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Short-Term Electric Load Forecasting of Integrated Energy System Considering Nonlinear Synergy Between Different Loads

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ABSTRACT As an efficient form of energy utilization, an integrated energy system integrates oil, natural gas, coal, and other energy sources and converts them into electric, cooling, and heating for users through energy conversion devices. In this process, integrated energy service providers need to make energy conversion decisions based on users' demand information feedback. Therefore, there is uncertainty and coupling between the electric cooling and heating loads, making it difficult to forecast the loads accurately. Firstly, this paper analyzes the integrated energy system's energy consumption characteristics and the interaction mechanism between the supply and demand sides, which fundamentally explains the coupling relationship between different loads of the integrated energy system. Secondly, REC, DEC, REH, and DEH are constructed from electric cooling and heating loads. The relationship between electric load and cooling and heating load is analyzed by a scatter distribution diagram and maximum information coefficient method. The nonlinear correlation between electric load and cooling and heating loads is proved. Based on this, the integrated energy system's synergetic electric load forecasting formula reflecting the nonlinear synergistic effect between loads is proposed. Finally, based on stacking ensemble learning, an integrated energy system electric load forecasting model considering the nonlinear synergy between loads is established by integrating BP neural network, support vector regression, random forest, and gradient boosting decision tree. Through the experimental analysis of the Arizona State University Tempe campus's integrated energy system project, it is found that the effect of the synergistic quadratic forecasting is better than that of the primary forecasting. Besides, the MAPE of the quadratic synergistic forecasting formula is lower than that of the other two forms, indicating that the proposed synergistic electric load forecasting formula considering the nonlinear synergy between loads can improve the accuracy of electric load forecasting of the integrated energy system.

INDEX TERMS Energy consumption characteristics, integrated energy system, synergetic forecasting, stacking ensemble learning.

I. INTRODUCTION

In recent years, problems such as energy shortage, inefficient use of energy, and environmental pollution have become increasingly prominent [1]. With the continuous development of energy technology, the traditional energy utilization mode of independent supply of different energy will be gradually replaced, and the IES (integrated energy system) is proposed in this context [2], [3]. The integrated energy system integrates the use of different types of energy and realizes the production, transmission, and supply of different energy sources through energy conversion and storage devices. Compared with the traditional single energy system, the integrated energy system can improve energy utilization efficiency [4], becoming a global research hotspot.

Due to the essential difference in energy utilization between the IES and the traditional energy system, the IES's load forecasting is also quite different from the conventional energy system. In the IES, in addition to the external factors such as weather and day type that affect the load, the internal interaction between different types of loads should be considered more critical. The operating mechanism of the IES determines this interaction. Therefore, comprehensive consideration of the interaction between different loads is the

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main difference between the IES and the traditional energy system in load forecasting.

The load forecasting category is divided according to the predicted time range [5]. Among all the categories, short-term load forecasting is the most common, and its forecast time range is dominated by hours, which is crucial to the power supply and demand scheduling of the power grid. For example, several independent system operators have implemented day-ahead demand response markets [6] and generator programs to achieve power system stability [7]. The research of this paper is based on such a goal.

In the traditional energy system, the load is supplied independently. It has become a mature way to use historical load data and influencing factors as the data basis of a load forecasting model. Supplemented by a variety of artificial intelligence algorithms with excellent data fitting ability [8]–[10], such as vector autoregression, support vector machine [11], neural network [12], and deep learning [13], can usually obtain satisfactory forecasting accuracy. These algorithms have their advantages in terms of feature extraction and learning ability and have useful application value in load forecasting. In recent years, the concept of algorithm fusion begins to rise and develop rapidly. It has become a popular method in academic research and data competition [14], [15]. On the one hand, Bagging and Boosting, integrated with the same algorithm, are typical representatives of Random Forest and Gradient Boosting Decision Tree [16], [17]. On the other hand, the Stacking ensemble learning method integrates different algorithms and shows a more excellent load forecasting effect.

However, IES is different from the traditional power system. It flexibly makes use of various energy sources in the region (such as oil, natural gas, solar, and wind), realizes the coupling and conversion between different energy sources through energy conversion devices and storage equipment, and finally provides users with loads of electric, cooling, heating, and gas to meet different demands. Therefore, compared with the single power load forecasting, the IES's load forecasting is more challenging [18], [19]. How to use the relationship between different loads to improve the forecasting accuracy has become a breakthrough in recent years. The existing research on the combined load forecasting of electric, cooling, heating, and gas mainly includes two aspects: on the one hand, similar to power load forecasting, the method of taking meteorological conditions such as temperature and humidity as exogenous variables and historical data of different loads as endogenous variables plays a particular role [20]–[22], because it reflects the correlation between different loads to a certain extent, and considers their cross-coupling relationship from the level of original data. [23] evaluates several different models and discusses each model's ability to accurately forecast hourly heating, cooling, and electrical loads for a district energy system up to 24 h in advance using weather and time variables (month, hour, and day) as inputs. [24] takes the historical load, temperature, cooling load, and gas consumption in the recent five days as input characteristics. CNN combined with attention block is used to extract the effective characteristics of load influence factors to forecast the next hour's load. [25] uses the Pearson correlation coefficient to measure the time correlation between the current load and the historical load, analyze the coupling relationship between the heat, gas, and electric load, and forecast the electric cooling and heating loads of the CCHP system. Another method that also plays a positive role is based on MTL (Multi-Task Learning) forecasting, which processes information of different types of energy loads through MTL's sharing mechanism [26] and achieves more effective forecasting results than single-task learning. A combined forecasting model based on the multi-task learning and least square support vector machine has been constructed with the help of the weight sharing mechanism in the multi-task learning and the idea of the least square support vector machine to forecast electricity, heat, cooling, and gas loads [27]. A combined short-term electricity-heat-gas load forecasting model based on the multi-task learning (MTL) considering the weather condition, historical load data, calendar information, and economic data has been introduced to improve forecast accuracy [28].

The current research shows that the coupling relationship between different IES loads has an essential contribution to improving load forecasting accuracy. From the perspective of endogenous variables and Shared information during model training, the forecasting accuracy of combined loads can be improved to a certain extent. However, its general concern is the direct impact between loads and the correlation of input characteristics, while the nonlinear relationship between different loads is still not well utilized. It can be found from the energy dissipation curves and distribution scatter diagrams of the electric cooling and heating loads of the IES that there is a linear relationship among different loads and a nonlinear relationship that cannot be ignored. Therefore, the quadratic synergetic forecasting based on the primary forecasting results and the nonlinear relationship between loads was proposed [29]. The quadratic synergetic forecasting synthesized the primary forecasting results, and combined with the nonlinear relationship between loads, the primary forecasting results were fitted again to obtain the final fitting results. However, there is no unified standard for synergetic load forecasting. In order to further analyze the interaction between different dimensions of loads, this paper refers to the idea of literature [29] and proposes a synergetic load forecasting formula reflecting the multi-dimensional nonlinear relationship between loads based on the correlation analysis between loads and the implication of the constructed correlation indexes, in this paper, the main work is as follows:

1. Describe the consumption characteristics of multiple loads of IES in different time scales, such as quarterly, weekly, and hourly. The seasonality and periodicity of the loads are verified from the loads' time series. It can be seen that there are certain similarities and complementarities among different loads, which preliminarily reflects the coupling relationship of multiple loads in the IES.

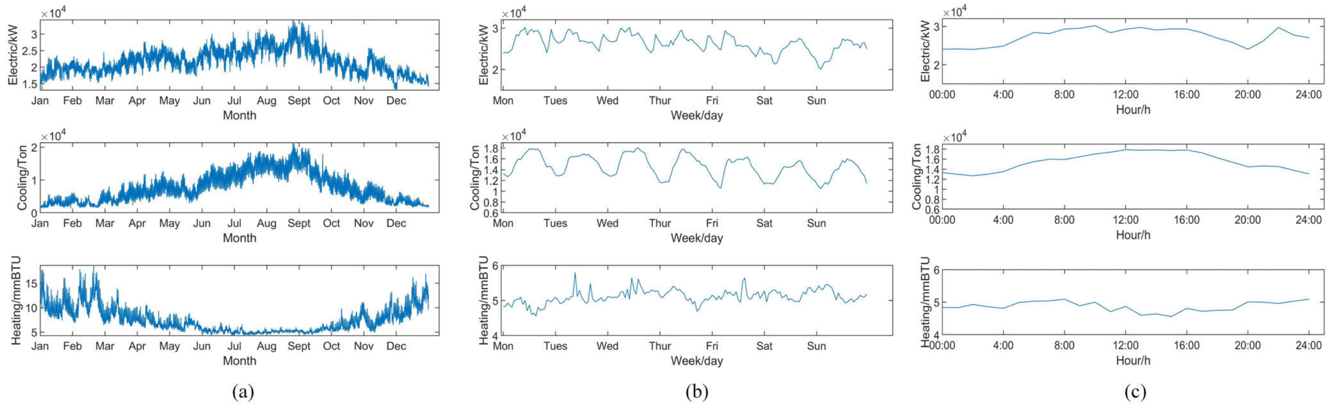


FIGURE 1. Variation curve electric cooling and heating loads: (a) Quarterly; (b) Weekly; (c) Hourly.

2. Analyze the interaction mechanism between supply and demand of IES and point out the coupling relationship between different loads in essence. Scatter plots are used to describe the linear and nonlinear relationship between different loads and related indexes. MIC is used to calculate the correlation coefficients of electric cooling and heating loads and indexes such as REC, DEC, REH, and DEH. Each correlation coefficient's absolute value is generally greater than 0.5, which indicates the multi-dimensional cooperative relationship between electric, cooling, heating loads, and related indexes.

3. Combined with the above research and considering each associated index's meaning, a synergetic electric load forecasting formula was constructed, considering the IES's multi-dimensional influence. The formula incorporates the effects of cooling and heating loads on electric load, reflecting the profound influence of multiple loads from multiple dimensions.

4. Using the grid search to obtain the optimal parameters, and the short-term electrical load forecasting model of the integrated energy system was established based on the fusion of support vector machine, BP neural network, random forest, and gradient boosting decision tree. Load data from the IES project at Arizona State University were selected for experimental analysis. The results show that the synergetic electric load forecasting formula considering the multi-dimensional interaction can effectively improve the electric load's forecasting accuracy.

II. CHARACTERISTIC ANALYSIS OF IES

A. CONSUMPTION CHARACTERISTICS

In actual industrial parks, commercial centers, residential buildings, and other typical IESs need to meet the user's electric, cooling, heating, and other energy needs, and users' energy demand is affected by meteorological conditions, human activities, and building characteristics.

In this paper, the 2019 electric cooling and heating load data of Tempe Campus of Arizona State University are selected as samples, and the forms of different loads of the IES are depicted from three-time scales of quarterly, weekly, and hourly, respectively, and the consumption characteristics are analyzed.

1) QUARTERLY CONSUMPTION CHARACTERISTIC

Divide March to May as spring, June to August as summer, September to November as autumn, December to February of next year as winter, and draw the quarterly change curve of electric cooling and heating load (Figure 1a). It can be seen that the seasonality of each load is quite apparent. The electric load and the cooling load reach a peak in summer, while the heating load reaches a peak in winter. The electric and cooling loads' variation trend is similar, while the heating load's variation trend is complementary to electric and cooling loads.

2) WEEKLY CONSUMPTION CHARACTERISTIC

Select the electric cooling and heating load of a week in August 2019 to draw its change curve (Figure 1b). It can be seen that the periodicity of electric and cooling loads in a week is relatively apparent, and the rest day load is reduced compared with the working day load, which is related to the reduction of various production activities in the rest day. The one-week change of heating load is relatively stable, considering that the heating load demand is less in summer and the system load is mostly rigid load.

3) HOURLY CONSUMPTION CHARACTERISTIC

Select 24 hours of electric cooling and heating loads on a day in August 2019 to draw an hourly load change curve (Figure 1c). It can be seen that the electric and cooling loads all reach their peak around 11:16, which is related to the residents' daily living habits. However, the heating load changes gently in a day, indicating that the heating load in summer is mainly a rigid load similar to the weekly consumption characteristic mentioned above.

B. THE INTERACTION MECHANISM BETWEEN SUPPLY AND DEMAND SIDES OF IES

As a new generation of the energy system, IES can meet different energy needs of users. In a mature IES, the integrated energy service providers on the side of the IES manage

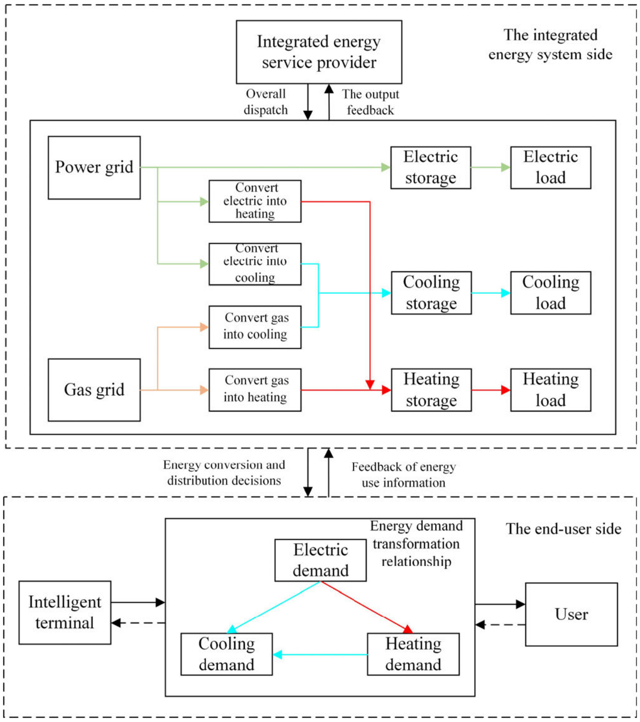


FIGURE 2. Interaction structure of IES and end-user sides.

and dispatch different forms of energy, and the energy use information of end-users is timely fed back to the integrated energy service providers, who make energy conversion and distribution decisions after summarizing and analyzing the energy use information, as shown in Figure 2.

Specifically, the power and gas grid's energy can be converted and stored through different energy conversion and storage devices and then provided to end-users on the IES side. On the end-user side, intelligent terminal equipment collects users' different energy needs and feeds them back to the system side to carry out energy conversion. As the coordinator of the whole interaction process, the integrated energy service provider plays a vital role in analyzing the feedback information in time and making correct decisions.

C. LOADS CORRELATION ANALYSIS

Traditional energy systems tend to ignore the energy quality when operating independently and focus on simple energy research forms. However, there are a large number of energy conversion equipment in the integrated energy system, which places more emphasis on refined energy quality and energy forms directly needed by users. The complex and complementary relationship between different loads not only depends on user behavior on the demand side but is also affected by meteorological factors. Changes in demand for multi-energy loads are often not absolutely independent, and sudden changes in a certain load are most likely transmitted to other loads as a signal.

In order to analyze the influence of this characteristic of IES on load forecasting, in this paper, four correlative

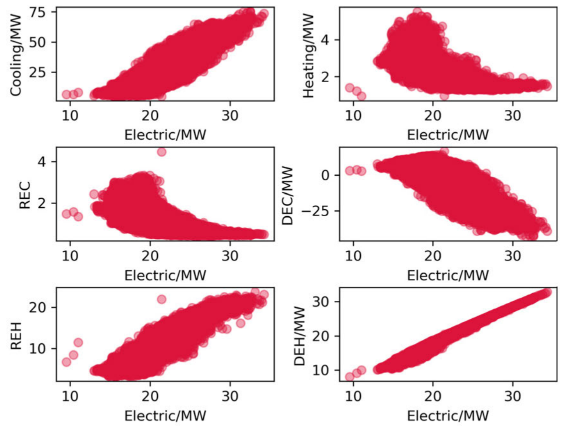


FIGURE 3. The scatter distribution of electric cooling and heating loads and related indexes.

indexes, including REC (The ratio of electric load to cooling load), DEC (The difference between electric load and cooling load), REH (The ratio of electric load to heating load) and DEH (The difference between electric load and heating load), are constructed based on electric cooling and heating load calculation, the above electric cooling and heating loads data of Arizona State University Tempe campus in 2019 were used to analyze the relationship between electric cooling and heating loads and related indexes.

Figure 3 reveals two fundamental characteristics of the correlation between different loads in the integrated energy system: 1) There is always a correlation (linear or nonlinear) among electric, cooling, and heating loads at any time. 2) The correlation between correlation index and electric load is generally more significant than that of cooling and heating load, and the coupling relationship cannot be ignored.

To deeply analyze the correlation between the IES's different loads, MIC (Maximal Information Coefficient) was used to measure the linear and nonlinear correlation between loads and related indexes.

MIC is a method used to calculate the degree of linear or nonlinear correlation between two variables. Compared with the correlation analysis methods such as the Person correlation coefficient, MIC has the advantages of universality, fairness, and symmetry and performs better in calculating the correlation degree of linear or nonlinear data.

MIC takes advantage of mutual information, and the calculation of mutual information involves joint probabilities, so the MIC's idea is to discretize the relationship between two variables in a two-dimensional space and use a scatter plot to represent it. Divide the current two-dimensional space into a certain number of intervals in the x and y directions, and then check how the current scatter points fall in each grid. That is the alternative calculation process of joint probability, which solves the problem that joint probability in mutual information is difficult to calculate. The MIC formula is as follows:

$$MIC\,(x,y) = \max_{a*b<B} \frac{I\,(x,y)}{\log_2 \min\,(a,b)} \tag{1}$$

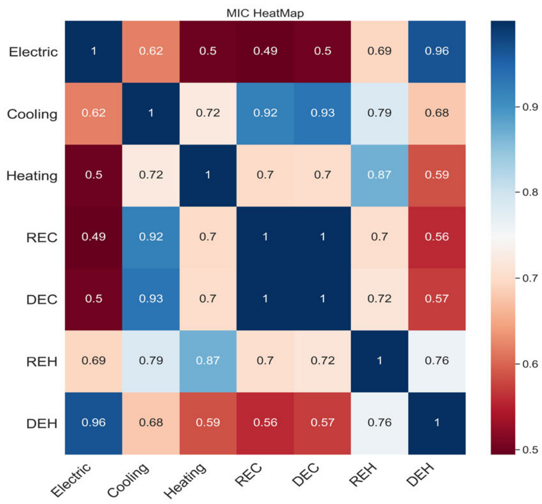


FIGURE 4. MIC matrix thermal diagram.

where $I(x, y)$ is mutual information, a and b are the number of grids divided in the x and y directions, B is a variable, and its value is generally about 0.6 to the data's power [30].

The 2019 electric cooling and heating loads data of Arizona State University Tempe campus were used as samples to calculate the MIC between electric cooling and heating loads and related indexes. The results are presented in terms of a thermal diagram shown in Figure 4. The MIC matrix thermal diagram shows that the correlation between electric load and DEH is the largest, and the MIC reaches 0.96, indicating a strong correlation. The second is cooling load and REH, with MIC of 0.62 and 0.69, respectively, indicating a moderate correlation with the electric load. Finally, heating load, REC, and DEC, with MIC of about 0.5, is also a moderate correlation. The correlation analysis results show that it is necessary to consider the nonlinear synergistic relationship among different loads, enhancing loads' predictability.

The IES is dominated by electric load and supplemented by cooling and heating loads. Previous studies on IES's load forecasting generally take the parallel relationship between different loads as the emphasis of the load forecasting model. The purpose of improving the load forecasting accuracy is achieved by sharing the information between different loads in model training. In this paper's analysis, how to use the nonlinear coupling relations between the IES's different loads is the key to improving the IES's load forecasting accuracy.

D. SYNERGETIC ELECTRIC LOAD FORECASTING FORMULA

From the analysis of energy consumption characteristics and linear and nonlinear coupling relations of the IES above, it can be seen that there is an apparent correlation between electric cooling and heating loads. In order to better measure the nonlinear relationship between IES's different loads and improve the forecasting accuracy of electric load, this paper considers constructing a synergetic electric load forecasting formula by selecting indicators reflecting the correlation between different loads such as REC, DEC, REH, and DEH as variables and combining the meanings of each indicator, as shown in Formula 2:

$$\begin{aligned} L''_{elec} = \alpha L'_{elec} + \beta L'_{cool} L'_{REC} + \gamma \left(L'_{cool} + L'_{DEC}\right) \\ + \delta L'_{heat} L'_{REH} + \varepsilon \left(L'_{heat} + L'_{DEH}\right) \end{aligned} \tag{2}$$

where L'_{elec}, L'_{cool}, and L'_{heat} are the forecasting values of electric cooling and heating loads, L'_{REC} and L'_{DEC} are the forecasting values of REC and DEC, L'_{REH} and L'_{DEH} are the forecasting values of REH and DEH, and, $\alpha, \beta, \gamma, \delta$ and ε are the coefficients of each indicator and its combined variables, and L''_{elec} is the forecasting value of the synergetic electric load.

The coefficients of each item in the synergetic load forecasting formula can be solved by multiple linear regression. Multiple linear regression is a method to analyze the linear relationship between two or more independent variables and one dependent variable. Its model can be expressed as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{3}$$

where β_0 is the regression constant, β_1 to β_n are the regression coefficients of the independent variable x_1 to x_n are independent variables, and y is the dependent variable. In this paper, independent variables include the forecasting values of electric cooling and heating loads, REC, DEC, REH, and DEH, and the dependent variable is the actual value of the electric load. Since the synergetic electric load forecasting formula only contains the variables composed by each indicator or its combination, and there is no constant term, the regression constant can be omitted in the multiple linear regression analysis.

The least-square method can be used to solve the regression coefficients of a multiple linear regression equation. First, construct the sum of squares of the residuals:

$$SSE = \sum \left(y - \hat{y}\right) \tag{4}$$

According to the minimum principle in calculus, the partial derivatives of SSE to β_0 to β_n are all 0 when taking the minimum value:

$$\frac{\partial SSE}{\partial \beta_i} = -2 \sum \left(y - \hat{y}\right) = 0 \tag{5}$$

$$\frac{\partial SSE}{\partial \beta_0} = -2 \sum \left(y - \hat{y}\right) x_i = 0 \tag{6}$$

By solving this set of equations, the estimated value $\hat{\beta}_0$ to $\hat{\beta}_n$ of each regression coefficient β_0 to β_n can be obtained.

The quadratic fitting based on the synergetic electric load forecasting formula aims to make full use of the nonlinear coupling relations between different types of loads to reflect the synergetic influence among loads to the greatest extent to achieve the goal of accurate load forecasting.

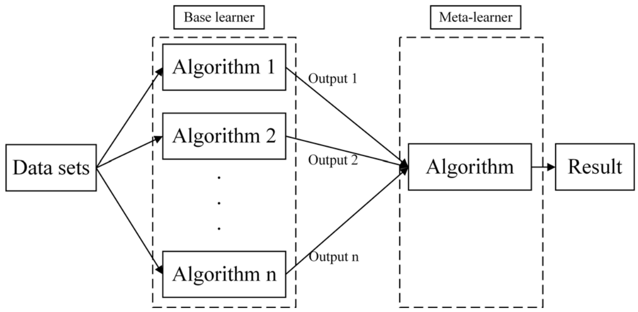


FIGURE 5. Principle of Stacking ensemble learning.

III. METHODS AND MODEL PROCESS

A. STACKING ENSEMBLE LEARNING METHOD

Stacking [31] is an ensemble learning approach widely used in data racing, which combines various algorithms to show powerful advantages in classification and regression problems. Unlike Bagging and Boosting, Stacking constructs two or more layers of models, each of which can contain multiple algorithms. When training, the upper layer model's output will be used as the input characteristics of the next layer's model, and train again, and so on, to get the final results. The principle of the two layers of the Stacking model is shown in Figure 5, the first layer is called the base learner, and the second layer is called the meta-learner.

In this paper, the BP neural network, SVR (Support Vector Regression), and RF (Random Forest) were selected as the model's base learners, and GBDT (Gradient Boosting Decision Tree) was selected as the model's meta-learner. This paper will introduce the principle of SVR and GBDT.

B. SVR METHOD

SVR (Support Vector Regression) is a regression method in machine learning. As an essential SVM (Support Vector Machine) branch [32], SVR adopts the idea of Support Vector and Lagrangian multiplier to conduct regression analysis on data during fitting. Unlike SVM, SVR aims to find a hyperplane to minimize the total deviation of all sample points to this hyperplane, that is, the expected risk is minimized. SVR is suitable for linear and nonlinear regression. Compared with general linear regression, SVR has a better regression effect on multicollinearity problems, and the errors caused by outliers are smaller.

In the given sample $\{x_i, y_i\}$, x_i is the input and y_i is the corresponding output, $i \in \{1, 2, \ldots, N\}$, N is the number of samples. For nonlinear samples, firstly, the nonlinear function is used to map the sample points to the high-dimensional space, and the estimation function f is obtained:

$$f(x) = w^T \varphi(x) + b \tag{7}$$

where w is the weight vector, and b is the constant. The coefficients w and b can be estimated by minimizing the objective function, which is:

$$\frac{1}{2}\|w\|^2 + c\sum_{i=1}^{n} |y_i - (w, \varphi(x_i)) - b|_\varepsilon \tag{8}$$

where c is the penalty factor, and ε is the insensitivity loss function. To further solve w and b, relaxation variables are introduced, and the Lagrange multiplier method is used to transform the constrained nonlinear programming problem into the Wolfe dual problem, and the corresponding Lagrange parameters are obtained. The expression of the final nonlinear regression model is:

$$f(x, \alpha) = \sum_{i=1}^{n} (\alpha_i^* - \alpha_i) K(x_i, x) + b \tag{9}$$

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \tag{10}$$

where α_i and α_i^* are Lagrange multiplier, $K(x_i, x)$ is the kernel function, and γ is the kernel function parameter.

The flow chart of SVR is shown in Figure 6.

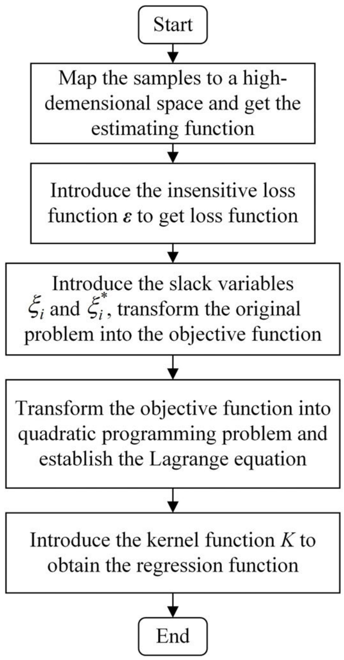


FIGURE 6. The flow chart of SVR method.

C. GBDT METHOD

GBDT (Gradient Boosting Decision Tree) [33] is an iterative algorithm that belongs to the Boosting ensemble learning class and established based on Decision Tree and Gradient Boosting. The core of GBDT is to use the value of the negative gradient of the loss function in the previous model as the approximation of the residual in the current Boosting tree algorithm to fit a decision tree and accumulate the results of all trees as the final result. The steps of GBDT are as follows:

(1) Initialize the weak learner to obtain the constant estimate that minimizes the loss function:

$$f_0(x) = \arg\min_c \sum_{i=1}^{N} L(y_i, c) \tag{11}$$

where y_i is the output value of the training sample, c is a constant and $L(y_i, c)$ is the loss function, usually the square loss function $(y_i - c)^2$.

(2) For $m \in \{1, 2, \ldots, M\}$:

a) For each sample, calculate the negative gradient, that is, the residual:

$$r_{im} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=f_{m-1}(x)} \tag{12}$$

b) Take the residual obtained in the previous step as the new actual value of the sample, and take (x_i, r_{im}) as the training data of the next tree, then a new regression tree $f_m(x)$ can be obtained. Its corresponding leaf node region is $R_{jm}, j \in \{1, 2, \ldots, J\}$. J is the number of leaf nodes of the regression tree T.

c) For the leaf node region $j \in \{1, 2, \ldots, J\}$, calculate the best fitting value:

$$r_{jm} = \arg\min \sum_{x_i \in R_{jm}} L(y_i, f_{m-1}(x) + r) \tag{13}$$

d) Update to the strong learner:

$$f_m(x) = f_{m-1}(x) + \sum_{j=1}^{J} r_{jm} I(x \in R_{jm}) \tag{14}$$

(3) Add up the results of the above steps to obtain the final regression tree model:

$$f(x) = f_M(x) = f_0(x) + \sum_{m=1}^{M}\sum_{j=1}^{J} r_{jm} I(x \in R_{jm}) \tag{15}$$

D. HYPER-PARAMETERS OPTIMIZATION BASED ON GRID SEARCH

Because the Stacking ensemble learning requires a certain difference between different base learners and each base learner has good performance, the selected base learners' performance needs to be tested. The performance of the learner is related to its selected hyper-parameters. Different learners have their hyper-parameters; however, different combinations of hyper-parameters of the same learner will also produce different performance. To obtain the best model performance, it is necessary to find the base learners' optimal hyper-parameters.

In this paper, grid search is used to obtain the optimal hyper-parameters of each base learner. Grid search is an exhaustive search method for specifying parameter values. The hyper-parameters of the model are optimized by cross-validation to obtain the optimal learning algorithm. Each parameter's possible values are arranged and combined, and all possible combination results are listed to generate a "grid." Then each combination is used to train the model, and its performance is evaluated by cross-validation. After the model has tried all the parameter combinations, the model's performance under each combination is compared, and an optimal set of hyper-parameters is returned.

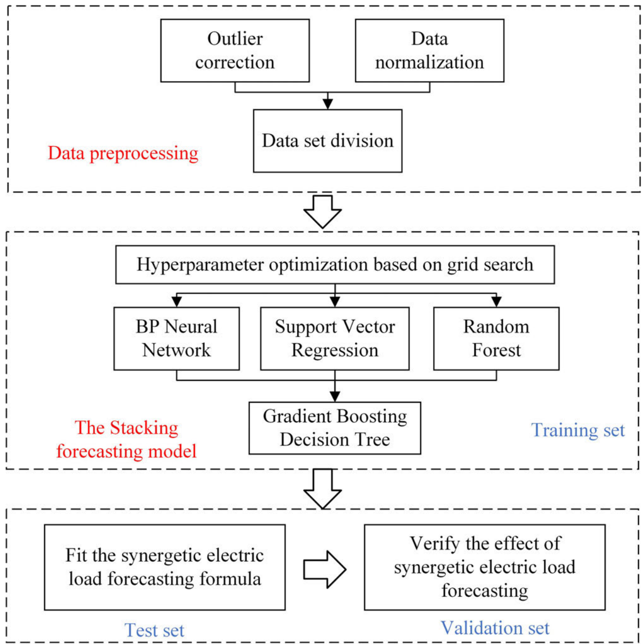


FIGURE 7. Process of integrated energy system synergetic electric load forecasting based on Stacking.

E. MODEL PROCESS

Based on the above analysis, the steps of short-term synergetic electric load forecasting of the integrated energy system based on Stacking are:

(1) Data preprocessing, including the correction of outliers with mean values and normalization of data, normalizes data of different dimensions to the interval of (0,1).

(2) Divide the data set into the train, test, and validation sets. The test set is used to fit the synergetic electric load forecasting formula, and the validation set is used to verify the effect of the synergetic electric load forecasting.

(3) Obtain the optimal hyperparameters of each base learner based on grid search, and forecast the electric cooling and heating loads and REC, DEC, REH and DEH based on the Stacking ensemble learning method.

(4) Based on the forecast of the test set, the synergetic electric load forecasting formula is fitted to obtain the weight coefficients of each item in the formula. Then compare the effects of the quadratic synergetic electric load forecasting and the primary forecasting (forecasting based only on Stacking) in the validation set.

The synergetic electric load forecasting process of the integrated energy system based on the Stacking ensemble learning method is shown in Figure 7.

IV. CASE STUDIES

In this paper, Arizona State University Tempe campus's electric cooling and heating loads data from 2015 to 2019 are

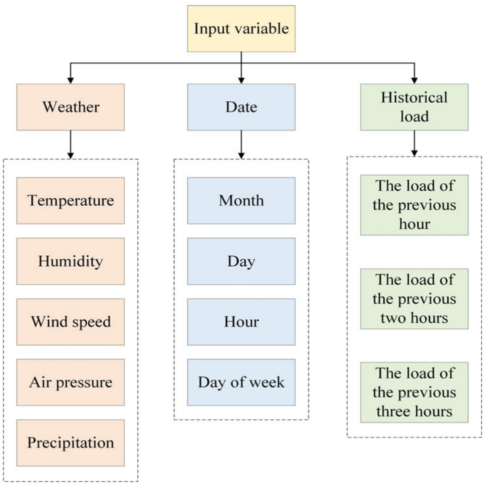


FIGURE 8. **Input variable types and corresponding indicators.**

selected for analysis. The data set includes 1826 days' hourly electric cooling and heating loads values for the Tempe campus from 2015 to 2019. Besides, meteorological information data for the Tempe campus from 2015 to 2019 were obtained from the meteorological website. According to the electric cooling and heating loads data, the corresponding indexes such as REC, DEC, REH, and DEH can be calculated. Before calculation, the cooling and heating load should be converted to the same unit (*kW*) as the electric load. During the conversion, the unit conversion calculation formula provided by the Campus Metabolism project is as follows: $1\ kW = 0.284\ Tons = 0.0034\ mmBtu$. The simulation analysis of the experiment is based on *MATLAB* and *Pycharm* platforms, and the implementation of the related machine learning algorithm calls Python's *Sklearn* machine learning library.

A. THE INPUT VARIABLES

For a forecasting model, the input variables are significant, usually determining the forecasting model's quality. In the load forecasting model, the input variables are related factors that affect the load, including weather, date, and other factors. The weather factor has a direct impact on the load. For example, in summer, when the temperature is high, the heavy use of refrigeration equipment such as air conditioning has a great demand for electric and cooling loads. Furthermore, the date factor also has a significant impact on the load. For example, the load demand on working days is higher than that on rest days, and the load demand for special holidays is higher than that on ordinary days. Besides, considering the regularity of load changes with time, the historical load also has a particular influence on the current load, so the historical load is also taken as an influencing factor.

To sum up, weather, date, and historical load are selected as input variables of the integrated energy system load forecasting model in this paper. The specific input variables types and corresponding indicators are shown in Figure 8.

B. DATA PREPROCESSING AND EVALUATION INDEXES

Before load forecasting, sample data should be preprocessed, including the correction of outliers and data normalization.

Due to the data acquisition devices' interference and other reasons, some outliers are usually produced, and the deviation between these outliers and the average values is large. If used in model training without treatment, the forecasting model will be adversely affected, and the accuracy will be reduced. So it is necessary to correct the outliers. The commonly used method is the average correction method, which replaces the outliers with the average value of the two observations before and after.

The dimension and value range of different input variables are different. If the original data is directly used in model training, the forecasting effect may be insufficient. Therefore, the variables of the data set need to be normalized before prediction. The normalization formula is as follows:

$$x_i^* = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{16}$$

where x_i and x_i^* respectively represent the values before and after normalization, $x_{\min}$ and $x_{\max}$ represent the minimum and maximum values in the sample variables, and the value range of each variable after normalization is (0,1).

In this paper, MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) are used as the load forecasting model's evaluation indexes to measure the forecasting. The formula of each evaluation index is as follows:

$$MAE = \frac{1}{m}\sum_{i=1}^{m}\left|y_i - \hat{y}_i\right| \tag{17}$$

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{18}$$

where y_i is the actual value of the load, $\hat{y}_i$ is the forecasting value of the load, and m is the number of samples.

C. ELECTRIC COOLING AND HEATING LOADS FORECASTING

The seasonal characteristics of different loads are different. This paper forecasts the electric and cooling loads in July in summer and the heating load in January in winter. The data of electric and cooling loads in July and heating load in January from 2015 to 2018 were taken as the training set to forecast the electric and cooling loads of 168 hours in a week in July and the heating load of 168 hours in a week in January 2019. The forecasting results by the Stacking forecasting model were compared with those of each base learner algorithm, and the load forecasting results are shown in Figure 9.

The results of various algorithms in different load forecasting are shown in Table 1. It can be seen that different algorithms had sound forecast effects on the electric and cooling loads in July because the electric and cooling loads change regularly in July, and all algorithms have learned the rules well from the training samples. However, the forecast results of heating load in January were relatively low, especially

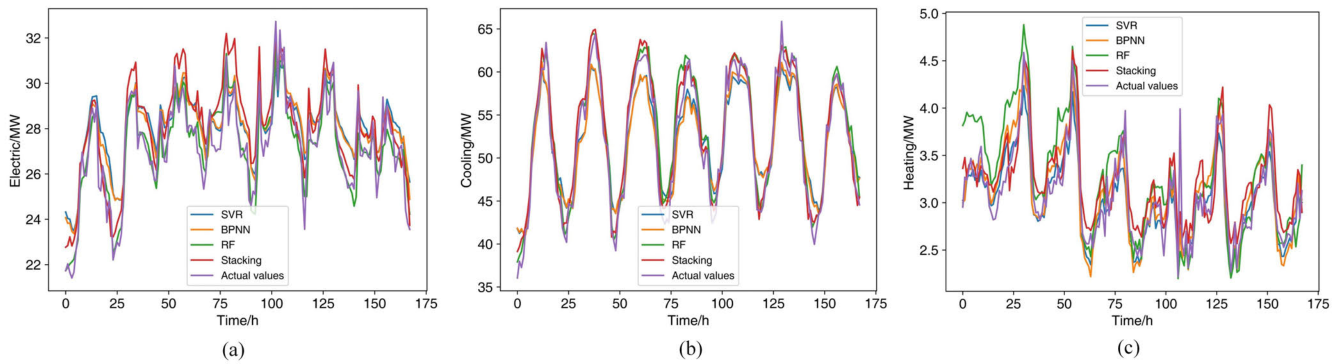


FIGURE 9. Loads forecasting results: (a) Electric load in July; (b) Cooling load in July; (c) Heating load in January.

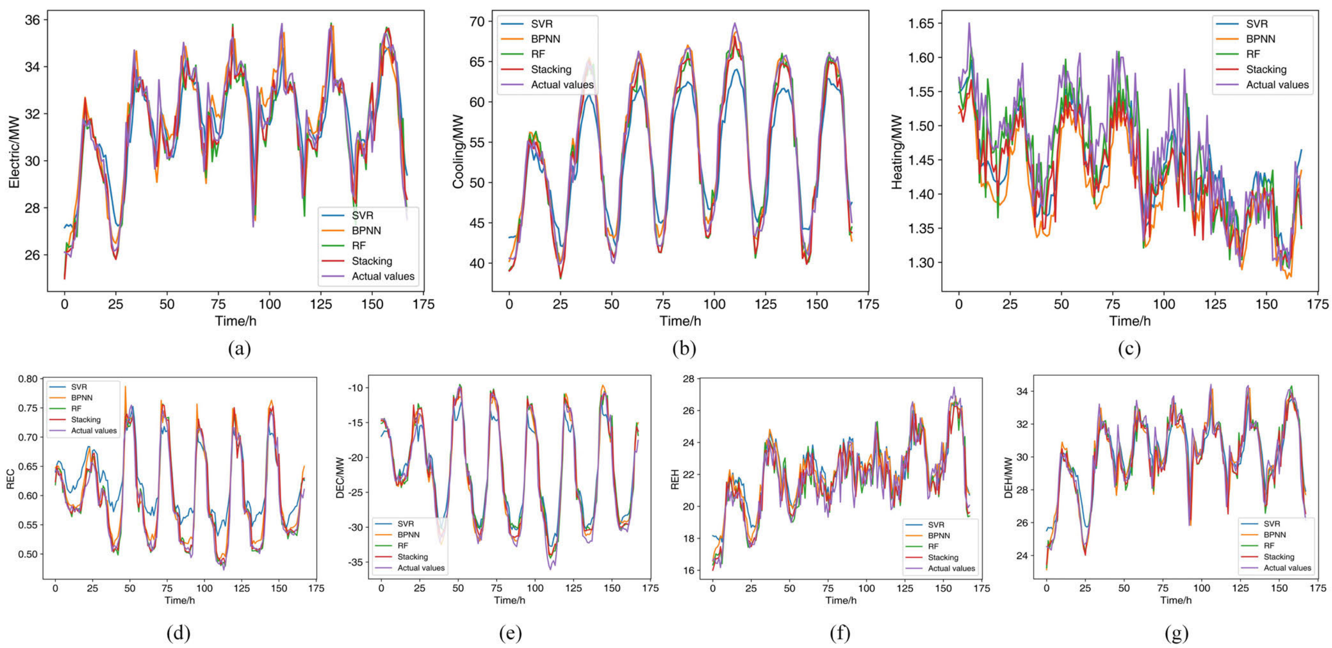


FIGURE 10. Loads and related indexes forecasting results: (a) Electric load; (b) Cooling load; (c) Heating load; (d) REC; (e) DEC; (f) REH; (g) DEH.

for the SVR algorithm, whose MAPE reached 9.1%, with a relatively large forecast error because the heating load in January have intense volatility and high randomness. Hence, the rules learned by each algorithm on the training set were relatively weak.

Also, the Stacking ensemble learning method had higher forecasting accuracy than other base learner algorithms. On the one hand, this is because the Stacking merges the advantages of the individual algorithm, and the influence of each algorithm's low forecast effect is weakened, thus strengthening the overall performance of the model. On the other hand, a single algorithm has low generalization ability; Stacking ensemble learning is a great way to overcome this shortcoming. Furthermore, unlike single algorithm training, which tends to fall into local minimum points, Stacking ensemble learning can effectively avoid this situation after the fusion of algorithms. So the Stacking ensemble forecasting model has a better effect than the ordinary single model.

D. SYNERGETIC ELECTRIC LOAD FORECASTING

The electric cooling and heating loads and their related indexes in summer from 2015 to 2017 were divided into the training set, the electric cooling and heating loads and their related indexes in summer of 2018 were divided into test set, and the electric cooling and heating loads and their related indexes in a week in July 2019 were divided into validation set. Firstly, the forecasting model was trained based on the training set, and then the test and validation sets were forecasted. Secondly, according to the forecasting and the actual values of the test set, the synergetic electric load forecasting formula proposed in this paper is fitted. Finally, the validation set's forecasting results by Stacking were compared with the synergetic electric load forecasting formula's fitting results.

The forecasting results of different loads and their related indexes in a week in the test set are shown in Figure 10.

Base on the forecasting results of different loads and their related indexes in the test set, to fit the synergetic electric load

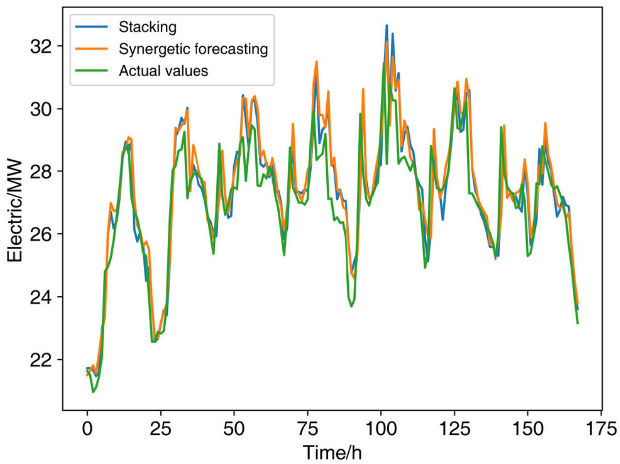


FIGURE 11. Forecasting results of Stacking and synergetic forecasting.

TABLE 1. Forecasting results comparison between different algorithms.

Load types	Algorithms	Evaluation indexes	
		MAE/MW	MAPE/%
Electric load in July	SVR	1.385	7.0
	BP	1.469	7.1
	RF	1.186	5.8
	Stacking	1.072	5.3
Cooling load in July	SVR	2.218	5.0
	BP	1.598	3.5
	RF	1.464	3.2
	Stacking	1.370	2.9
Heating load in January	SVR	0.241	9.1
	BP	0.219	8.5
	RF	0.164	6.3
	Stacking	0.146	5.4

forecasting formula proposed in this paper, the forecasting values of the electric cooling and heating loads, REC, DEC, REH, and DEH were taken as independent variables, and the actual values of the electric load were taken as dependent variables. The fitting results are shown in Table 2.

It can be seen that the coefficients α, β, and γ are positive, while δ and ε are negative. Indicating that the quadratic synergetic electric load forecasting values L''_{elec} are positively correlated with the forecasted values of the electric load L'_{elec}, the product $L'_{cool}L'_{REC}$ of the forecasted values of cooling load and REC, and the sum $\left(L'_{cool}+L'_{DEC}\right)$ of the forecasted values of cooling load and DEC, and the correlation between L''_{elec} and L'_{elec} is strong. However, the synergetic electric load forecasting values L''_{elec} are negatively correlated with the product $L'_{heat}L'_{REH}$ of the forecasted values of heating load and REH, the sum $\left(L'_{heat}+L'_{DEH}\right)$ of the forecasted values of heating load and DEH.

After obtaining each part of the synergetic electric load forecasting formula's weight coefficients, the forecasted values of different loads and their related indexes of the validation set were substituted into the formula. The obtained

TABLE 2. Coefficient values of synergetic electric load forecasting formula.

Coefficients	α	β	γ	δ	ε
Values	0.7941	0.3878	0.2044	-0.2033	-0.2456

TABLE 3. Evaluation indexes of electric load forecasting results.

Algorithms	Evaluation indexes	
	MAE/MW	MAPE/%
Primary forecasting based on Stacking	1.072	5.3
Quadratic synergetic forecasting	0.936	4.7

TABLE 4. Average MAPE in June, July, and August.

Formulas	Average MAPE/%		
	June	July	August
F1(proposed in this paper)	2.57	2.80	2.82
F2	3.34	3.45	3.33
F3	3.03	2.94	2.83

synergetic electric load forecasting values were compared with the forecasted values of Stacking in 4.2 and the actual values. The results are shown in Figure 11.

Comparison of evaluation indexes of electric load forecasting results based on Stacking alone and synergetic forecasting is shown in Table 3. It can be seen that compared with the electric load forecasting based on Stacking alone, MAE of synergetic forecasting decreased from 1.072 MW to 0.936 MW, MAPE decreased from 5.3% to 4.7%, which decreased by 0.6%.

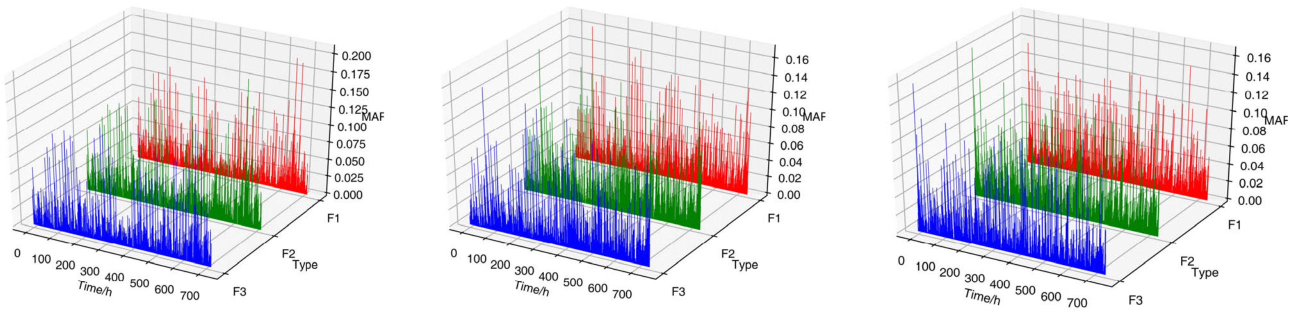
To thoroughly verify the effectiveness of the synergetic electric load forecasting formula proposed in this paper for improving the forecasting accuracy, we take the synergetic electric load forecasting formula proposed in this paper as F1, two other synergetic forecasting formulas F2 and F3 are constructed. F2 is a linear fitting formula base on the forecasting values of electric load, and F3 is a linear fitting formula base on the forecasting values of electric, cooling, and heating loads. The formulas of F2 and F3 are as follows:

$$L''_{elec} = aL'_{elec} \tag{19}$$

$$L''_{elec} = bL'_{elec} + cL''_{cool} + dL''_{heat} \tag{20}$$

Take the data of June, July, and August of 2019 as the validation set, and the formula F1, F2, and F3 were used to quadratic fit the forecasting values of the electric load of 3 months. Hourly and average MAPE in June, July, and August are shown in Figure 12 and Table 4.

It can be seen that, compared with formulas F2 and F3, which only consider the linear relationship, the synergetic electric load forecasting formula proposed in this paper shows higher accuracy in the validation set. Each month's mean absolute percentage error is 2.57%, 2.80%, and 2.82%, respectively, which are all lower than those of 3.34%, 3.45%, and 3.33% of formulas F2 and 3.03%, 2.94%, and 2.83% of formulas F3.



(a) (b) (c)

FIGURE 12. Hourly MAPE in June, July, and August: (a) June; (b) July; (c) August.

Synergetic electric load forecasting explores the deep nonlinear relationship between the actual values of electric load and forecasting values of electric cooling and heating loads and their related indexes. It not only corrects the deviation between the primary forecasting and the actual values of the electric load to some extent but also considers the influence of cooling load, REC and DEC, heating load, REH and DEH on the electric load, and integrates the synergistic effect between different types of loads, therefore, the synergetic electric load forecasting proposed in this paper can effectively improve the short-term electric load forecasting accuracy of the integrated energy system.

V. CONCLUSION

Integrated energy system synergetic electric load forecasting improves forecasting accuracy because the quadratic fitting considering the nonlinear synergetic relationship between different loads covers the influence of cooling and heating load on electric load. It corrects the primary forecasting error and transforms the indescribable correlation between electric cooling and heating loads into a combination of weighted independent variables to quantify the relationship between loads from multiple perspectives. At present, the integrated energy system has mature technical support in load data acquisition. Therefore, the synergetic electric load forecasting of the integrated energy system has an individual application space. As an essential part of the day-ahead scheduling, the accurate integrated energy system electric load forecasting is bound to get enough attention.

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