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Review of multiple load forecasting method for integrated energy system

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In order to further improve the efficiency of energy utilization, Integrated Energy Systems (IES) connect various energy systems closer, which has become an important energy utilization mode in the process of energy transition. Because the complex and variable multiple load is an important part of the new power system, the load forecasting is of great significance for the planning, operation, control, and dispatching of the new power system. In order to timely track the latest research progress of the load forecasting method and grasp the current research hotspot and the direction of load forecasting, this paper reviews the relevant research content of the forecasting methods. Firstly, a brief overview of Integrated Energy Systems and load forecasting is provided. Secondly, traditional forecasting methods based on statistical analysis and intelligent forecasting methods based on machine learning are discussed in two directions to analyze the advantages, disadvantages, and applicability of different methods. Then, the results of Integrated Energy Systemss multiple load forecasting for the past 5 years are compiled and analyzed. Finally, the Integrated Energy Systems load forecasting is summarized and looked forward.

KEYWORDS

integrated energy system, load forecasting, statistical analysis, machine learning, multiple load

1 Introduction

1.1 Motivation and background

Energy is the basis for human survival and development and the lifeblood of the national economy. How to ensure the sustainable supply of energy for human society while reducing environmental pollution in the process of energy use is a common concern in the world today. The further consumption of non-renewable energy leads to serious energy crisis and environmental pollution, which forces us to break the original mode of separate planning, separate design, separate construction and independent operation of each energy source and ultimately to achieve the construction and development of IES. In other words, the development and construction of IES is an inevitable choice to solve the energy crisis, improve environmental pollution, achieve optimal energy efficiency, and promote the use of renewable energy on a large scale.

The IES takes the electric power system as the core and realizes cooperative management and complementary mutual assistance among various energy systems through its many types of energy conversion equipment and energy storage equipment (Li et al., 2021; Zhu et al., 2021). The synergistic operation of multiple energy systems results in a strong coupling of

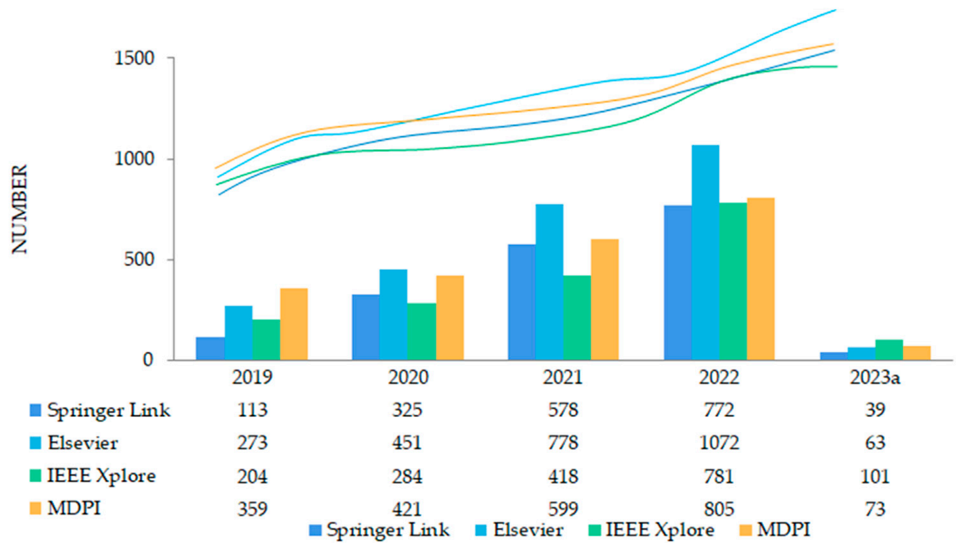

FIGURE 1
Graphic representation of preliminary search results in four electronic databases.

multiple loads, which makes multiple load forecasting more complex and allows a greater amount of internal information to be mined than traditional single load forecasting. Therefore, it is of great practical significance to explore the load forecasting under the coupling conditions of multiple loads of integrated energy systems. In this context, it is crucial to keep track of the latest research progress of load forecasting methods and grasp the current research hotspots and directions of load forecasting for the development and construction of integrated energy systems.

1.2 Research methodology

The methodology of this paper takes four important steps: step 1, choosing electronic databases; step 2, setting the query formulations and search scope; step 3, conducting preliminary search; step 4, performing manual filter.

In Step 1, it was decided to use four publicly available databases - Springer Link, Elsevier, IEEE Xplore, and MDPI. These databases cover a large number and variety of journals, and more influential factors are considered in the citation index, making these databases include a wider range of disciplines, more comprehensive and objective content, and higher authority in relevant research fields. Therefore, it would be more authoritative to screen the literature from these databases for research that fits the topic of study.

In Step 2, the query formulations and search scope are set in these databases. The query formulations consist of key words, logical operators, and search instructions. The keywords were set to load forecasting in the field of integrated energy systems, multi-energy systems, energy internet or multi-energy co-generation systems. The following query formulations were entered to search for relevant literature matching the research topic in the time frame from January 2019 to March 2023:

1) ("Integrated energy system" OR "multi-energy system" OR "energy internet" OR "energy coupling system") AND ("load forecasting" OR "multiple load forecasting") AND ("machine learning" OR "deep learning" OR "intelligent learning algorithm").

2) ("integrated energy system" OR "multi-energy system" OR "energy internet" OR "energy coupling system") AND ("load forecasting" OR "multiple load forecasting") AND ("statistical analysis" OR "regression analysis" OR "time series").

In step 3, the preliminary search result data obtained after step 2 is shown in Figure 1. Figure 1 presents the number of published papers concerning multiple load forecasting for IES from January 2019 to March 2023. Among them, there are 1827 compliant papers in Springer Link database, 2637 compliant papers in Elsevier database, 1788 compliant papers in IEEE Xplore database, and 2257 compliant papers in MDPI database. Despite the fact that 2023 is not over yet (the research was conducted until 31 March 2023), it is easy to see a growing trend in the number of papers published in the years 2019–2022. This confirms that the topic of multiple load forecasting for IES is current. The increasing trend in the annual publications indicates that multiple load forecasting for IES is a developing field of study and has received a lot of attention from scholars.

In Step 4, the papers from the initial search are manually filtered. Considering the lack of artificial intelligence when searching the literature using these databases, the mismatched papers need to be removed. The search results were carefully screened, analyzed and filtered to ensure that the core contents of the literature were consistent with the topic of integrated energy system load forecasting. The preliminary filtered literature was browsed in full to ensure that the papers focused on load forecasting. A total of 61 papers were finally selected. A generalized analysis of these 61 selected articles shows that load forecasting methods can be divided into two categories: traditional forecasting methods and intelligent forecasting methods. Among them, there are 15 papers related to traditional forecasting methods and 46 papers related to intelligent forecasting methods. The specific screening process is shown in Figure 2.

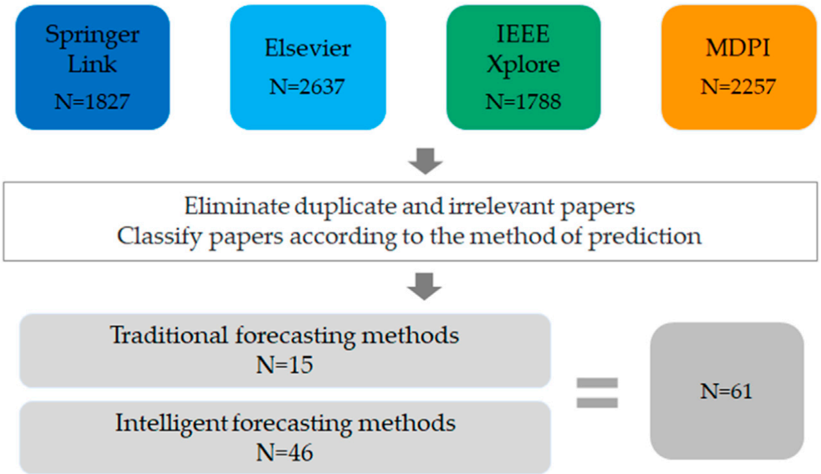

FIGURE 2
Manual filtering process and results.

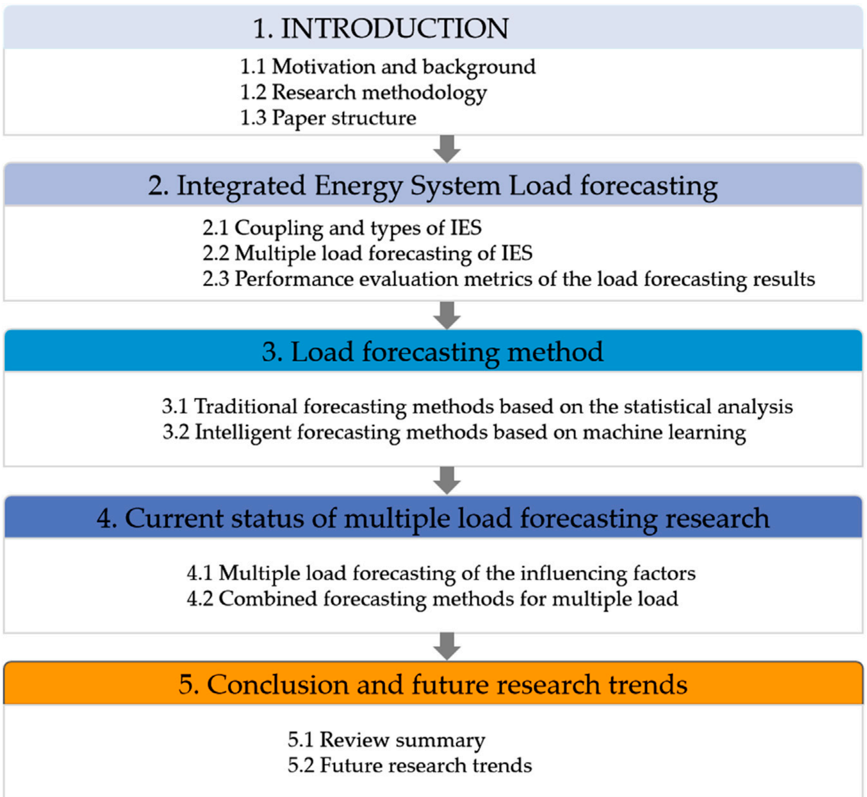

FIGURE 3
Diagram of paper structure.

1.3 Paper structure

The rest of the paper is structured as follows. Section 2 provides a brief overview of integrated energy systems and load forecasting. Section 3 discusses the commonly used forecasting methods in two directions: traditional forecasting methods based on statistical analysis and intelligent forecasting methods based on machine learning, and analyzes the advantages, disadvantages, and applicability of different methods. Section 4 summarizes and analyzes the results of IES multivariate load forecasting in the past 5 years. Finally, Section 5 concludes the paper with a summary and outlook on

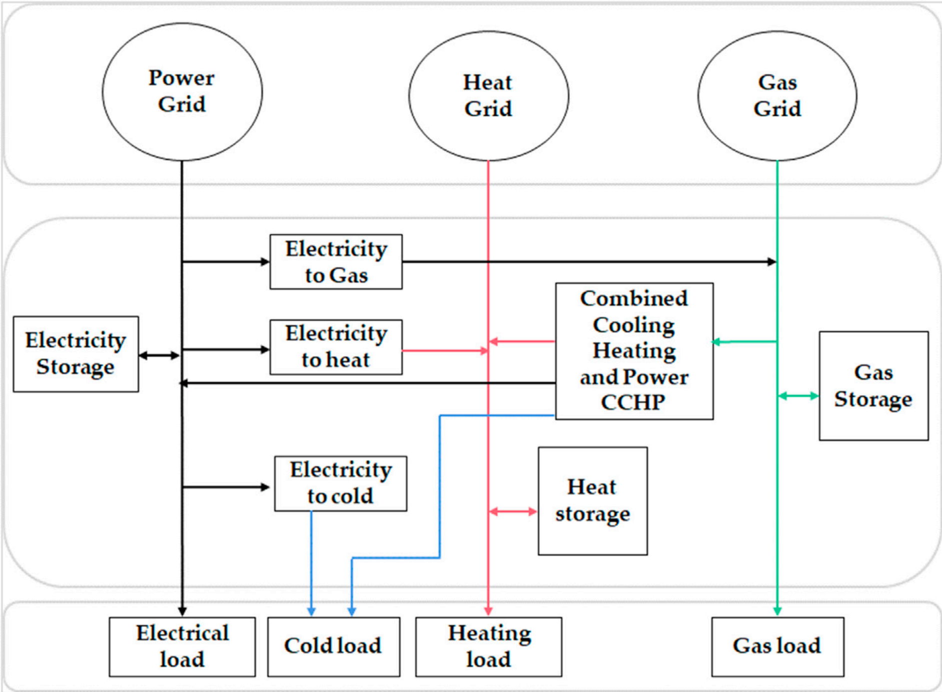

FIGURE 4
Schematic diagram of integrated energy system structure.

IES load forecasting. The structure of this paper is shown in Figure 3.

2 Integrated energy system load forecasting

2.1 Structure and types of IES

2.1.1 Coupling structure of IES

IES is based on energy input, conversion, storage and output to achieve the coupling and complementarity of different energy sources, promote the full consumption of renewable energy and flexible conversion between supply and demand of multiple energy sources, so as to meet the demand of multiple loads and improve the efficiency of energy utilization. The IES is a multi stream integrated system, which breaks the traditional compartmentalized state of multiple energy streams such as cold, heat, electricity, and gas. Figure 4 shows the structure of the IES, in which the multi energy coupling characteristics are shown visually.

Multiple energy flows in the system operate in concert through energy conversion devices. These include electricity to gas, electricity to heat, electricity to cold, and combined cooling heating and power (CCHP). A CCHP system typically include Waste Heat Boiler, Absorption Refrigerator and Gas Turbine. The gas uses the gas grid to supply natural gas combustion to generate electricity to the power grid, while the combustion produces flue gas to provide heat to the system through a waste heat boiler and cold energy to the system through an absorption refrigerator.

2.1.2 Different types of IES

Multiple types of I applications, i.e., classification of integrated energy systems. This chapter discusses the categorization for different application scenarios and application subjects, subdividing the integrated energy system into industrial park integrated energy system, agricultural integrated energy system and urban integrated energy system. These categorized integrated energy system multi-energy coupling structures are designed to combine specific application subjects on the basic structure. Integrated energy systems containing renewable energy generation and hydrogen storage are also mentioned in the classification discussion.

Integrated energy systems for industrial parks are the most common type of application. Industrial parks are dominated by industrial loads, and the forms of terminal energy use are mainly electricity, heat, gas and cold, etc. The characteristics of energy loads are complex, the requirements for reliability and stability of energy supply are harsh, the operation and scheduling of transmission and distribution systems are complicated, and there is a strong demand for clean, highly efficient, reliable, and economical integrated energy supply services.

The agricultural integrated energy system focuses on gas supply and synergizes renewable energy sources such as solar, wind and geothermal energy to meet the energy needs of the three farmers (farmers, rural areas and agriculture). Farmers' energy use includes residents' daily life and travel, rural energy use includes medical care, catering and commerce, and agricultural energy use includes cultivation and harvesting. Comprehensive energy systems for agriculture can realize local energy use and local utilization and alleviate the crisis of industrial and urban energy use.

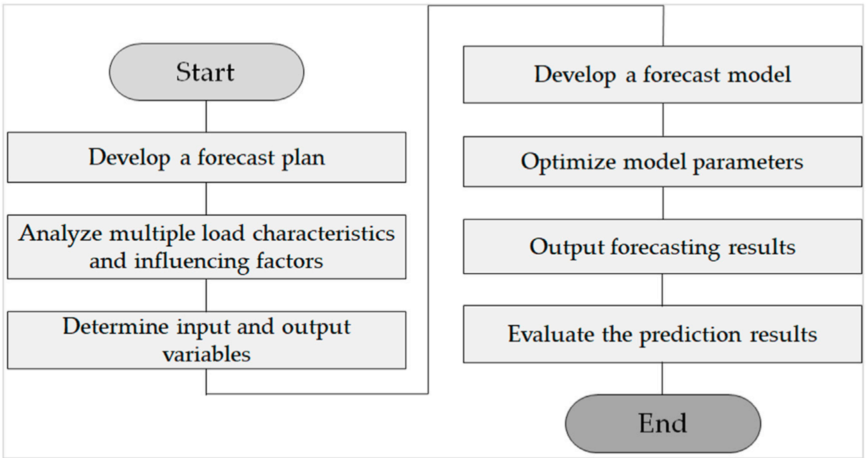

FIGURE 5
IES multiple load forecasting steps.

Unlike the integrated energy system for industrial parks, the urban integrated energy system is closer to the lives of residents with limited energy resources, and focuses more on energy saving and environmental protection (Ke et al., 2022a). The system takes solar energy, distributed wind power, natural gas, and external grid as energy sources, and utilizes internal coupling elements, such as gas turbines, gas boilers, heat pumps, etc., to connect cold, hot, and electrical multi-energy streams as a whole to ensure the load demand of urban residents in their daily lives. The load demand of the residents is usually the cold load for air conditioning, the heat load for heating, the gas load for kitchen and other electrical loads to maintain the normal life of the residents.

At this stage, integrated energy systems that include renewable energy generation (Ke et al., 2022b; Xu et al., 2020a) and hydrogen storage (Xu et al., 2020b) are widely used. For example, the wind-photovoltaic-hydrogen storage integrated energy system (Ke et al., 2023) consists of five parts: an electric power subsystem, a hydrogen storage subsystem, a thermal energy subsystem, a cryogenic subsystem and a natural gas subsystem, where large-scale wind and solar power generation is incorporated into the electric power subsystem, and unabated power is converted into hydrogen energy for storage by using electrolysis cells. The stored hydrogen can be rationalized and used whenever needed regardless of time, location and grid capacity.

2.2 Multiple load forecasting of IES

As the basis for optimal design, operation scheduling and energy management of IES, multiple load forecasting plays an important role. Adopting accurate forecasting methods can make the operation of IES more stable and reliable (Talaat et al., 2020). Short-term multiple load forecasting follows roughly the same steps as short-term load forecasting for power systems. In general, the input and output vectors are first determined based on the characteristic analysis and the actual demand, and then a suitable forecasting model is established for multiple load forecasting. The general steps are shown in Figure 5. In recent years, the traditional statistical analysis-based forecasting method has a more mature theoretical system, mainly using regression analysis (Wu et al., 2022; Feng et al., 2022; Nano et al., 2019) and time series (Ervural et al., 2016; Yu et al., 2019; Wu et al., 2020; Guefano et al., 2020). Their models are simple to calculate and easy to implement, but in the face of complex nonlinear load data, the forecasting effect is unstable and the forecasting accuracy cannot meet the research demand.

2.3 Performance evaluation metrics of the load forecasting results

In order to cope with complex nonlinear load data and coupling relationships, intelligent prediction methods based on machine learning are widely used in integrated energy system load forecasting. Due to the wide variety of equipment involved in the system, diverse energy coupling relationships, and complex internal structure, feature selection for multivariate load forecasting is crucial, and it is also a research difficulty in the field of multivariate load forecasting at this stage. Some researchers consider the comprehensiveness of the influencing factors and try to exploit all the factors as input features as much as possible, but this will lead to some irrelevant factors being input into the prediction model, which will affect the accuracy of the prediction; some researchers analyze the correlation of the influencing factors in order to select the most relevant factors as the input features, e.g., the correlation analysis is used to select the input features, but the actual relationship between the multiple loads and the influencing factors is not completely linear. However, the actual multivariate load and the influencing factors are not completely linear, and the application of correlation coefficient has strict condition constraints, and the correlation degree between the factors and the load obtained by correlation analysis may be biased, which affects the final prediction accuracy.

Highly accurate load forecasting is of great importance to the planning and operation of IES. However, there must also be errors between the forecast results and the actual values that cannot be completely eliminated. We can analyze the errors in depth through a

TABLE 1 Model performance evaluation metrics.

Metric	Formula
Mean Square Error (MSE)	$\frac{1}{n}\sum (y-\hat{y})^2$
Root Mean Squared Error (RMSE)	$\sqrt{\frac{1}{n}}\sum (y-\hat{y})^2$
Mean Absolute Error (MAE)	$\frac{1}{n}\sum \lvert y-\hat{y}\rvert$
Mean Absolute Percentage Error (MAPE)	$\frac{1}{n}\sum \lvert\frac{y-\hat{y}}{y}\rvert$
R-squared (R^2)	$1-\frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2}$

series of scientific methods, which can help us have a clearer perception of the forecast results and model performance. The most used metrics and their calculation formulas are discussed in Table 1. In these formulas, y is the actual value, $\hat{y}$ is the forecasting value, $\bar{y}$ is the mean value of all of the data and n is the number of forecasting samples. Usually, the performance evaluation metrics of forecasting (Rafi et al., 2021) contains Mean Square Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and R-squared (R^2). The smaller the value of MAE, RMSE and MAPE, the smaller the error, the more accurate the forecasting result and the better the performance. R^2 takes a range between 0 and 1, and the closer the value is to 1, the better the fitting effect, and the closer the forecast result is to the true value.

MSE and RMSE are squared operations on the difference value, so the larger error value will have a greater impact on the fit, which helps to capture the prediction error of the model more sensitive. Because the squared difference of outliers will be magnified, these two performance evaluation indicators are greatly affected by the outliers. When using them for model evaluation, it is necessary to pay attention to the treatment of outliers and the robustness of the model.

MAE and MAPE have little influence on outliers and are not affected by the positive or negative direction, but do not consider the square of the difference, so it does not magnify the square of the difference value. These two performance evaluation indicators reflect the absolute size of the prediction error rather than the square size of the error relative to MSE and RMSE.

Higher R^2 values indicate that the model can fit the data well and its predictive value can explain the variability of the dependent variable. However, R^2 can only measure the goodness of fit of the model to the dependent variable, and cannot judge whether the model is overfit or suitable for application in other data sets. Therefore, when using R^2 values, other indicators and domain knowledge should be combined for comprehensive evaluation.

3 Load forecasting method

Current load forecasting methods can be divided into traditional forecasting methods based on statistical analysis and intelligent forecasting methods based on machine learning. This chapter briefly introduces the forecasting methods such as Regression Analysis, Artificial Neural Network (ANN), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN). It also summarizes and outlines the advantages, disadvantages and applicability of each forecasting method in order to provide reference for future load forecasting.

3.1 Traditional forecasting method based on the statistical analysis

3.1.1 Regression analysis

The regression analysis method builds a regression equation to predict the future trend of the dependent variable based on the analysis of the dependent and independent variables. The model is simple to construct and faster to predict. However, regression analysis requires high historical data, its structural form is too simple, and for more complex problems, it tends to ignore the intrinsic regularity of load changes and has low forecasting accuracy. To solve the problems of slow forecasting speed and low forecasting accuracy of regression analysis model (Wu et al., 2022), proposed an improved regression model based on small batch stochastic gradient descent. Experimental results show that the improved algorithm has significantly improved the forecasting speed than the traditional algorithm. In order to better load forecasting with the help of massive data (Feng et al., 2022), proposed a load forecasting method based on a combination of clustering and iterative logistic regression by taking data analysis as the entry point and choosing logistic regression method as the basic model (Nano et al., 2019). used "calendar" as an important influencing factor as an entry point and used multiple linear regression for load forecasting on different dates to test the feasibility and applicability of load forecasting on Indian calendar with two data sets.

In short, the regression analysis model has a simple principle and structural form and cannot describe the relationship between multiple influences on the fac-tors and load forecasts in detail. Therefore, it is a suitable basis model for addressing short- and medium-term load forecasting problems with large historical data sets.

3.1.2 Time series

3.1.2.1 Univariate time series forecasting

A univariate time series is a series with a single time-dependent variable. The commonly used analytical methods are autoregressive (AR) (Ren et al., 2022), Moving Average (MA) (Hu et al., 2013), Autoregressive Moving Average ARMA (Ervural et al., 2016) and Autoregressive Integrated Moving Average (ARIMA) (Yu et al., 2019; Wu et al., 2020). The advantages, disadvantages and applicability of the four analytical methods are shown in Table 2. Among them, the ARMA model constructed by combining the structural advantages of AR and MA is more accurate and flexible in fitting the data in univariate time series forecasting scenarios (Ervural et al., 2016). constructed a combined forecasting model to improve the accuracy of natural gas load with the help of ARMA model in combination with genetic algorithm (GA). Validated against actual data from a residential and commercial area, the combined GA-ARMA model forecasting results deviated less from the actual data and provided more accurate and effective forecasting.

The three methods, AR, MA and ARMA, are suitable for forecasting smooth time series. And ARIMA model has good

TABLE 2 Summary of univariate time series load forecasting methods.

Classification	Advantages	Disadvantages	Applicability
AR	less information required; fast calculation speed	high requirement for the smoothness of the original time series	Short and medium-term load forecasting with large amounts of historical data; broadly smoothed data; autocorrelated; highly influenced by own historical factors
MA	eliminate the effects of cyclical and random fluctuations in the time series	large amount of historical data required	can be uncorrelated; short-term and ultra-short-term load forecasting with large amounts of historical data
ARMA	solve the problem of random noise variations	cannot deal with non-stationary time series	for non-stationary time series, especially those with both short-term and long-term correlation
ARIMA	simple modeling	cannot handle non-linear relationships	processing of smooth and non-white noise time series for load forecasting

ability to handle smooth series or unsteady series and has become a widely used time series forecasting model for most of the scenario forecasting. The ARIMA model attempts to extract the time series patterns hidden behind the data by means of autocorrelation and differencing of the data, which are then used to predict future data (Yu et al., 2019). Integrated ARIMA model and ANN model to deal with the strong dynamic of electricity load data by integrating seasonal and cyclical characteristics of power load data (Nano et al., 2019). optimized the parameters of ARIMA model with the help of Cuckoo Search (CS) algorithm cuckoo search algorithm to forecast based on the actual electricity load data and proved that ARIMA model showed relatively high accuracy and effectiveness in forecasting short-term electricity load.

3.1.2.2 Multivariate time series forecasting

Multivariate time series have two or more variables that change over time. Each variable is affected not only by its own historical data but also by other variables. Commonly used analytical methods are Vector Autoregressive (VAR) (Jeong et al., 2021) and Vector Autoregressive Moving Average (VARMA) (Razghandi et al., 2021). The VAR model is a generalization of the univariate autoregressive model to a vector autoregressive model consisting of multivariate time series variables. It is used to predict time series vectors or multiple parallel time series (Guefano et al., 2020). combined Grey Model and VAR to construct GM-VAR forecasting model. The MAPE value of the GM-VAR forecasting model was 1.628%, which was validated by the real data set, and achieved a good forecasting result. The higher-order model of the vector autoregressive model, VARMA, incorporates the moving average, which makes the model have stronger time series modeling ability and can also smooth out the noise in the time series data.

The time series method establishes a mathematical model describing the change of load over time based on historical load data, then builds a load forecast expression based on the model, and finally forecasts the future load. This method only considers the time variable, requires less data, and has a fast prediction speed, but the model theory is complex, the smoothing degree of the original data is required to be taught, and other uncertainty influencing factors are not considered, which makes the final prediction accuracy error is larger.

The advantages and disadvantages and the scope of application of traditional prediction methods based on statistical analysis are shown in Table 3. The theoretical system is relatively mature and has the advantages of simple calculation and easy implementation. However, when dealing with large-scale data of diversity, complexity and nonlinearity, the prediction effect is unstable, and the prediction accuracy cannot meet the research needs. Therefore, scholars have shifted their research direction to intelligent prediction methods based on machine learning.

3.2 Intelligent forecasting methods based on machine learning

In recent years, the amount of multivariate load has increased significantly, and the number of factors affecting multivariate load is increasing, and the difficulty of load forecasting has also increased. This makes the limitations of traditional load forecasting methods based on statistical analysis significant. In order to consider multivariate loads and multiple influencing factors in forecasting, machine learning-based load forecasting methods have shown better forecasting performance in the field of load forecasting and are therefore widely used.

Machine learning is divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, we can have an accurate knowledge of the class of the object of study and the model can predict the output based on prior experience. It mainly addresses two types of problems, regression and classification, and commonly used methods include Linear Regression (Dhaval and Dhshpande, 2020), Logistic Regression (Alquthami et al., 2022), SVM (Emhamed and Jyoti, 2021), and ANN (Xu and Wang, 2022). In unsupervised learning, we can analyze the commonalities and differences between the studied objects. It mainly addresses two types of problems, clustering and association, and commonly used methods include K-means (Xiao et al., 2022) and Principal Component Analysis (Veeramsetty et al., 2022). And reinforcement learning (Park et al., 2020) is different from the first two. It does not require any data to be given in advance, but obtains learning information and updates model parameters by receiving feedback from the environment on the actions. It is used to describe and solve the problem of learning strategies by an intelligent body during its interaction with the environment in order to reach reward maximization or achieve a specific goal. In this paper, it is important to introduce SVM, ANN, CNN, RNN and Ensemble Learning (EL) related models. The algorithms are summarized in Table 4.

TABLE 3 Summary of univariate time series load forecasting methods.

Classification	Advantages	Disadvantages	Applicability
VAR	rich structure to capture more data features	large number of model parameters; large sample size	capturing linear relationships between multiple variables in a time series; load forecasting by analyzing the influence relationship between different variables
VARMA	strong modeling capabilities	complex structure	Multivariate time series suitable for removing trend and seasonal components
	rich parameterization process	large number of operations	

3.2.1 Support Vector Machine

SVM was first used mainly for data classification and has been widely used to deal with load forecasting problems due to its good nonlinear data handling capabilities. Emhamed et al. [21] used SVM to predict the electric load. With the help of real data the MAPE of SVM is minimum compared to other forecasting models. It is proved that SVM has become a reliable and useful forecasting model. SVM converges fast and does not have the problem of number of network layers and local optimal solutions, but the difficulty in determining hyperparameters leads to its poor forecasting results. Therefore, optimization of SVM hyperparameters with optimization algorithms is a key research direction (Dai et al., 2022). proposed a hybrid model incorporating feature selection and parameter optimization to improve SVM (Li et al., 2022). designed an improved sparrow search algorithm to solve the hyperparameter selection problem of SVM models (Zulfiqar et al., 2022). carefully tuned the three parameters of SVM using Multivariate Empirical Modal Decomposition (MEMD) and Adaptive Differential Evolution (ADE) algorithms (Zhao et al., 2022). optimized the combination of SVM hyperparameters by maximizing the fitness function based on particle swarm optimization algorithm. The optimized and improved SVM model outperformed other comparative methods with the lowest MAE, RMSE, MAPE and the highest R^2, improving the accuracy and stability of forecasting, as verified by the respective test sets.

The SVM can be extended from classification problems to regression problems to obtain Support Vector Regression (SVR). The SVR model solves forecasting and regression problems by seeking the optimal hyperplane, which can be well suited for high-dimensional computations and reduces generalization errors (Tan et al., 2020; Liu et al., 2022) combined Multivariate Phase Space Reconstruction (MPSR) and SVR. The two complement each other and the predicted values of hot and cold electrical loads derived from this model have minimal errors with the true values, which strongly demonstrates the effectiveness of the SVR forecasting model (Valente and Maldonado, 2020). proposed a kernel penalized SVR algorithm for automatic lag selection and nonlinear regression. The improved SVR algorithm has significant advantages over time series methods and state-of-the-art automated model selection methods in terms of forecasting performance and correct identification of relevant lags and seasonal patterns.

3.2.2 Artificial Neural Network

ANN is a mathematical model based on the basic principles of neural networks in biology, which simulates the processing mechanism of the nervous system of the human brain for complex information. It has good nonlinear feature learning ability and generalization ability (Yu et al., 2019). The model has the function of associative memory, high accuracy of classification, strong distributed parallel processing capability, and strong robustness and fault tolerance for data sets containing a large amount of noisy data. However, ANN also has many drawbacks, such as the large number of parameters required for neural networks, the difficulty of tuning parameters, and the need for extensive data pre-processing work for non-numerical data (Chen and Wang, 2022). applied a multi-objective grasshopper optimization algorithm to optimize the parameter settings of ANN (Xu and Wang, 2022). built a dynamic ANN model based on a simple ANN by applying meta-learning and continuous adaptive ideas. The simulation results show that the optimized ANN model has high accuracy and robustness. However, the deviation of the predicted value from the actual value is also an important indicator to judge the effectiveness of the model. Therefore, to address the deviation forecasting problem (Khwaja et al., 2020),combined integrated learning with ANNs to construct bagged-boosted ANNs models, and (Oreshkin et al., 2021) used the pinball-mape loss function to control the forecasting deviation and achieve a model with lower forecasting error lower and smaller variance and bias.

3.2.3 Deep learning

Under the background of continuous upgrading of computational tools and large-scale increase in the amount of training data, the application of deep learning methods in the field of load forecasting has been widely emphasized. Deep learning models show strong performance in load forecasting by extending the implicit layers or superimposing some specific structures to improve the nonlinear fitting ability. The widely used algorithms are CNN and RNN.

3.2.3.1 Convolutional Neural Network

CNN are used to extract features from things with certain models, and later classify, identify, predict or decide on that thing based on the features, etc. Its structure is highly scalable, and the deep model using multiple layers has a stronger expressive power and can handle more complex classification problems (Aouad et al., 2021; Huang et al., 2022a). However, manual adjustment of parameters is required, model training requires a large sample size, and its physical meaning is unclear. Therefore, research scholars have adopted the “CNN+" approach and combined it with other algorithms to build a combinatorial forecasting model to solve the problems of CNN (Aouad et al., 2021). proposed a CNN-Seq2Seq model with an attention mechanism (Walser and Sauer, 2021).

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TABLE 4 Summary of intelligent forecasting methods based on machine learning.

Classification		Advantages	Disadvantages	Applicability
SVM		overcome dimensional catastrophe and nonlinear differentiability	difficult to implement for large-scale training samples; unsatisfactory for solving multi-category inter problems	short-term load forecasting for small samples
ANN		high parallel distribution processing capability; high fault tolerance for noise	the need for a large number of initial parameters; long training time	load forecasting by analyzing large amounts of data and multiple influencing factors
CNN		automatic feature extraction; stress-free for high-dimensional data processing	no memory function; need to manually adjust parameters; need a large number of samples	extract coupled interaction features from large amounts of data for load forecasting
RNN	BiRNN	access to historical and future information at a point in the sequence	unable to process while receiving sequences	handle the problem that the preceding sequence elements cannot sense the output of the following sequence
	LSTM	solve the long-term dependency problem and gradient disappearance problem	complex model structure; time-consuming training; difficult parameter selection	short and long term load forecasting by processing and predicting interval and delayed events in time series
	GRU	effective suppression of gradient disappearance or explosion	Non-parallel computation	flexible and versatile load forecasting; ability to memorize for a long period of time
DL		Good feature extraction ability; can effectively avoid discrete spatialization	many hyperparameters; difficult to adjust the parameters; complex model structure; long training time	Solve load forecasting for complex energy systems
EL		good learning ability	complex training process	solve load forecasting with complex impact factors
		high forecasting		
		accuracy		

proposed a combinatorial model by combining the advantages of two basic models, decision trees and CNN (Wu et al., 2022). used a K-shape clustering method to divide users with the same electricity consumption habits and characteristics, which provided a better choice of user clusters for forecasting, and then applied CNN to capture the features, making CNN has better performance in load forecasting. It is experimentally demonstrated that the new combined model has significantly reduced the values of several performance evaluation indexes such as MAE, RMSE and MAPE compared to the related forecasting models, which improves the overall quality of forecasting.

3.2.3.2 Recurrent Neural Network

RNN is an extension of traditional feedforward neural network. It can handle variable length sequences and effectively solve the gradient vanishing and explosion problems. RNN are roughly divided into two broad categories: derived RNN and combined RNN.

The first class is derived RNN, which modifies the internal structure of RNN. For example, Gate Recurrent Unit (GRU) to solve the long-term dependency relationship problem, Long Short-Term Memory Neural Network (LSTM) to solve the gradient disappearance or gradient explosion problem, and Bi-directional Recurrent Neural Network (BiRNN) to solve the bi-directional information acquisition problem.

1) Long Short-Term Memory Neural Network

(Ouyang et al., 2023) used LSTM forecasting algorithm for electric cooling load forecasting (Wu et al., 2023). developed a load forecasting model based on LSTM neural network for industrial enterprises. It was proved by example that LSTM performs well in load forecasting. However, the LSTM itself has a complex structure and has a significant drawback that it has more parameters and is not easy to adjust the parameters than a normal neural network. To address this problem (Hu et al., 2022), applied the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and the Improved Grasshopper Optimization Algorithm (IGOA) were applied to the parameter optimization of LSTM to obtain a load forecasting model with optimal parameters. With the help of test set validation, the optimized LSTM ranks highest in forecasting performance and has higher forecasting accuracy when performing load forecasting compared to related models (He et al., 2019). used variational mode decomposition (VMD) method to optimize LSTM based on Bayesian optimization algorithm (BOA). The proposed forecasting method is applicable to time series data of various types of loads. Using data from four-quarters of a certain year in Hubei Province, China for simulation, the results show that the forecasting model can better fit the actual load curve and has high forecasting accuracy.

The problem of "long-term dependence" is common in RNN training, resulting in gradient disappearance or gradient explosion, which is effectively solved by LSTM (Sun et al., 2022). used LSTM model for load forecasting and optimized the model with parameter values. After the test set validation, the load forecasting curve derived with the help of LSTM model is more consistent with the actual load curve and has good forecasting performance. Although the LSTM can solve the long-term dependence problem, there is still the problem of not capturing the short-term interdependence when the time series is too long. To solve this problem (Ren et al., 2022), used an autoregressive algorithm that combines LSTM and CNN to extract spatio-temporal features in multiple time dimensions. The combined CNN-LSTM model was compared with ARIMA and LSTM forecasting models, and the forecasting accuracy was improved by 2.169% and 17.887%, respectively, proving that the model has higher forecasting accuracy in the short-term load forecasting performance of electricity, heat and cooling.

In recent years, to further load the forecasting accuracy, research scholars have proposed many variants of LSTM to obtain shorter training time and better forecasting results. For example (Pei et al., 2020), changed the characteristics of the original gates of the LSTM and the transmission method of the units to perform multi-step forecasting (Zheng et al., 2021). improved the LSTM infrastructure in order to solve the nonlinear relationship between multiple loads and the influencing factors in IES, and proposed the Deep Bidirectional Long and Short-Term Memory (DBiLSTM). This model learns historical load data simultaneously in both forward and backward directions to mine more useful information (Deepanraj et al., 2022). construct an Attention-based Bidirectional Long and Short-Term Memory (ABiLSTM) (Wang et al., 2021). construct a multitask learning model based on ResNet-LSTMand attention mechanism. With the help of MAE, MAPE, RMSE, R^2 and other indicators to evaluate the electric cooling and heating gas load forecasting results, it can be concluded that the variant model has better forecasting performance and higher forecasting accuracy than the base model, and will still play an important role in the field of load forecasting in the future.

2) Gate Recurrent Unit

RNN is difficult to capture dependencies with large time step distances in time series in practice. The GRU is proposed to capture this layer of dependencies better. Compared with the LSTM, the GRU has fewer parameters and is faster to train and run. However, GRU cannot consider the state at future time, so the forecasting accuracy cannot be further improved. To solve this problem, (Xuan et al., 2021). Improved the traditional one-way GRU into a Bidirectional Gated Recurrent Unit (BiGRU) to capture valid information from the past and the future. Compared with a single CNN and GRU forecasting model, the hybrid CNN-BiGRU model has smaller values for two evaluation metrics, MAPE and RMSE, which respond to the degree of deviation of the predicted value from the true one. To make GRU play a greater role in load forecasting (Wang et al., 2021), incorporated quantum-weighted neurons into the GRU to construct a Quantum-Weighted GRU (QWGRU) with stronger information processing and optimization capabilities and higher forecasting accuracy than the traditional GRU.

The second category is combinatorial RNN. It combines simple RNN with other algorithms or forecasting models. The combined models have complementary advantages, which results in better model results and is a very effective means.

(Li et al., 2022) proposed a combined CNN-GRU forecasting model based on IES small sample data by combining the advantages of coupled feature extraction of CNN and time series processing of GRU. The combined model extracts coupling and correlation features from the input data better than other models, further optimizing the model performance. Using this model, the forecasting accuracy of hot and cold electrical loads is improved. In terms of the performance metric MAPE, the CNN-GRU model improved the forecasting accuracy by at least 1% compared to the single model and other combined models. Du et al. (Du et al., 2020) combined three-dimensional CNN (3D CNN) and GRU to extract valuable data from three dimensions, depth, width, and height, to capture the temporal attributes with features. The features are then mapped to future predictive loadings using nonlinear regression with memory. Finally, the forecasting error evaluation index values of MAE and RMSE are 2.14% and 2.76%, respectively, as verified by the test set, and the combined forecasting scheme achieves good accuracy and stability.

3.2.3.3 Deep learning combination model

Deep learning models can mine the features of load datasets at a deeper level and improve the forecasting accuracy. However, problems such as complex model framework and difficult parameter selection need to be solved. Selecting models with complementary strengths for combination is a very effective solution.

It is known from the above introduction that LSTM can accurately capture the pattern information of time series, and CNN can extract valuable features from time series. Therefore, research scholars integrate the advantages of both the long time series processing potential of LSTM and the feature extraction capability of CNN to construct forecasting models as a way to improve the speed and accuracy of load forecasting. Ren et al. (Ren et al., 2021) proposed a hybrid CNN-LSTM. The convolutional layer of CNN is used to capture the features of power load data and LSTM unique cellular structures are used for power load forecasting. Zhang et al. (Zhang, 2022) extracted data features by CNN to construct feature vectors, and then input the feature vectors into the Simulated Annealing Particle Swarm Optimization (SAPSO) modified LSTM by simulated annealing particle swarm optimization algorithm for training. Shang et al. (Shang et al., 2021) proposed a multivariate and multistep hybrid model based on CNN and LSTM by considering historical load data and influencing factors such as weather, date and economy, namely, MMCNN-LSTM. After experimental demonstration and comparative analysis, the combined model containing CNN-LSTM has the best performance in error performance index, with high accuracy and good practicality and stability.

3.2.4 Ensemble Learning

Ensemble Learning (EL) belongs to the algorithmic model of machine learning. It is different from the principle of combinatorial model building. Instead of combining individual sub-models complementarily, it accomplishes the task by building multiple learners. Firstly, it generates a set of base learners and then combines these base learners according to certain rules to improve the generalization ability of the model, which has good results and is widely used in various fields (Xu and Wang, 2022; Yao et al., 2022). The commonly used EL algorithms are Bagging, Boosting, Stacking and Blending.

Bagging is one of the first EL algorithms. It is simple in structure but superior in performance. Bagging takes several weak machine learning models and aggregates their forecasting to produce the best forecasting. Bagging greatly reduces errors due to random volatility of training data, thus avoiding overfitting and improving forecasting accuracy and stability (Cai et al., 2022; Qiu et al., 2017) used the Bagging algorithm to sampling to construct a sample set, and used historical load data and influencing factors such as weather conditions as input data to construct a combined kernel function vector machine forecasting model for short-term load forecasting, which effectively reduced the forecasting error and improved the forecasting accuracy.

Boosting is similar to Bagging. It also obtains multiple base learners by repeated sampling, and then finally a strong learner is obtained. However, unlike the Bagging, Boosting is weight-based learner integration where the sample weights are continuously updated (Khwaja et al., 2020). combined bagging and boosting to train ANN to construct a combined bagged-boosted ANN forecasting model. This combined model contains several ANN models trained in parallel and the forecasting load results from these models are averaged to obtain the final forecasting load, which effectively reduces the forecasting error and improves the forecasting accuracy.

Stacking integrates multiple primary learners. It combines the advantages of different learners to make the forecasting model with strong generalization capability. Further, meta-learner is used to optimize the output results of primary learners to improve the overall forecasting accuracy (Gao et al., 2022; Chen and Wang, 2021) developed an IES electric load forecasting model considering load synergy based on Stacking Ensemble Learning, combining Back Propagation network, SVR, Random Forest and Gradient Augmented Decision Tree. It was experimentally verified that the synergistic forecasting model has lower MAE and MAPE metrics and higher forecasting accuracy (Shi et al., 2023). proposed a load forecasting method based on multiple differentiated models under Ensemble Learning architecture. The validity of the model was verified by using Swiss load data to calculate multiple model forecasting error metric values.

The Blending fusion algorithm consists of two forecasting parts, the base learner and the meta-learner. The data is divided into two parts: training data and test data. The training data is subdivided, and after the division, part of the training data is used to train the base model and part is used as a new feature to train the meta-model after model forecasting. The test data is similarly predicted by the base model to form the new test data. The Blending model can take advantage of the differences in the forecasting principles of each model to achieve the complementary advantages of each model (Xu and Wang, 2022). selected weak machine learning models such as KNN, GRU, SVR, etc. to embed the EL model of Bagging as the base learner of the Blending fusion model to enhance the stability of the model. Finally, the model is validated with New England electricity load data. The proposed model has the lowest forecasting error and the best stability and generalization ability of the forecasting model compared with other related models.

To summarize, machine learning-based forecasting models have been widely used for short-term load forecasting. However, some models ignore the importance of feature mining, parameter fine-tuning, and forecast stability. Therefore, intelligent forecasting methods based on machine learning are still in the process of optimization and upgrading.

4 Current status of multiple load forecasting research

Through the literature collation and analysis in the past 5 years, the difficulties of load forecasting in IES are mainly reflected in two aspects: complex influencing factors and difficulties in solving the forecasting model. Since IES comprehensively covers energy forms such as electricity, gas, heat and cold, it will be influenced by numerous factors, such as time, weather and economy. Ignoring these influencing factors will greatly reduce the accuracy of forecasting. The complexity and diversity of the influencing factors also lead to a significant increase in the difficulty of solving IES load forecasting models.

Some researchers consider the comprehensiveness of the influencing factors and try to exploit all the factors as input features as much as possible, but this will lead to some irrelevant factors being input into the prediction model, which will affect the accuracy of the prediction; some researchers analyze the correlation of the influencing factors in order to select the most relevant factors as the input features, e.g., the correlation analysis is used to select the input features, but the actual relationship between the multiple loads and the influencing factors is not completely linear. However, the actual multivariate load and the influencing factors are not completely linear, and the application of correlation coefficient has strict condition constraints, and the correlation degree between the factors and the load obtained by correlation analysis may be biased, which affects the final prediction accuracy.

4.1 Multiple load forecasting of the influencing factors

Therefore, research scholars explore the coupling relationship between loads and loads and loads and influencing factors in the integrated energy system, and construct a combined forecasting model with multi-model fusion to improve the efficiency and accuracy of multivariate load forecasting.

In contrast to a single energy system, the different types of energy in IES are coupled to each other through energy conversion equipment. Therefore, different types of loads are coupled with each other. It is necessary to consider the coupling relationship between different types of loads when making integrated energy load forecasting.

Ren et al. (Ren et al., 2022) analyzed the nonlinear relationships among cold, heat, and electricity loads and the relationships between loads and influencing factors such as temperature and holidays based on Copula theory, and screened the input factors for load forecasting based on the degree of influence (Li et al., 2022). used Pearson correlation coefficients to quantify the coupling relationships among loads and the temperature and humidity, wind speed, and solar intensity, etc. and the correlation information between historical loads. The most correlated influences were selected as input variables for the model, reducing the redundancy of influences (Niu et al., 2022). used Pearson correlation coefficients to analyze the correlation between cold, heat, and electrical loads and external factors (e.g., new energy power, temperature, and humidity) (Liu et al., 2022). qualitatively analyzed the coupling characteristics between IES cold, heat, and electrical loads and used Pearson correlation coefficients the coupling characteristics. And Pearson correlation coefficient is used to quantitatively describe the correlation between multiple loads (Zhang, 2022). introduced a multi-task learning method to extract the coupling relationship between IES temperature, humidity, wind speed and multiple energy sources (Wang et al., 2020). constructed a coupling feature matrix to represent the multi-energy coupling characteristics. It breaks the independence between different forms of energy, effectively reflects the cross-influence between cooling, heating and electrical loads, and achieves a comprehensive multi-energy analysis of IES. Huang et al. (Huang et al., 2022) used feature clustering to analyze the influence of different environmental factors on the electric cooling, heating and air load forecasting results, and then used the K-means clustering algorithm to establish feature clustering models of various energy loads to obtain IES load forecasting results. In the subsequent experimental validation, it is known that the load forecasting error of the model considering the coupling relationship between loads is the smallest, which confirms the necessity of coupling analysis.

In summary, there are four categories of possible input variables for the IES multivariate load forecasting model.

1) weather factors: temperature, humidity, wind speed, and barometric pressure.
2) Temporal factors: weekdays, holidays.
3) Economic factors: GDP *per capita*, electricity price, electricity, new energy, carbon trading price, hydrogen price.
4) Technical conditions: historical load data such as cold, heat, electricity, gas, and hydrogen (Ke et al., 2023).

Analyzing the load historical data and influencing factors, considering the coupling relationship between load and other factors in the system, makes the multivariate load forecasting with high forecasting efficiency and accuracy. It can better guide the optimal design and energy management of IES, thus ensuring that IES can operate economically, safely and reliably.

4.2 Combined forecasting methods for multiple load

The complexity and diversity of influencing factors lead to a significant increase in the difficulty of solving IES load forecasting models. The selection of models with complementary strengths for combination construction is a hot topic in current load forecasting research.

Different multivariate load prediction models differ greatly in terms of sample processing, feature selection, model parameter optimization, etc., which makes it difficult to have a complete prediction model that can be applied to all data analysis domains, i.e., each model has its own advantages and applicable scenarios. Meanwhile, real data often contain many uncertainties, such as noise, random interference, distortion, missing values, etc., which all have a great impact on the performance of prediction models. At this time, different types of models can be combined to play their respective advantages, avoiding the shortcomings of each model to achieve the purpose of improving the prediction performance. The common form of the combined prediction model is the weighted average of the individual prediction models, so the focus of the combined prediction model is on the determination of the weighting coefficients. If the weighting coefficients of the individual prediction models are assigned reasonably, the prediction accuracy of the whole combined prediction model will be improved accordingly.

From the literature review results, it can be found that CNN combined with LSTM for correlated multivariate load forecasting is widely used (Qi et al., 2020). constructed a CNN-LSTM combined model to extract the coupling features between electric, cooling and thermal loads using CNN and input the coupling features into LSTM for load forecasting. The experimental results show that the combined CNN- LSTM model has higher forecasting accuracy than the wavelet neural network model, CNN model and LSTM model (Ren et al., 2022). effectively combined the linear statistical capability of AR with the ability of CNN and LSTM to extract features to build a multidimensional feature fusion AR-CNN-LSTM multi-load forecasting model. This model can extract coupled and periodic features implied in IES load data from multiple time dimensions (Wang et al., 2020). proposed a CNN-BiLSTM-based load forecasting method to fully exploit the temporal and spatial correlation of data and improve the forecasting accuracy (Yao et al., 2022). constructed Attention-CNN based on the attention mechanism -DBILSTM for short-term load forecasting method. With the help of real IES data for forecasting, the proposed model reduces the average forecasting error by about 2%, which effectively improves the forecasting accuracy.

In addition, multi-task learning (Guo et al., 2022) has also received much attention in model design because it can effectively extract features (Zhang, 2022). constructed a CNN-Seq2Seq model with the help of a multi-task learning approach to extract the complex coupling relationships between different energies of IES, taking into account the coupling relationships of temperature, humidity, wind speed and multiple energy sources. The training set validation yielded that the cold, heat and electricity load forecasting results were closer to the real values (Huan et al., 2020). proposed a load forecasting method based on deep learning and multi-task learning. The forecasting curves of electricity, hot and gas loads were validated by the actual data set loads, and the MAPE values of the proposed model for electricity, hot and gas were lower than those of the comparison model. It proved that the proposed forecasting model has excellent performance in terms of computational efficiency and forecasting accuracy (Wang et al., 2022). used a multi-task model to establish a joint electric-heat-cool load forecasting model considering the strong and complex coupling characteristics among multi-energy loads. The average variation value of MAPE obtained from the experiment was 0.0356%, and the forecasting error was extremely small (Zhang et al., 2020). proposed a deep multitask learning method for electricity, hot and gas loads forecasting based on deep belief networks and multitask regression layers, with the help of which the model can effectively analyze the complex coupling relationships between several input information types, resulting in an improvement in the forecasting accuracy of all three loads by The forecasting accuracy is significantly improved by about 2%.

5 Conclusion and future research trends

5.1 Review summary

Nowadays, demand is changing dramatically and the total demand for energy continues to grow. IES has achieved rapid development and widespread application in the field of energy to meet the different energy needs, while ensuring as much efficiency and efficiency as possible in energy supply. Complex and interdependent loads require accurate and effective load forecasts to provide data support for subsequent system planning. In this context, the paper examines many references to track the latest research progress of load forecasting methods and to understand current research points and load forecasting directions. The results of the IES multi-load forecast research over the past 5 years have been compiled and screened, and detailed comparisons and analyses are carried out to provide intuitive and practical references for subsequent multi-variable load forecast research.

1) Introduction of integrated energy systems' coupling structures and energy conversion equipment, analysis of the coupling relations between energy conversion pathways, transmission characteristics, and multiple energy sources such as heat and cold, and studies of the intrinsic connections between multiple loads and related factors such as climate (such as temperature and humidity, solar radiation intensity, wind speed, rainfall), economy (such as GDP, energy prices), and date. The intrinsic link has shown that IES can successfully achieve optimal planning and synergistic use between different energy systems and maximize the benefits of IES while increasing the proportion of renewable energy.
2) Traditional statistically-based forecasting methods (such as regression analysis, one-variable time series, and multivariable time series) are introduced, and three aspects are studied in comparison to commonly used forecasting methods: advantages, disadvantages, and applicability. Today, integrated energy systems collect large amounts of data with decentralization, diversity, complexity and real-time characteristics. Therefore, traditional statistical analysis prediction methods require a high requirement for sample sizes, dimensions, depths and data quality, and in future research, input data sets must be improved to obtain more accurate forecast results.
3) Intelligent forecasting methods based on machine learning, such as SVM, ANN, DL, EL and combinatorial prediction, are introduced, and relevant derivative models, such as GRU, LSTM and DbiLSTM, are further explored on the basis of simple models. By studying the intelligent forecasting methods, it can be concluded that, firstly, the forecasting effect of the combined model is significantly better than that

brought by a single model in the case of large amount of data and many influencing factors. Second, with the powerful feature learning ability and fault tolerance of deep learning, applying it to traditional machine learning algorithms, such as SVM and genetic algorithm, can effectively handle the massive data and complex calculations in load prediction and improve the precision of multivariate load prediction. However, the training process is more complex and time consuming, and hyperparameter optimization is difficult, which requires in-depth research in related fields in the future. Third, deep learning algorithms based on an integrated learning framework can effectively extract the advantages of each base model, discard the shortcomings of deep learning algorithms in model training, weight setting, hyperparameter optimization, etc., and then use metamodels for classification and achieve excellent forecasting results.

5.2 Future research trends

At present, IES multiple load forecasting is still a relatively cutting-edge topic, and the related theoretical system is not yet perfect. It is believed that in the near future, a more complete system and more accurate forecasting methods will appear. In this paper, only some of the IES multiple load forecasting methods are summarized, and the methods not covered still need to be studied in depth. Regarding the future research directions, based on the literature study in this paper, the following points are proposed:

First, there are many factors affecting IES multiple load, and only some current mainstream and highly relevant influencing factors are selected for discussion in this paper. However, the influencing factors always increase with the development of IES, such as geographic conditions like topography and landscape, demand response, user characteristics, and major social events also affect the accuracy of multiple load forecasting to some extent, which should continue to be explored in depth in the subsequent research.

Second, as the structure of new power systems becomes more and more complex, data-driven methods that are more adapted to the development of IES should be applied, and the future development trend is more focused on deep learning, integrated learning, reinforcement learning, migration learning, and new machine learning such as meta-learning and fuzzy reasoning. Among them, Deep Learning algorithms are the most widely used among many data-driven methods, and the three areas of hyperparameter optimization, parameter training tuning and performance evaluation of its prediction models are the focus of future scholars' research. Processing with heuristic algorithms, such as particle swarm optimization algorithm, ant colony optimization and simulated annealing method, can make the load forecasting based on DL algorithms more effective.

Third, the goal of combinatorial predictive modeling is to take advantage of the strengths of the models involved, integrate the strengths of different models through an effective combination approach, and overcome the shortcomings of each of the models, so that the combinatorial predictive model can better mine the useful information present in the data. At the present stage, the combined prediction model is based on the weight assignment method, which assigns different weights according to the performance of individual models. The method is easy to be realistic and has strong adaptability to the data, and the prediction performance is relatively stable, but the weights of individual models are often assigned based on experience or simple calculations, which is not very scientific. In the future, more attention should be paid to the combination method based on model structure and parameter selection. Because the hyperparameters determine the solution rate and accuracy of the model, this combination method is to optimize the prediction model to improve the performance of the model, and it is also one of the key research directions in the field of multivariate load forecasting in the future.

Fourth, after the new energy sources, such as wind power and photovoltaic, and the new loads, such as energy storage, electric vehicles and virtual power plants, are connected to the grid on a large scale, the integrated energy system presents highly complex volatility and uncertainty, and the large amount of multiple heterogeneous data increases the difficulty of data analysis. In this context, with the help of the deterministic forecasting methods discussed in this paper, the forecasting results are subject to ineradicable errors, and the multiple loads are difficult to be accurately forecasted. Therefore, the future research direction may be more inclined to probabilistic forecasting. Probabilistic forecasting differs from deterministic forecasting methods in that the output result is not a definite value, but the probability distribution, quantile, and forecasting interval of the forecasting object as the output form. Meanwhile, machine learning algorithms such as neural networks and deep learning have powerful nonlinear mapping capabilities, which can significantly improve the reliability of probabilistic forecasting when combined with probabilistic forecasting methods, and should be widely applied in subsequent research.

Author contributions

YujL: Writing–original draft, Writing–review and editing, Conceptualization, Investigation, Methodology. YaL: Writing–original draft, Writing–review and editing, Funding acquisition, Investigation, Methodology. GL: Writing–original draft, Writing–review and editing, Investigation, Methodology, Project administration, Resources. YuqL: Writing–original draft, Writing–review and editing, Data curation, Investigation, Methodology. RW: Writing–original draft, Writing–review and editing, Conceptualization, Data curation, Funding acquisition, Methodology. YF: Writing–original draft, Writing–review and editing, Data curation, Methodology.

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