IEC-FOF: An Industrial Electricity Consumption Forecasting and Optimization Framework

Fei Teng, Yanjiao Chen(✉), and Wenyuan Xu

College of Electrical Engineering, Zhejiang University, Hangzhou, China
{tengfei118,chenyanjiao,wyxu}@zju.edu.cn

Abstract. To achieve carbon peaking and carbon neutrality goals, large-scale electricity consumption units such as factories and buildings need comprehensive solutions for energy saving and cost reduction. We propose a framework for industrial electricity consumption prediction and optimization based on multi-source information fusion named IEC-FOF. We design the electricity consumption prediction module by utilizing historical data, weather, and date info. Besides, we realize an electricity consumption optimization module based on clustering methods, including typical abnormal electricity consumption action identification, electricity consumption pattern recognition, and electricity consumption optimization suggestions.

Keywords: Industrial electricity · Electricity consumption forecasting · Time series analysis

1 Introduction

With the global warming and increase in pollution, in response to the United Nations' call to reduce carbon emissions, many countries have proposed carbon emission reduction programs suitable for their national conditions. In China, the government proposed carbon peaking and carbon neutrality goals [1]. According to the current carbon calculation scheme, a large proportion of carbon emissions come from the use of electricity. Through electricity usage optimization such as changing electricity schedule, people can achieve significant electricity savings without changing the facility infrastructure and thus reduce carbon emissions.

The existing work of electricity forecasting mainly relies on statistical methods and traditional time series forecasting models, which has achieved acceptable results in different scenarios [2–5]. In addition, in recent years, many DNN-based works have made innovations in the time series data prediction model and anomaly detection model, such as [6,16].

However, most of the existing research methods study the electricity consumption of a single area and electrical equipment, they cannot efficiently and

Z. Xiao et al. (Eds.): ICECI 2022, LNICST 478, pp. 97–110, 2023.
https://doi.org/10.1007/978-3-031-28990-3_8

precisely process the electricity consumption data under cross-industry and multi-scene conditions. In the current new scenario, we can summarize the following two technical challenges.

- The factors affecting electricity consumption are multifarious, resulting in the result that the traditional modeling and estimation methods are difficult to adapt to the current scene.
- Electricity consumers in different industries or regions have different action patterns. A unified model is difficult to model complex electricity consumption scenarios.

To address the above challenges, we propose IEC-FOF (An Industrial Electricity Consumption Forecasting and Optimization Framework). The framework is mainly composed of two parts: the data layer and application layer, the data layer includes data source collection, data preprocessing, and feature engineering module. Besides, the application layer includes electricity consumption prediction and an optimization module.

The granular data processing and feature engineering modules support the performance of the application layer. We used historical electricity usage information, weather, date, and other information to make predictions for future electricity consumption behavior, and split the model based on industry information for personalized training.

After obtaining the predicted values through a time series model, we can flexibly add application modules according to the specific business needs, such as anomaly detection based on prediction error and electricity consumption pattern recognition based on historical electricity consumption information. Based on the application layer services described above, we can generate recommendations for electricity consumption behavior, such as migrating electricity usage during peak periods to valley periods.

We summarize our main contributions as follows.

- We present a integrated electricity optimization solution for industrial scenarios that can automated response to multiple industries and multiple information sources.
- We deploy and apply the algorithm on an industrial electricity dataset. Some typical experimental results are presented to verify the universality and validity of IEC-FOF.

2 Related Work

2.1 Electricity Consumption Forecasting

There are many resultful methods for time series forecasting, and one application scene is electricity consumption forecasting. People can utilize historical information and some supplementary information like weather conditions, to predict electricity consumption levels in the future. The most widely used prediction algorithms include the following three:

- 1. Traditional sequence model like ARIMA [18], Prophet [10]. These methods decompose time series to obtain the seasonal term, trend term, noise, and other components, which are then processed and predicted respectively and then synthesize the prediction results finally.
- 2. Regression model like XGBoost [19], LightGBM [11]. This kind of method is the most widely used method in the industry. It needs to sort out data sources, conduct data preprocessing, feature engineering, and finally use the machine learning method to conduct regression modeling, and then employ future time features for prediction.
- 3. Sequence model like RNN, LSTM [7]. These models extract states from sequences using recurrent neural networks and reconstruct future sequences from the hidden state.

2.2 Time Series Pattern Recognition

Sequence pattern recognition here refers to the extraction of specific and representative pattern information from a sequence, such as recurring short curve, some segments with distinguishing effects, etc. This section focuses on techniques, anomaly detection, and operational research optimization that are relevant to the topics of our work.

As for anomaly detection, common methods include statistical methods, reconstruction error based methods, prediction error based methods [16], etc. As for pattern recognition, sequence clustering, and classification, the current prevalent method is to learn multi-dimensional data by representation, obtain fixed-length vectors and carry out subsequent applications [13–15].

3 System Overview

As is shown in Fig. 1, IEC-FOF consists of the data source layer, preprocessing layer, feature engineering layer, forecasting layer, and optimization layer. We will detail the information for each layer in the next section, and introduce a top-down structural explanation in this section.

To achieve the goal of electricity saving, we need to disassemble the target itself to get several specific business directions. This paper mainly focuses on the detection of abnormal electricity consumption behavior and the generation of suggestions for electricity consumption optimization. Such business demands need to be based on the prediction of future electricity consumption behavior, so we need the forecasting layer to support the business optimization layer at the top of the framework.

Meanwhile, predicting future electricity consumption needs to be based on historical data and information that can be accurately estimated in the future. In IEC-FOF, it refers to historical electricity consumption data, weather, date, and other information respectively.

In summary, IEC-FOF can be roughly divided into data modules with supporting functions and application modules with practical business value.

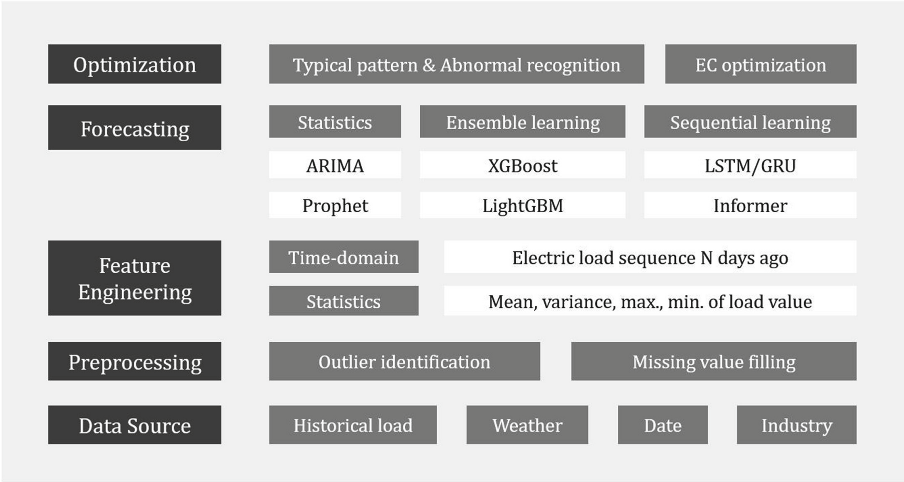

Fig. 1. Framework of IEC-FOF.

4 Methods

4.1 Electricity Consumption Forecast

Similar to a traditional data mining pipeline, we can summarize our methods into 4 steps: (The electricity consumption values mentioned below are obtained by smart electric meter, which calculate additive electricity consumption value in a period manner.)

1. Data Source Ingestion.

- **Historical data.** For most electricity consumers, the history of electricity usage is more or less indicative of habits. For example, for the apartment of an ordinary company employee, the peak of electricity consumption is after work in the evening, the electricity consumption on weekdays may be more regular, and the electricity consumption behavior on weekends will be more random, etc. We can use smart electric meter or other devices to record the amount of electricity a customer uses regularly to build up a historical time series of electricity consumption.
- **Weather info.** The weather factor is relatively easy to obtain and has a great influence on electricity consumption. By accessing external data sources, IEC-FOF can obtain key weather information such as temperature, humidity, and radiation in different geographical locations. For example, people turn on air conditioners more during high temperature and humidity, leading to a surge in electricity consumption.
- **Date characteristics.** The characteristics of a date can also serve as key features to support the model. Whether it's a workday, a holiday, a consumer goods promotion day, etc., can be used as valid information.

– **Industry categories.** Different industries have different habits of electricity consumption and different levels of regularity in electricity consumption. For example, the electricity consumption of a factory may vary greatly with the start and stop of production lines at any time, while the total electricity consumption of a school is highly correlated with holidays and weather. Industry attributes are also one of the information dimensions that must be considered. Because industry types are so broad and cross-cutting, we don't include them directly in the model as features, but rather as segment criteria for personalized models.

2. Data Preprocessing.

– Outlier identification. Obvious outliers will affect the effect of the prediction model, so they need to be filtered in the pretreatment stage. We use two simple strategies to filter outliers. One is based on distribution and the other is based on isolated forest.
– Missing value filling. Null values will be left after the above outliers are removed, and there are many null values to be dealt with in the sensor-based data. Here, IEC-FOF applies a simple forward-fill method to fill the missing values, that is, the values before the null values are used to fill the missing values.

3. Feature Engineering.

– Time-domain characteristic. In the time domain, IEC-FOF directly outputs the value of electricity consumption in certain historical periods as feature items, such as the sequence from 7 day ago can be used as a 24-dimensional feature.
– Statistical characteristic. Statistical values can also represent valid information, such as the average electricity consumption of the past day, the average electricity consumption of the last 3 days, and the variance of electricity consumption in a certain period. All of them have an impact on the value of the current moment.

Detailed features are shown in Table 1.

4. Forecasting. Since all the electricity consumption data we can collect is generated by the electricity consumption behavior that has already occurred, and many of our services are future-oriented, such as informing the approximate electricity consumption in advance, giving the electricity consumption plan for tomorrow in advance, etc., we need to make time series forecasts first. Based on the data we already have, we can use a variety of time series forecasting models, the details of which are shown below.

– Prophet [10] is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. Otherwise, Prophet is robust to missing data

Table 1. A feature example. We use four major types of features, in which industry information is not directly exported to the model, but is used as a label to slice the data, and different models are used for training and deployment respectively. (EC = electricity consumption)

Feature	Example	Category
All EC value from 1 day ago	[2.88 kW, 3.88 kW, ..., 45.88 kW]	Historical
EC value average over 3 days	48.6 kW	Historical
EC value variance from 7 days ago	27.8	Historical
Max. EC value from 1 day ago	123.8kW	Historical
The current temperature	14°C	Weather
Daily temperature variance	3.75	Weather
Max. humidity from 1 day ago	67%	Weather
Is weekday or not	True	Date
Is holiday or not	False	Date
Is evening or not	True	Date
Is meal time or not	False	Date
Category of Industry	IT	Industry

and shifts in the trend, and typically handles outliers well, which is suitable for the industrial scene. The general principle can be summarized as the following formula, where g represents the trend term, s represents the seasonal term, h represents the holiday term, and ϵ represents the remaining term. A prediction example using Prophet is shown below as Fig. 2.

$$\mathrm{y}(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

- LightGBM [11] is a gradient boosting framework that uses tree-based learning algorithms. It is designed to be distributed and efficient with many advantages, such as faster training speed and higher accuracy.
- Long short-term memory (LSTM) is a type of recurrent neural network (RNN) specially designed to prevent the neural network output for a given input from either decaying or exploding as it cycles through the feedback loops [7].

4.2 Optimization

Anomaly Detection. Since we have obtained a prediction of the future electricity use, we can directly take out the predicted value of the relatively short time, compared with the real value, if there is a very large prediction error, much greater than the prediction error of the model on the test set, it can actually represent that the real electricity consumption action is abnormal.

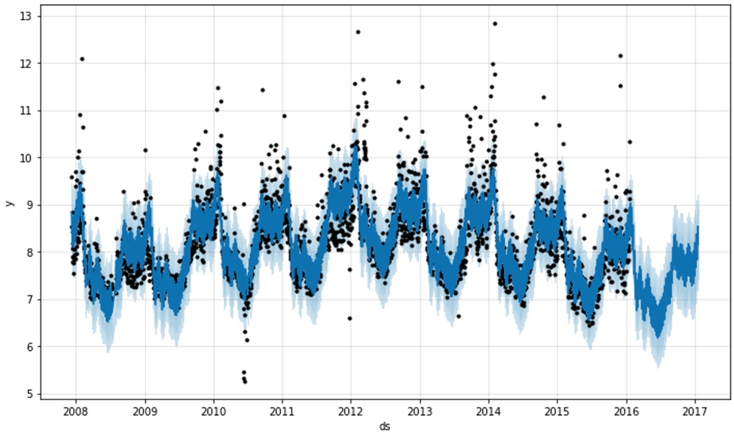

Fig. 2. A forecast example generated by Prophet [10]. Black points represent original data points, and blue lines and regions represent fitted curves and confidence intervals (Color figure online).

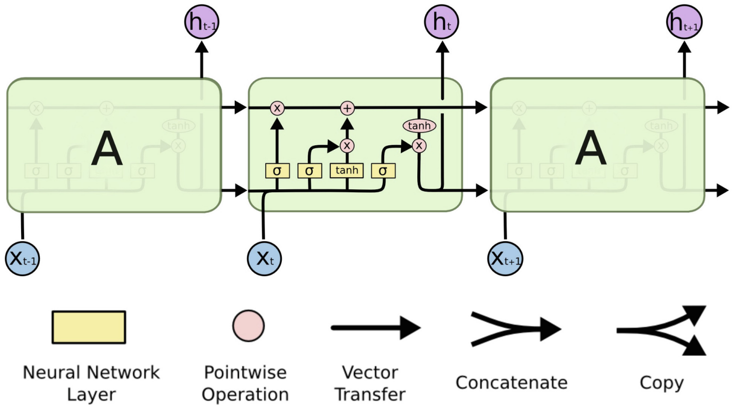

Fig. 3. Structure diagram of LSTM [7]. This structure contains forget gate, input gate and output gate, which can finally make the model remember the further sequence of information.

Typical Pattern Recognition and Optimization Recommendation Generation. We can extract typical electricity consumption patterns from historical electricity consumption sequences, so that users can quickly perceive that they have several common electricity consumption scenarios and habits. In addition, the typical electricity consumption mode can also allow us to perceive and suggest the user's electricity consumption, such as the user often uses a large amount of electricity during peak periods, as a service provider, we can inform users to reduce the consumption behavior during peak periods.

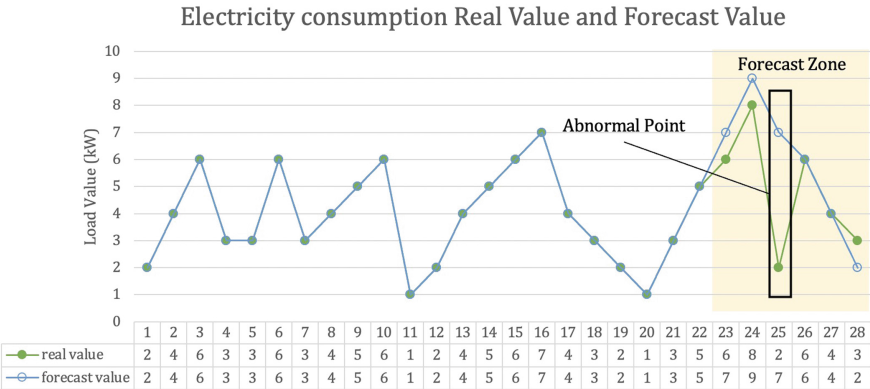

Fig. 4. A example of abnormal detection method. In the prediction area of this figure, there is a time-point whose real value differs greatly from the forecast value, and we can regard this time-point as an abnormal point.

Typical pattern recognition methods can be clustering algorithm, such as K-Means [8], DBSCAN [9], etc. We take the raw historical electricity sequence, break it down by day, and get some 24-dimensional vectors. Cluster these vectors and find the cluster center, which is a typical electricity consumption pattern sequence we want. The typical sequences found by this method are described in the experimental section.

Taking K-Means algorithm as an example, we briefly introduce its operation principle here. K-Means is a classic unsupervised learning algorithm that attempts to learn patterns in unlabeled datasets and discover similarities or regularities.

K-means groups similar data points into clusters by minimizing the average distance between geometric points. To do this, it iteratively divides the data set into a fixed number (K) of non-overlapping subgroups (or clusters), where each data point belongs to the cluster closest to the mean center of the cluster [8].

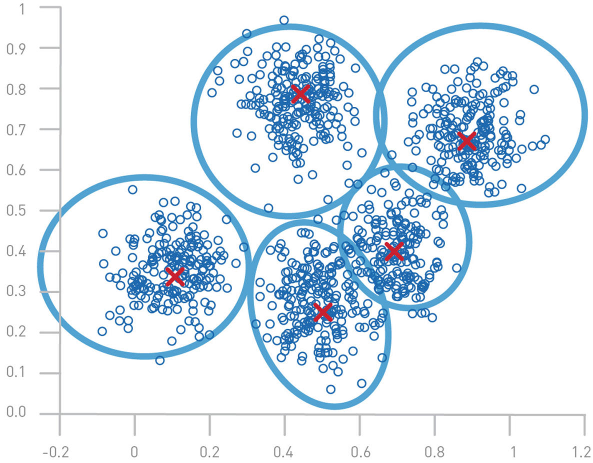

Fig. 5. A K-Means example. This figure shows the clustering effect in a two-dimensional space. The blue circle surrounding the point in the space is regarded as a cluster, and the red cross represents the center of the cluster. [12] (Color figure online)

5 Experiments

5.1 Implementation

At the data level, we used a dataset of electricity consumption that includes multiple industries and multiple electricity consumption facilities. A sample of the dataset is shown in Table 2. Each row represents the accumulated electricity consumption between the current point in time and the previous point in time. The sampling period of electricity consumption is 1 h, and the unit of electricity consumption is kW. At the model level, we used the following models, i.e. Prophet, Logistic Regression, XGBoost, LightGBM, and LSTM, using the frameworks of the native framework, sklearn, and Keras.

5.2 Forecasting Performances

We used SMAPE [17] indicators to quantify the effect of the prediction. A larger SMAPE value represents a larger error, and a smaller SMAPE value represents a better prediction accuracy. The specific formula of SMAPE is shown below, where A_t is the actual value and F_t is the forecast value. The reason why we chose SMAPE instead of MAPE, MSE, etc. is that the denominator of SMAPE takes into account the predicted value and has the characteristic of normalization, which brings fairer judgment in our scene.

In addition to verifying the accuracy of the predictions, we also recorded the training and testing time cost of the model, and the overall performance of LightGBM is the best, which achieves SMAPE = 27.32% and prediction time cost = 19.83 s over 7 days forecasting task.

Table 2. A sample of electricity consumption dataset

timestamp	electricity consumption	user id	industry category
2022-01-03 19:00:00	44.94	F238FIYL8	IT
2022-01-03 20:00:00	48.63	F238FIYL8	IT
2022-01-03 21:00:00	NaN	F238FIYL8	IT
2022-01-03 22:00:00	67.33	F238FIYL8	IT
2022-01-03 19:00:00	2.94	A238FI88U	Agri.
2022-01-03 20:00:00	4.88	A238FI88U	Agri.
2022-01-03 21:00:00	55.23	A238FI88U	Agri.
2022-01-03 22:00:00	9.13	A238FI88U	Agri.

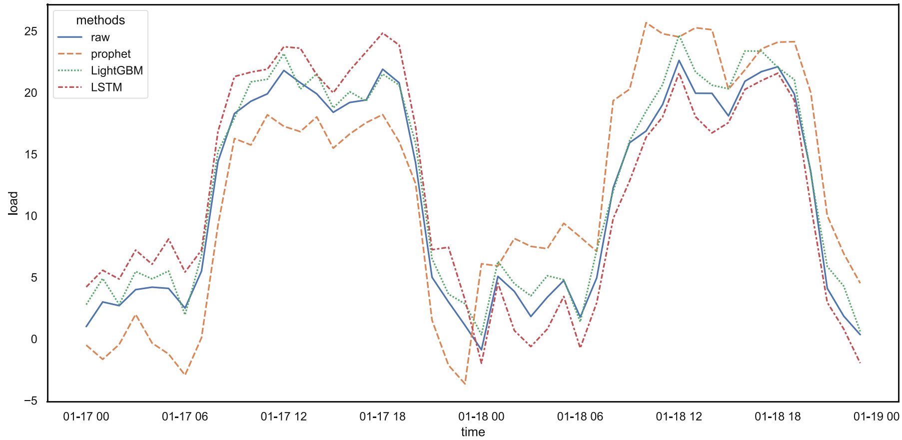

Fig. 6. A electricity consumption forecast example. We show the forecast sequence from various models, which can show forecasting performance to some extent. The predicted value can be negative and is set to 0 when used.

As to why the Prophet and LSTM didn't get the best performance, based on the experience, they are more suited to capture trends and laws, have the obvious time depend on the time series prediction scenarios, and very many scenes for influence factors, such as the industrial scenario described in this article, their performance may not be as feature engineering + tree model of the scheme. Due to different scenarios having different prediction effects and performance requirements, we reserved these various algorithms in IEC-FOF.

$$\text{SMAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2} \tag{2}$$

5.3 Optimization Effectiveness Evaluation

Based on the prediction error comparison, we present the anomaly detection service in Fig. 7; Based on K-Means clustering, we demonstrate typical electricity consumption pattern recognition services in Fig. 8; Based on sequence comparison and prior domain knowledge, we present the optimization recommendation service in Fig. 9.

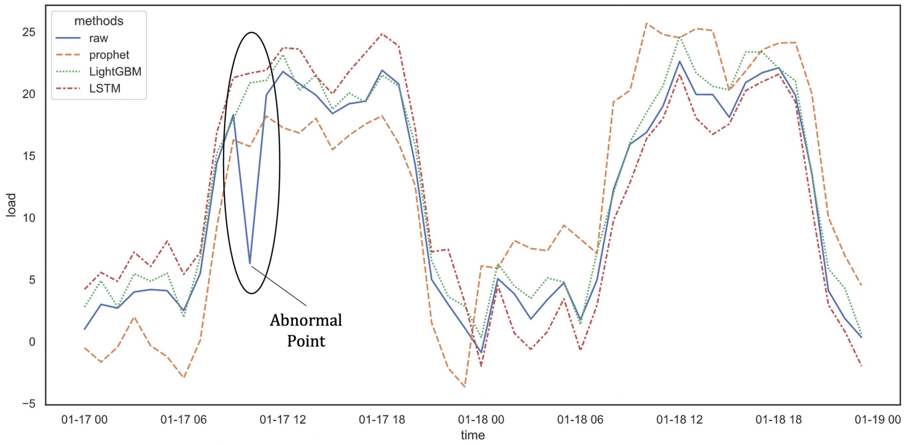

Fig. 7. An anomaly detection sample. The circled part of the figure has a large prediction error and is marked by the anomaly detection service of the IEC-FOF application layer. Note that some of the pictures in this article may be uniform in time, but do not correspond to the same electric customer, so the curve may be different. The predicted value can be negative and is set to 0 when used.

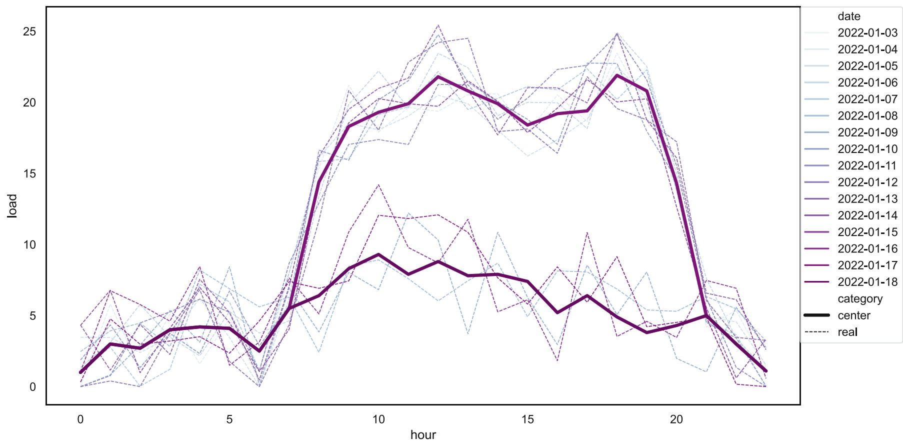

Fig. 8. A typical pattern recognition case. The dashed lines in the figure are the electricity consumption curves for several days, and the two solid lines are two typical electricity consumption modes, corresponding to weekdays and weekends.

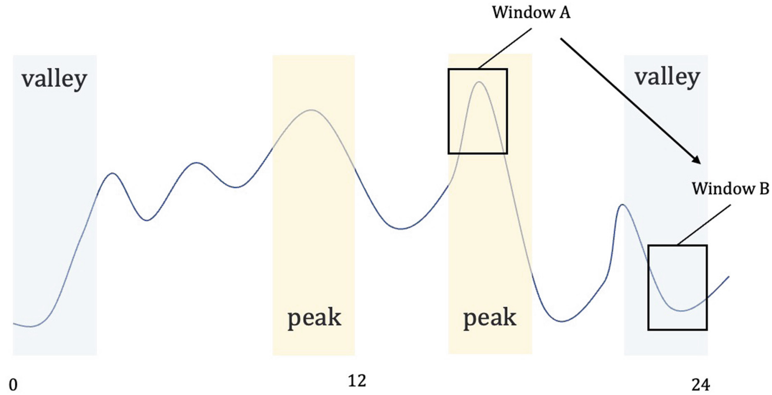

Fig. 9. An example of electricity consumption optimization. The yellow area is the peak of electricity consumption, the most expensive electricity price, and the light blue area is the electricity valley value, the lowest electricity price. The IEC-FOF application layer recommendation generation service informs the user to shift electricity consumption from window A to window B to reduce the cost of electricity. (Color figure online)

6 Discussion

In the industrial electricity consumption scenario described in this paper, through the capture of historical information, we can obtain a prediction of future conditions, so as to obtain more effective services. Forecasting electricity consumption and behavior not only plays a role in enterprises and households but also plays a significant role in electricity distribution and abnormal location.

However, the research application framework proposed by us is not perfect enough. For example, the time series prediction model used is not good at compensating for the long-time dependence. Such task scenarios may require a similar architecture to Transformer to complete, such as the Informer model.

For the design and application of top-level services, we believe that researchers are worthy of further research on the optimization of electricity consumption behavior, such as using operational optimization methods to guide users to make optimal adjustments to electricity consumption. A qualified recommendation needs to measure the elasticity of electricity demand, detect and warn of possible anomalies, and much more can be done.

7 Conclusion

In this paper, we introduce an algorithmic application framework for industrial electricity consumption prediction and optimization, called IEC-FOF, which can provide a variety of electricity consumption-related derivative services. We explained its principles and ideas in detail, and the evaluation result also confirmed the practicality of IEC-FOF.

References

1. Wei, Y.M., Chen, K., Kang, J.N., Chen, W., Wang, X.Y., Zhang, X.: Policy and management of carbon peaking and carbon neutrality: a literature review. Engineering (2022)
2. Vivas, E., Allende-Cid, H., Salas, R.: A systematic review of statistical and machine learning methods for electrical power forecasting with reported MAPE score. Entropy **22**(12), 1412 (2020)
3. Ugurlu, U., Oksuz, I., Tas, O.: Electricity price forecasting using recurrent neural networks. Energies **11**(5), 1255 (2018)
4. Akhter, M.N., Mekhilef, S., Mokhlis, H., et al.: Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. IET Renew. Power Gener. **13**(7), 1009–1023 (2019)
5. Demolli, H., Dokuz, A.S., Ecemis, A., et al.: Wind power forecasting based on daily wind speed data using machine learning algorithms. Energy Convers. Manage. **198**, 111823 (2019)
6. Zhou, H., et al.: Informer: beyond efficient transformer for long sequence time-series forecasting. In: Proceedings of the AAAI Conference on Artificial Intelligence, vol. 35, No. 12, pp. 11106–11115 (2021)
7. Yu, Y., Si, X., Hu, C., et al.: A review of recurrent neural networks: LSTM cells and network architectures. Neural Comput. **31**(7), 1235–1270 (2019)
8. Krishna, K., Murty, M.N.: Genetic K-means algorithm. IEEE Trans. Syst. Man Cybern. Part B **29**(3), 433–439 (1999)
9. Schubert, E., Sander, J., Ester, M., et al.: DBSCAN revisited, revisited: why and how you should (still) use DBSCAN. ACM Trans. Database Syst. **42**(3), 1–21 (2017)
10. Taylor, S.J., Letham, B.: Forecasting at scale. Am. Stat. **72**(1), 37–45 (2018)
11. Ke, G., et al.: LightGBM: a highly efficient gradient boosting decision tree. In: Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS 2017), pp. 3149–3157. Curran Associates Inc., Red Hook, NY, USA (2017)
12. Nvidia data-science page: https://www.nvidia.com/en-us/glossary/data-science/k-means/. Accessed 21 July 2022
13. Li, W., et al.: FingFormer: contrastive graph-based finger operation transformer for unsupervised mobile game bot detection. In: Proceedings of the ACM Web Conference 2022, pp. 3367–3375 (2022)
14. Pu, J., et al.: Unsupervised representation learning of player behavioral data with confidence guided masking. In: Proceedings of the ACM Web Conference 2022, pp. 3396–3406 (2022)
15. Wu, R., Deng, H., Tao, J., Fan, C., Liu, Q., Chen, L.: Deep behavior tracing with multi-level temporality preserved embedding. In: Proceedings of the 29th ACM International Conference on Information & Knowledge Management, pp. 2813–2820 (2020)
16. Xu, J., Wu, H., Wang, J., et al.: Anomaly transformer: time series anomaly detection with association discrepancy. arXiv preprint arXiv:2110.02642 (2021)

17. Chicco, D., Warrens, M.J., Jurman, G.: The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. PeerJ Comput. Sci. **7**, e623 (2021)
18. Ho, S.L., Xie, M.: The use of ARIMA models for reliability forecasting and analysis. Comput. Ind. Eng. **35**(1–2), 213–216 (1998)
19. Chen, T., He, T., Benesty, M., et al.: Xgboost: extreme gradient boosting. R Package Version 0.4-2 **1**(4), 1–4 (2015)