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Forecasting Supply and Demand in Electricity Spot Market Based on Time Series Forecasting Algorithm with Cloud Native Platform Construction

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Abstract This paper proposes an electricity price prediction methodology and computational framework that integrates time series prediction algorithms and cloud native architecture for the multi-dimensional characteristics of the electricity spot market. The operation mechanism and tariff formation mechanism of three types of electricity market models, namely, pool-type, bilateral-type and hybrid-type, are systematically analyzed, and the normal distribution test is used to quantify the tariff distribution law. The dynamic similar subsequence prediction model is proposed, and the error correction mechanism is constructed by the time window optimization algorithm. We design a cloud-native edge computing framework for the Internet of Things (IoT), which solves the real-time computing and data security problems in resource-constrained scenarios at the edge in a multi-dimensional way. Building the arithmetic example, the proposed model improves significantly in prediction accuracy compared with traditional ARIMA and ANN methods, and the average absolute error is reduced to 0.249, which has the best prediction results.

Index Terms time series forecasting, dynamic similar subsequence, cloud native, electricity market, electricity price forecasting

I. Introduction

In recent years, China's demand for electric energy has been increasing, and the construction of the spot market for electricity has been improving [1], [2]. In the new power system reform, the spot market, as an important part of it, cooperates with the medium- and long-term market to achieve the optimal allocation of resources [3], [4]. With the further deepening of China's power reform, the spot market will become the core of China's power market construction [5].

The development of China's electric power spot market is generated in the context of realizing China's electric power reform and development goals, which plays a very important role in realizing the rational use of China's electric power resources, and at the same time further promotes the rapid development of China's socio-economic [6]-[9]. At present, the electric power spot market mainly includes day-ahead, intraday and real-time trading markets for electric energy and auxiliary services such as standby, and the spot market, together with the medium- and long-term direct trading market and the futures electric power derivatives market, basically constitutes the modern electric power market system [10]-[13]. Electricity spot market in the development can realize the balance of the use of electricity power, but also in the development to ensure that always meet the requirements of the masses of electricity, for the realization of social and economic development has a very important significance [14], [15]. Its basic rules are an important institutional framework for regulating market trading behavior, maintaining market order, and guaranteeing the security of power supply, with the core being to guide the optimal allocation of power resources through price signals [16], [17]. Based on this, the study of supply and demand prediction and the construction of cloud native platform in the electricity spot market is of great significance for the optimization of electricity resource allocation and the efficient operation of the collaborative new power system [18], [19].

In this paper, we first analyze the game rules and the path of electricity price formation in the electricity market, and propose a probabilistic characterization method of electricity price based on the normal distribution test. A dynamic similarity subsequence prediction model is introduced to capture the local similarity of electricity price fluctuations through a time window adaptive optimization algorithm. A cloud-native edge computing framework is designed for power IoT to overcome the real-time computing bottleneck in resource-constrained scenarios on the edge side. Select an electricity market data for arithmetic analysis and use the prior seasonal index method to remove the seasonal effect. The proposed model is compared with ARIMA and ANN models in controlled experiments to investigate the effectiveness and superiority of the proposed model in practical applications.

II. Combining Dynamic Similarity Subsequence and Cloud Native Electricity Spot Market Supply and Demand Forecasting

As the core link in the reform of electric power system, the precision of supply and demand forecasting directly affects the efficiency of electricity price formation and the decision-making of market participants. However, the electricity market is characterized by strong nonlinearity, high stochasticity and multi-subject game, and the traditional forecasting methods are difficult to cope with the dynamic changes in the complex market environment. Existing research focuses on single-market models or static statistical laws, but lacks systematic analysis of the dynamic coupling mechanism and tariff probability distribution characteristics of hybrid markets, and real-time forecasting technology under the constraints of terminal computing resources is in need of a breakthrough.

This chapter focuses on two core issues: first, how to construct dynamic prediction models adapted to the characteristics of multiple types of electricity markets, and second, how to realize high-concurrency and low-latency computing empowerment at the edge side through cloud-native architecture.

II. A.Electricity market model

Although in the practice of countries around the world, there are many models of the electricity market, but from the point of view of the organization of the market, there are a total of three basic market model, the existing market model is based on these three basic market model development and enrichment.

(1) Associated market: Associated power market is a centralized market for power sellers and buyers to clear the market results. The buyer or seller provides the pool market with an offer for the quantity and price of electricity to be purchased or sold, and then the pool organization clears the market based on the offers of the buyer and seller, and the two parties conduct transactions in accordance with the cleared price of electricity. In the pool electricity market, each seller competes with each other for the right to sell a certain amount of electricity, not some specific buyer, if the offer is too high, it is possible that the clearing price is lower than its price offer and lead to the failure of the sale of electricity; similarly, each buyer is competing for the right to buy a certain amount of electricity, if its price offer is too low, the clearing price is higher than the offer price, which will lead to the failure of the purchase of electricity. Failure to purchase power. In a pooled market, the Independent System Operator (ISO) is responsible for the economic dispatch of the power system and offers a uniform tariff to the market that best reflects the marginal costs of market participants and maximizes market competitiveness. In a pooled market, the price paid by all purchasers who win an offer is the clearing price, which is the highest price offered by all sellers who win an offer.

(2) Bilateral market: Bilateral trading contracts are contracts for trading electricity that are negotiated and coordinated between power purchasers and power sellers. This trading model exists independently of the Independent System Operator. However, in this trading model, the Independent System Operator needs to verify that the transmission lines involved in each bilateral trading contract have sufficient capacity to transmit electricity and ensure system security when transmitting electricity. The bilateral trading model is very flexible because the parties can specify exactly what they want. However, this model also has its own disadvantages, on the one hand, the cost of negotiating and writing contracts is high, on the other hand, bilateral trading involves the problem of negotiating the other party's reputation risk.

(3) Hybrid market: the hybrid market model is a combination of the affiliate market model and the bilateral transaction model. In the hybrid market, participation in the pool market offer is not mandatory, each seller and buyer of electricity can be in the market with other buyers and sellers of electricity directly signed bilateral transaction contracts, but also they can choose to participate in the pool market so as to accept the spot market price of electricity in the pool market. In this market model, the pool market is responsible for serving all participants who do not choose to enter into bilateral power trading contracts. The hybrid market gives electricity market participants full choice and space to find the best possible provider to meet their electricity needs, which helps to improve market efficiency.

II. B.Characteristics of the probability distribution of electricity prices

Under a transparent, open and competitive electricity market, since there is a great deal of uncertainty in the fluctuation of electricity prices at any moment, electricity prices can be approximated as random variables obeying a certain probability distribution, therefore, in the analysis of the characteristics of electricity prices, in addition to grasping the above characteristics of electricity prices, it is also necessary to grasp the characteristics of probability distribution of electricity prices.

In the study of certain problems in the power market, when it comes to the probability distribution of electricity price, the researcher usually assumes that the electricity price in the power market under study obeys the normal distribution. However, whether the electricity price can be assumed to obey the normal distribution under different electricity markets is a problem that needs to be verified and analyzed through mathematical methods.

When analyzing the probability distribution of a random variable, it is common to first test whether the random variable obeys a normal distribution, and if it does not, then consider what kind of distribution it may obey. The steps for analyzing the probability distribution of a random variable are as follows:

(1) By the distribution of the random variable graph intuitively determine whether the graph coincides with the normal distribution curve.

(2) Use mathematical methods to verify whether the random variable obeys a normal distribution.

1) Probability density function and numerical characteristics of the normal distribution : $N(\mu,\sigma)$

Probability density function of the normal distribution $N(\mu,\sigma)$:

$$f(x)=\frac{1}{\sqrt{2\pi}\sigma}e^{-\frac{1}{2\sigma^2}(x-\mu)^2}\left(\text{Constant } \sigma>0\right) \tag{1}$$

Numerical characterization of the normal distribution $N(\mu,\sigma)$:

$$E(x)=\mu \tag{2}$$

$$D(x)=\sigma^2 \tag{3}$$

where μ is the mean, σ is the standardized variance, $E(x)$ is the mathematical expectation, and $D(x)$ is the variance.

2) Skewness and kurtosis are used to initially test whether a random variable obeys a normal distribution:

Skewness and kurtosis are used to describe the shape and symmetrical nature of the distribution of a random variable, as well as the degree to which the distribution of a random variable deviates from the normal distribution.

The skewness of the random variable x:

$$S=\frac{E\left(x-E(x)\right)^3}{\left[D(x)\right]^{\frac{3}{2}}} \tag{4}$$

The kurtosis of the random variable x:

$$K=\frac{E\left(x-E(x)\right)^4}{\left[D(x)\right]^2} \tag{5}$$

where $E(x)$ is the mathematical expectation and $D(x)$ is the variance.

The smaller the S, the closer the distribution of the random variable is to the normal distribution; conversely, the more it deviates from the normal distribution. S greater than 0 indicates that the distribution of the random variable is right-skewed relative to the normal distribution; S less than 0 is the opposite. The larger the K, the sharper the graphical curve of the random variable's distribution; the opposite is the flatter.

3) The Jarque-Bera (J-B) test is used to verify whether the random variable obeys a normal distribution:

The normality test of the overall distribution is generally taken as the J-B test. A normal distribution has a skewness $S=0$ and a kurtosis $K=3$. If the samples are from a normal distribution, they are in the neighborhood of 0 and 3, respectively, based on which a statistic containing χ^2 (chi-square) is constructed:

$$JB=\frac{n-d}{6}\left(S^2+\frac{(K-3)^2}{4}\right) \tag{6}$$

where n is the sample capacity, d is the degree of freedom, S is the skewness, and K is the kurtosis.

The J-B test proves that the JB statistic asymptotically obeys a chi-square distribution with 2 degrees of freedom under the assumption of a normal distribution. If JB exceeds the value of the critical chi-square at a certain level of significance, the assumption of normal distribution is rejected; otherwise, the assumption of normality is accepted.

II. C.Dynamic similar subsequence prediction model

II. C. 1) Prediction algorithms

After selecting the dynamic similarity subsequence, the prediction of the parameter to be measured is based on the dynamic similarity subsequence and the internal change process of the target parameter in the subseries of the parameter to be measured. In this section, the rate of change of $L_r(W)$ with respect to $L_r(W-1)$ is considered approximately equal to the rate of change of $L_i(W)$ with respect to $L_i(W-1)$. As a result, the parameter to be measured $L_r(W)$ can be predicted by the following equation.

$$\hat{L}_r(W)=\frac{L_i(W)\cdot L_r(W-1)}{L_i(W-1)} \tag{7}$$

where $\hat{L}_r(W)$ is the theoretical predicted value of the parameter to be measured $L_r(W)$.

The relative error between the theoretical predicted value $\hat{L}_r(W)$ and the actual value $L_r(W)$ can be expressed as:

$$\varepsilon_W=\frac{\hat{L}_r(W)-L_r(W)}{L_r(W)} \tag{8}$$

The corresponding relative error ε_W will be different for different dynamically similar subsequences selected. It can be assumed that the relative error ε_W is approximately equal to the average relative error of the rate of change of the first $W-1$ target parameters of the parameter subsequence to be measured.

$$\begin{aligned}\bar{\varepsilon}_W&=\frac{1}{W-2}\sum_{b=2}^{W-1}\left[\frac{L_r(b)-L_r(b-1)}{L_r(b-1)}-\frac{L_i(b)-L_i(b-1)}{L_i(b-1)}\right]\\&=\frac{1}{W-2}\sum_{b=2}^{W-1}\left[\frac{L_r(b)}{L_r(b-1)}-\frac{L_i(b)}{L_i(b-1)}\right]\end{aligned} \tag{9}$$

$$\varepsilon_W\approx\bar{\varepsilon}_W \tag{10}$$

where $\bar{\varepsilon}_W$ is the average relative error of the rate of change of the first $W-1$ target parameters of the subseries of the parameter to be measured.

Therefore, associating Eqs. (7) to (10), the parameter to be measured $L_r(W)$ can be calculated by the following equation.

$$L_r(W)=\frac{L_i(W)\cdot L_r(W-1)}{L_i(W-1)\cdot(\bar{\varepsilon}_W+1)} \tag{11}$$

II. C. 2) Method for determining the length of the time window

The length of the time window (i.e., the value of W) depends on the duration of the cumulative effect in the case under study. Therefore, in order to determine the value of W before applying the proposed methodology to time series forecasting, it is first necessary to train the data set.

Mathematically, the value of W can be determined by minimizing the prediction error when the proposed model is applied to the training data set. In this paper, the mean absolute percentage error (MAE) is used to evaluate the prediction error.

$$MAPE=\frac{1}{N}\sum_{h=1}^{N}\left|\frac{\hat{X}(h)-X(h)}{X(h)}\right| \tag{12}$$

where $\hat{X}(h)$ is the predicted value at the moment h, which can be obtained by the proposed prediction model; $X(h)$ is the actual recorded value at the moment h; and N denotes the number of the predicted objects in the training data set.

In practice, the time window length W can be calculated and derived by the method of cross-validation. Cross-validation is to group the data samples, with one part as the training set to train the classifier and the other part as the validation set to validate the model obtained from the test training. In this section, n fold cross-validation can be used to obtain the optimal series value of W. In n fold-cross validation, the original dataset is divided into n groups of subseries sets. In all n subseries sets, $n-1$ subseries sets are trained as a training set and a subseries set is used to validate the model generated from the training of this $n-1$ training set. Thus, this process is repeated n times, each time using one of the subsequence sets for validation once. The obtained n results are then averaged and combined to produce the final result. The advantage of this method is that all samples are trained and validated.

The prediction error $e_{fold}\{W=j\}$ is calculated for each fold by varying the size of W, where $j=1,2,\cdots,W_{\max}$. The value of $W_{\max}$ can be set by actual experience. The average prediction error corresponding to different time window lengths can be calculated by the following equation:

$$e_j=\frac{1}{n}\sum_{i=1}^{n}e_{fold}\{W=j\} \tag{13}$$

The value of W corresponding to the smallest hour of e_j is the length of the selected time window. However, it is worth noting that W is a positive integer and the value of W will not be very large in practice. Therefore, it is not necessary to find out the appropriate value of W through too many attempts.

$$W=\arg\min\{MAPE\} \tag{14}$$

New data can be added to the training set to redefine the length of the time window. However, when the development of the time series is relatively stable, i.e., there are no major events or incidents that can have a sustained impact on the process of time series change, the length of the time window only needs to be revised periodically as planned. On the contrary, if major events or accidents occur that can have a sustained impact on the time series process, these newly recorded data need to be added to the training set in a timely manner and the length of the time window needs to be redetermined.

II. D.Construction of Cloud-Native Based Edge Computing Framework for Power IoT

In order to better solve the problems of terminal, operation and maintenance, business, ecology and other dimensions, it is necessary to analyze and outline the technical characteristics of the power IoT edge computing terminal and build its basic framework based on cloud native. In the following, we will analyze and discuss these dimensions one by one in terms of the underlying arithmetic hardware facilities, the platform layer arithmetic resource engine, the platform functional components, the application layer power business, and the ecological development direction.

(1) In terms of arithmetic hardware facilities: Cloud Native has built an arithmetic resource pool based on X86, ARM and even mixed server clusters, and considering the limited arithmetic resources of power edge computing, the current cutting-edge mainstream and grid-oriented power-specific domestic chips can be used in hardware, and of course, according to different scenarios of the security and controllability requirements can be used for non-domestic ARM architecture chips;

(2) In terms of arithmetic resource engine: the current mainstream Kubernetes container cluster management engine of cloud native provides management tools for container creation and resource allocation for the operation of business applications, and in order to improve the resource utilization rate of electric power edge computing and the execution efficiency of business applications, it is also necessary to build a special operating system and container engine for electric power edge computing;

(3) In terms of platform functional components: cloud native has a series of components such as message middleware, database, operation log, interface, mirror warehouse, etc., and considering the unified model and statute of data transmission on the edge side, the power edge computing should pay more attention to the integration of protocol conversion, secure and trustworthy computing, in order to safeguard the communication security of the fuzzy area outside the traditional security protection boundary;

(4) In terms of power business applications: cloud native both based on microservices and monolithic application architecture based on the construction of business systems and deployed in the server, while considering the computational parallelism and execution speed, power edge computing can also draw on microservices decomposition of the execution of the idea of different types of power microservices with different functional characteristics can be deployed in the multi-core heterogeneous system-on-a-chip;

(5) In the direction of ecological development: electric power edge computing should pay more attention to the construction of application stores and develop in the direction of software-defined terminal functions, in order to cultivate the ecology of the convergence and symbiosis of multiple electric power applications.

After analyzing the technical characteristics of cloud-native based power IoT edge computing, the constituent elements of power IoT edge computing can be summarized, and its hardware and software framework is shown in Fig. 1, which contains a total of four sub-layers: hardware layer, platform layer, engine layer, and application layer.

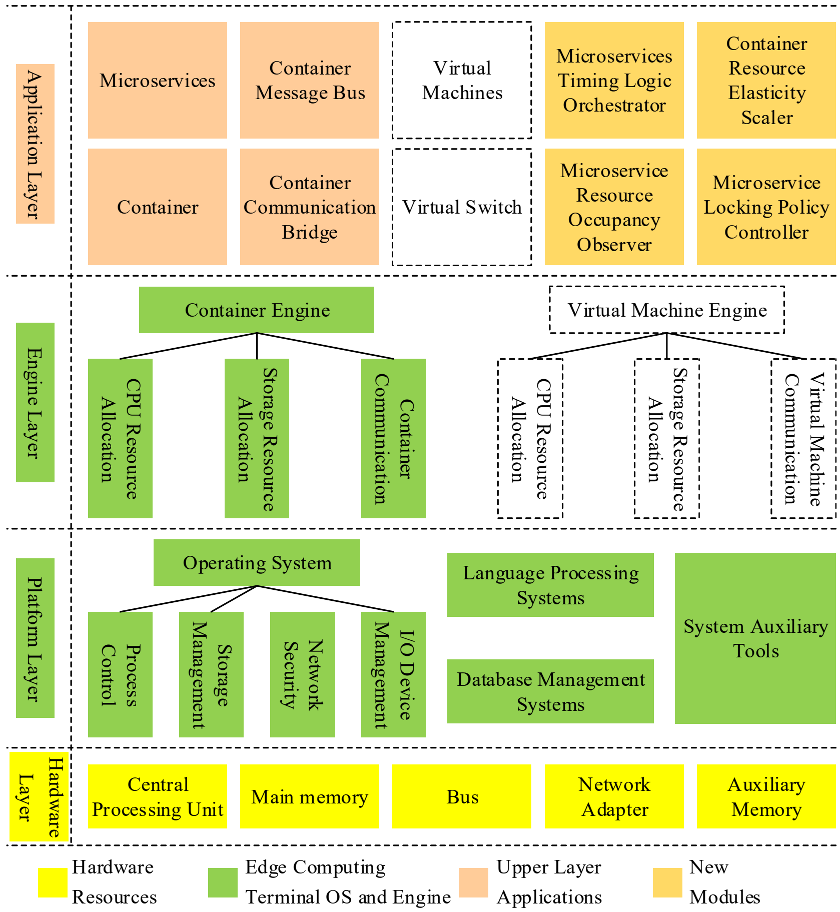


Figure 1: Cloud-native edge computing framework for power iot

III. Example analysis of electricity spot market supply and demand forecasting based on time series forecasting algorithm

III. A. Modeling

In this paper, the electricity price data from September to December 2024 of an electricity market is selected for modeling and analysis. Remembering these electricity price data as a time series yt, the electricity price data of this electricity market is shown in Figure 2.

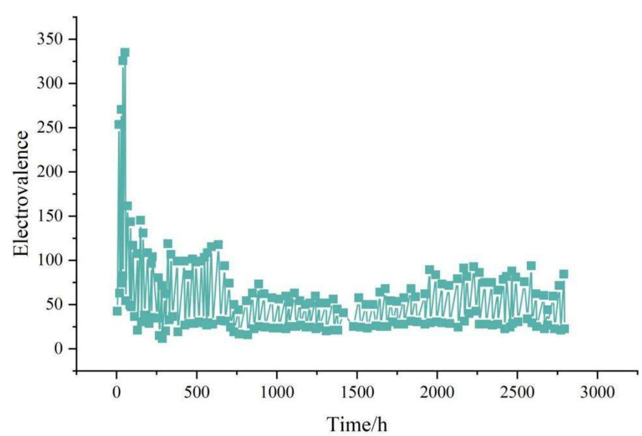


Figure 2: Electricity price data for a power market from September to December 2024

As the fluctuation of the electricity price data change is relatively large, in order to reduce the fluctuation of the sequence, the natural logarithmic transformation, i.e., the sequence ly, is used to make the change relatively smooth, which is conducive to modeling and analysis. The sequence ly of electricity price through logarithmic conversion is shown in Figure 3.

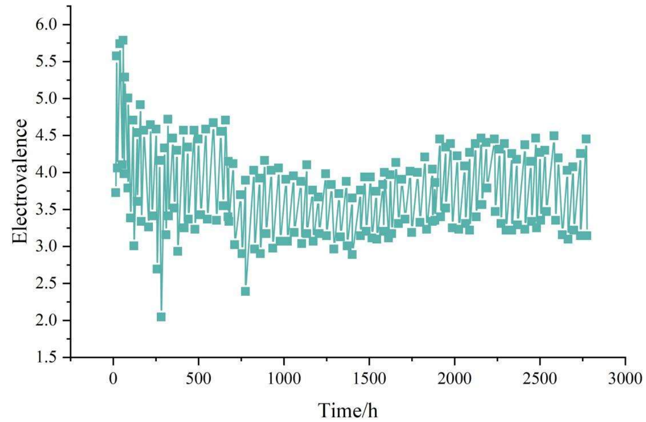


Figure 3: Time-series with Log conversion

In time series forecasting methods, the dynamic similar subsequence method analysis is performed for smooth time series, so the series needs to be made to satisfy the smoothness requirement before modeling the electricity price series. Generally, the smoothness of the series is determined by analyzing the autocorrelation and partial autocorrelation analysis plots of the electricity price series. In reality, the electricity price series often has some or several trends, such as trend terms, seasonal terms, heteroskedasticity and so on. From the above figure, it can be seen that the tariff series is non-smooth, and the trend term of the tariff series is judged to be eliminated by analyzing the correlation and partial autocorrelation plots of the original tariff series and the autocorrelation and partial autocorrelation plots of its d-order difference. It can be seen that the trend term is basically eliminated after the natural logarithmic transformation of the 2nd-order difference, but the electricity price series repeats the feature of non-zero significance around the interval point of 24. Therefore, the presence of seasonal terms in the tariff series is considered.

Seasonal differencing is performed on the tariff series of order 24, and the autocorrelation (AC) and partial autocorrelation (PAC) plots of the series after seasonal differencing are shown in Figure 4.

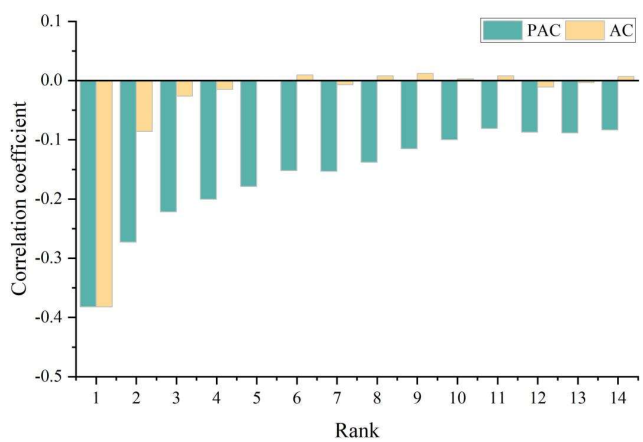


Figure 4: Analysis of autocorrelation and partial autocorrelation

It is not difficult to realize that the electricity price data are clearly cyclical by observation. Seasonal adjustment is carried out by eliminating the seasonal terms using the prior seasonal index method, where the period l=48 and the number m=8. The values of seasonal index for each half hour are shown in Table 1. Then, then the dynamic similar subsequence method is used to forecast the electricity price.

Table 1: Seasonal index values

Time	Seasonal term	Time	Seasonal term	Time	Seasonal term	Time	Seasonal term
0:00	0.8038	6:00	0.6375	12:00	1.0289	18:00	2.1863
0:30	0.7835	6:30	0.8723	12:30	0.9963	18:30	2.3904
1:00	0.7511	7:00	0.9411	13:00	0.9737	19:00	1.9375
1:30	0.6947	7:30	0.8937	13:30	0.8668	19:30	1.6375
2:00	0.6022	8:00	1.1835	14:00	0.8375	20:00	1.4652
2:30	0.5738	8:30	1.2846	14:30	0.8262	20:30	1.2937
3:00	0.5344	9:00	1.2248	15:00	0.8107	21:00	1.1194
3:30	0.4836	9:30	1.2058	15:30	0.8038	21:30	1.0863
4:00	0.4522	10:00	1.1735	16:00	0.9287	22:00	0.9286
4:30	0.4185	10:30	1.1433	16:30	0.9822	22:30	1.0737
5:00	0.4726	11:00	1.0975	17:00	1.0783	23:00	0.9275
5:30	0.5824	11:30	1.0663	17:30	1.8263	23:00	1.0386

III. B. Analysis of model prediction effects

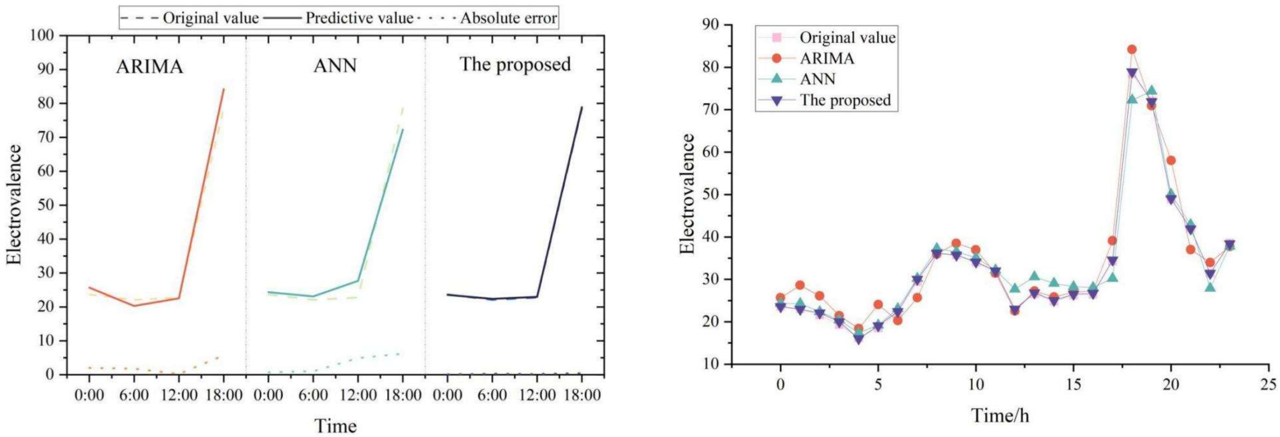
Finally, the ticked-off seasonal indices are restored. In this paper, 2 mainstream forecasting models, ARIMA and ANN, are introduced for comparison, and the forecasting results of the three models for one of the randomly selected days are shown in Table 2.

It is not difficult to find that in the [0:00,10:00] time period, the average absolute error of the ARIMA model prediction is significantly higher than that of ANN and dynamic similar subsequence model. In the time period [12:00,17:00], the average absolute error of the ANN model prediction is higher than that of the ARIMA and dynamic similar subsequence models. The proposed model has the highest prediction accuracy at all moments, i.e., it has the best prediction results.

Table 2: Pairs of the three forecasting methods

Time	Original value	Forecasting method		
		ARIMA	ANN	The proposed
0:00	23.65	25.6863	24.3586	23.5642
1:00	23.06	28.6203	24.3164	22.9467
2:00	21.58	26.0974	22.3752	22.0947
3:00	19.33	21.4678	20.4186	20.0183
4:00	16.22	18.3872	17.3861	16.0372
5:00	18.57	24.0483	19.2285	19.0376
6:00	22.09	20.2864	23.1084	22.3861
7:00	29.47	25.6865	30.2047	30.0383
8:00	36.09	35.9743	37.2261	36.2084
9:00	35.73	38.4979	36.5273	35.7251
10:00	34.02	36.9473	35.1232	34.1085
11:00	31.58	31.4753	32.2078	32.0178
12:00	22.77	22.5363	27.6863	22.9741
13:00	26.58	27.2486	30.5862	26.7973
14:00	24.84	25.8381	29.0484	25.0184
15:00	26.29	26.9731	28.2861	26.5022
16:00	26.42	27.2753	28.0583	26.7031
17:00	34.28	39.0863	30.2286	34.5613
18:00	78.49	84.2078	72.2861	78.9104
19:00	72.05	70.9103	74.3862	71.8935
20:00	48.93	58.0376	50.0375	49.0284
21:00	42.08	37.0286	42.9081	41.9026
22:00	31.44	33.9927	27.9368	31.4147
23:00	38.56	37.7386	37.8015	38.4028

The results of the comparative analysis of the three prediction models are shown in Fig. 5, which demonstrates that the prediction results of the proposed model can better overlap with the real values with an average absolute error of only 0.249, i.e., the prediction effect is better than the two control models. The example analysis results further verify that the dynamic similar subsequence model proposed in this paper captures the cyclical and time-varying characteristics of electricity price through time window optimization, which is more adaptive to the dynamic coupling mechanism of the hybrid market compared with the traditional static model, and the parallel deployment of the cloud-native edge computing framework further improves the prediction efficiency.



(a)Partial time point (b)Total time

Figure 5: Comparative analysis results of the three prediction models

IV. Conclusion

In this paper, combining dynamic similar subsequence and cloud native, we design a power spot market supply and demand prediction model, and select examples to explore its application effect.

One day is randomly selected for analysis, and in the time period of [0:00,10:00], the average absolute error of the ARIMA model prediction is significantly higher than that of the ANN and dynamic similar subsequence model. During the time period [12:00,17:00], the average absolute error of the ANN model prediction is higher than that of the ARIMA and dynamic similar subsequence models. The proposed model has the highest prediction accuracy at all moments, and the prediction results can be better overlapped with the real values, and the average absolute error is only 0.249, i.e., it has the best prediction results.

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