the square of the error. The values of the two types of indicators are between [0%, 100%], and the smaller the value, the higher the accuracy.

This paper utilizes electricity data from a city in the North China region to validate the effectiveness of the proposed method in characterizing typical output traits and correlations among different users. The dataset spans two years and primarily includes three types of users: Industrial Load, Residential Load, and Commercial Load, as shown in Table 1. The region has a permanent population of 800,000. Following standard data cleaning and fragmentation organization, further analysis on load characteristics and demand response capability modeling was conducted.

Table 1: Data overview

No.	User type	Load capacity
1	Industrial Load	50MW
2	Residential Load	340MW
3	Commercial Load	30MW

B. *Experimental Setup and Model Parameters*

The experiments in this study were conducted using Python (version 3.9.10). The deep learning models were primarily built on PyTorch (version 1.9.1), while the clustering models were developed using sklearn (version 1.7.1). The computer setup included an Intel(R) Core(TM) i7-10210U CPU @ 1.60 GHz, with the operating system being Windows 11. The structural parameters of the deep embedding clustering model and the hyperparameter settings for the training process are detailed in Table 2.

Table 2: Model hyperparameters and parameter values

Model	Value
OPTICS	min_samples=8, max_eps=12, metric='euclidean', cluster_method='DBSCAN'
∞-former	num_layers=12, d_model= 128, dropout_rate=0.2, num_heads = 8
Optimizer	Adam
Hyper Parameters	Learning_rate=0.001, Bath_size=32

C. *Load Process Clustering*

This section verifies the effectiveness of the proposed OPTICS -based multivariate load typical fluctuation process clustering. The first step involves determining the number of typical scenarios for each type of user load based on clustering performance evaluation metrics. Subsequently, current mainstream clustering models are selected as comparative methods. The effectiveness of the proposed method is validated by comparing the values of clustering performance evaluation metrics.

1) *Evaluation Metrics*

For evaluation metrics, this paper adopts the Calinski-Harabasz (CH) index as the value for assessing clustering performance. The calculation method is as follows:

$$c(k)=\frac{tr(B_k)}{tr(W_k)}\frac{m-k}{k-1} \tag{10}$$

where $\mathrm{tr}()$ denotes the trace of a matrix, B_k is the between-cluster covariance, W_k is the within-cluster covariance, m is the number of samples, and k is the current number of categories. A higher CH index indicates a greater difference between within-cluster covariance and between-cluster covariance, implying better clustering performance.

2) *Clustering Centers*

We determine the number of clustering centers for each type of user load based on the CH index. Figure 4 illustrates the changes in clustering performance evaluation metrics for the three types of users as the number of clustering centers increases. It is evident that the clustering performance is optimal when the number of clustering centers is set to three.

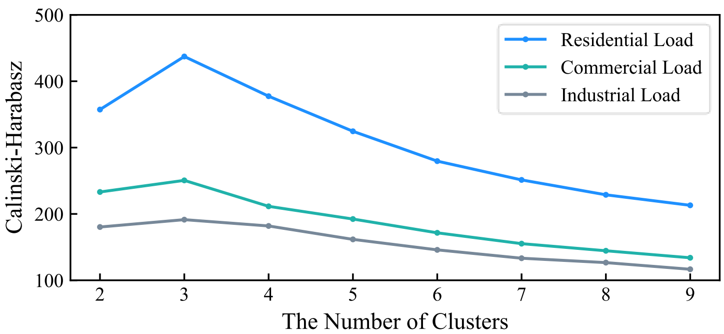

Figure 4: Changes in CH coefficient index value with the number of cluster centers

3) *3.3.3 Typical Output Scenarios for Multivariate Users*

Based on the determined number of clustering centers, the typical output scenarios for each type of user load can be identified, as shown in Figures 5(a)-(c). In these figures, the red curve represents the clustering center for each output scenario.

The figures reveal significant variations in the process differences among various output scenarios, as well as the emergence of potential regular patterns of electricity usage and the demand response capabilities of users. If the comprehensive electricity usage characteristics of diverse electricity usage scenarios can be fully understood, it would effectively represent the overall response capability of the demand side.

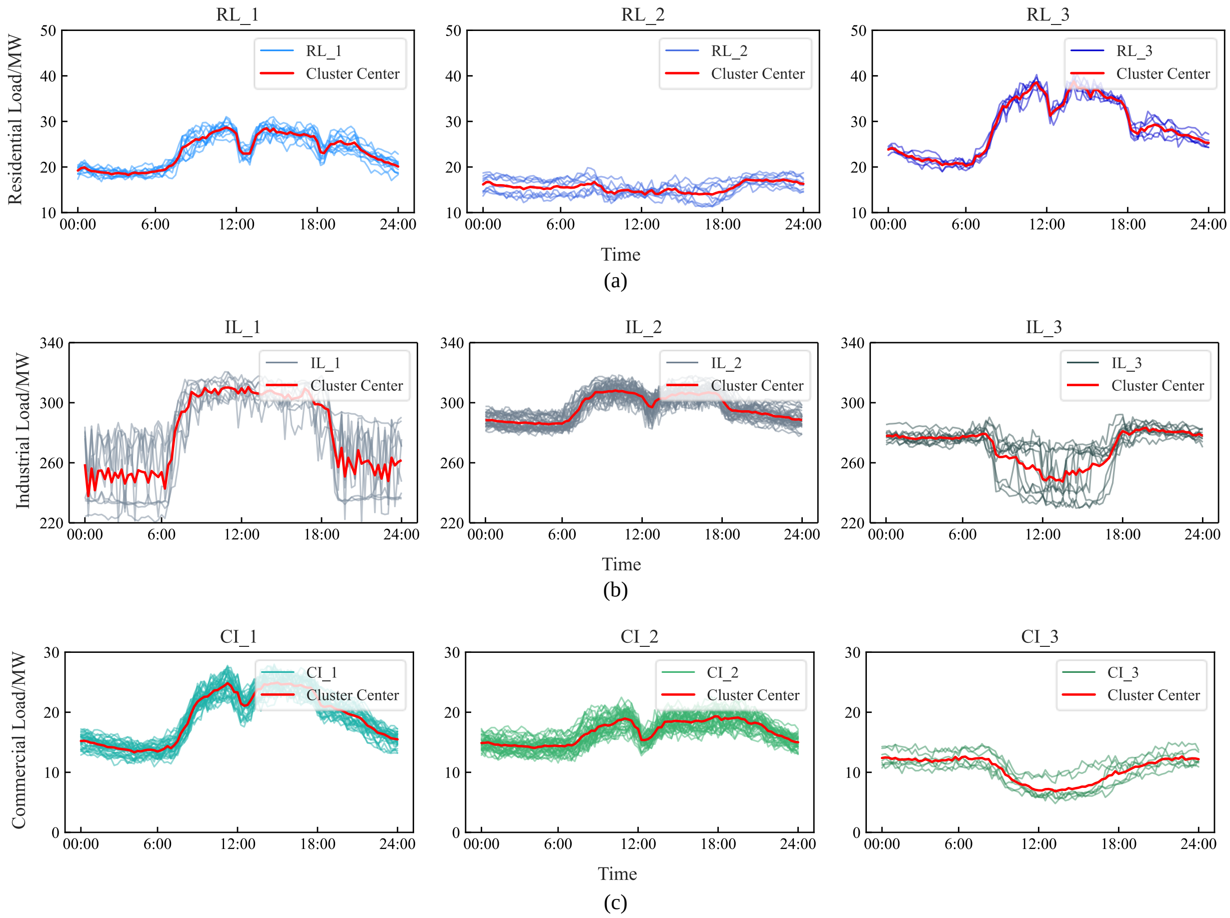

Figure 5: Typical scenarios of various types of user loads. (a) is the residential load, (b) is the industrial load, and (c) is the commercial load.

4) 3.3.4 Evaluation of Clustering Effectiveness

In this section, we validate the effectiveness of the proposed method by comparing it with several mainstream time series data clustering models, including the fully connected neural network-based deep autoencoder, X-means, K-means, and DBSCAN. The CH index values for each clustering method are presented in the table 3.

Table 3: Model hyperparameters and parameter values

Methods	RL	IL	CL
OPTICS	455.14	269.37	187.25
AE	422.33	220.56	160.56
VAE	431.76	252.82	168.38
Xmeans	386.43	203.85	136.60
Kmeans	305.29	189.91	121.74
DBCSAN	275.96	215.76	124.21
Improvement ratio/%	24.92	24.37	31.59

As indicated by the table, the proposed method achieves the highest clustering evaluation metric values compared to other methods. Specifically, the Residential Load (RL) saw an improvement of 24.92% over traditional methods, Industrial Load (IL) improved by 24.37%, and Commercial Load (CL) improved by 31.59%.

D. Load Simulation

1) Evaluation of Clustering Effectiveness

Utilizing the typical scenario database established above and the proposed load simulation neural network based on ∞-former, we conducted a case study to validate the load simulation. The traditional methods used for comparison include the fully connected neural network NBEATS, the convolutional neural network-based TCN, time-series attention mechanism-based models such as ConvTrans, Autoformer, Reformer, and the decision tree-based LightGBM.

The simulation results, as illustrated in the figure 6, show that the proposed method closely matches actual values and performs the best among all tested models. The other models exhibit varying degrees of fitting deviation, with the LightGBM and TCN models showing poorer trend fitting capabilities. The NBEATS model has a better trend fitting performance but with some inherent bias.

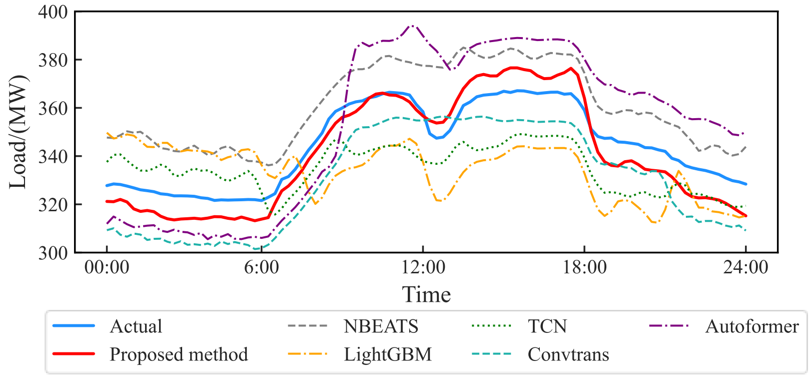

Figure 6: Load simulation results based on the above comparison model

2) Load Simulation Accuracy Evaluation Metrics

To further quantify and compare the load simulation accuracy of different models, this section employs MAPE, RMSE, and MAEas evaluation metrics for load simulation accuracy.

Table 5: Load simulation accuracy of different models

	MAPE/%	RMSE/MW	MAE/MW
Propoesd method	9.75	20.02	18.19
NBEATS	11.25	25.31	20.12
TCN	12.43	25.98	23.37
Convtrans	12.54	28.17	25.67
Autoformer	13.71	28.11	28.26
Reformer	12.68	30.86	28.50
LightGBM	13.57	30.23	27.51

The table shows that the proposed method achieves the highest accuracy. Compared to various control models, the proposed method reduces the MAPE error by 2.95%, the RMSE error by 8.09 MW, and the MAE error by 7.38 MW. This validates the effectiveness of the proposed method.

IV. Conclusion

This paper presents an advanced load simulation methodology that significantly improves upon traditional approaches by addressing the intricate variations and interdependencies within diverse load groups. The method emphasizes a refined analysis and simulation of load behaviors through a series of innovative modules, each contributing to the overall precision and effectiveness of the simulation.

Firstly, the introduction of a clustering model for analyzing typical user load processes resulted in a notable enhancement, with the CH index of the clustering model increasing by 26.96%. This achievement underscores the model's ability to accurately identify and categorize the complex fluctuation patterns of different load types.

Secondly, we streamlined the description of our methodology by focusing on the precise characterization of user correlation relationships. It was achieved through the implementation of convergence cross-mapping algorithms, which facilitated a nuanced representation of these relationships, further enriching the load simulation's input data.

Lastly, the culmination of these methodological advancements led to a significant improvement in load simulation accuracy, with a precision increase of 2.95%. This enhancement not only demonstrates the efficacy of our proposed ∞-former neural network model grounded in multitask learning, but also marks a substantial stride toward achieving parallel high-precision simulation of multivariate user load processes.

By succinctly integrating these modules, our approach not only achieves a higher level of precision in load simulation but also lays a solid foundation for future exploration in the field, aiming at more efficient and reliable power system operations.

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