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A hybrid multi-objective optimizer-based model for daily electricity demand prediction considering COVID-19

Hongfang Lu a, Xin Ma b,*, Minda Ma c

a Construction Engineering and Management, Purdue University, West Lafayette, IN, 47907, United States
b School of Science, Southwest University of Science and Technology, Mianyang, 621010, China
c Department of Earth System Science, Tsinghua University, Beijing, 100084, China

ABSTRACT

Electricity consumption has been affected due to worldwide lockdown policies against COVID-19. Many countries have pointed out that electricity supply security during the epidemic is critical to ensuring people's livelihood. Accurate prediction of electricity demand would act a more important role in ensuring energy security for all the countries. Although there have been many studies on electricity forecasting, they did not consider the pandemic, and many works only considered the prediction accuracy and ignored the stability. Driven by the above reasons, it is necessary to develop an electricity consumption prediction model that can be well applied in the pandemic. In this work, a hybrid prediction system is proposed with data processing, modelling, and optimization. An improved complete ensemble empirical mode decomposition with adaptive noise is used for data preprocessing, which overcomes the shortcomings of the original method; a multi-objective optimizer is adopted for ensuring the accuracy and stability; support vector machine is used as the prediction model. Taking daily electricity demand of US as an example, the results prove that the proposed hybrid models are superior to benchmark models in both prediction accuracy and stability. Moreover, selection of input parameters is discussed, and the results indicate that the model considering the daily infections has the highest prediction accuracy and stability, and it is proved that the proposed model has great potential in real-world applications.

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1. Introduction

1.1. Background

On December 31, 2019, a group of pneumonia cases was reported in Wuhan, China. It was confirmed as SARS-Cov-2 and was officially named COVID-19 by the WHO [1]. With the popularity of COVID-19, the global situation has become severe. On March 11, 2020, WHO announced COVID-19 as a pandemic. In the first quarter of 2020, the epidemic affected almost everyone in the world. According to data from Johns Hopkins University, as of May 29, nearly 6 million people have been infected and approximately 365,000 people have died worldwide (see Fig. 1). In this context, many countries have introduced lockdown policies to prevent people from contact and thus control the spread of the epidemic [2]. At the same time, the global energy sector is also profoundly affected by the epidemic. According to the statistics of IEA, except for the slight increase in the demand for renewable energy in the first quarter, the rest of the energy has declined to vary degrees, of which oil has fallen the most, reaching 9%. Moreover, electricity demand fell by 2.5% [3].

Some scholars have suggested that energy and medical care are equally important during the epidemic. Among these energy sources, electricity may be most relevant to people's lives. Many countries have issued policies requiring the power supply department to provide uninterrupted power supplies and allow users to delay payment [4]. In this case, the requirements for the power supply department to accurately allocate power resources are higher than usual. Thus, in electricity management, the importance of accurate prediction of electricity demand is self-evident.

1.2. Related works and problem statement

In recent years, numerous studies on energy demand...
needs to consider too many external factors, and it is difficult to drive a model is used more because the physical simulation model into data-driven models and physical simulation models. The data-driven model is considered to be one of the most useful methods for energy demand prediction methods can be roughly divided into two years and gives information for the utilized models. It reveals that the forecasting have emerged. Table 1 lists the relevant works in recent two years and gives information for the utilized models. It reveals that the accuracy of the prediction model, not the stability; global events such as COVID-19; weather and other factors regarding prediction accuracy and stability. Thus, the work is innovative in that it discusses the adaptability of various factors related to COVID-19 in the model application. Besides, the proposed prediction model takes into account both accuracy and stability. The main contributions of this paper are as follows:

1) according to the literature review, most scholars only considered the accuracy of the prediction model, not the stability;
2) electricity demand prediction studies did not consider major global events such as COVID-19: weather and other factors considered may not be essential factors in this particular period. In other words, these models may lack applicability in the context of major global events.

1.3. Motivations, contributions, and article organization

Driven by the problems described in Section 1.2, the purpose of this paper is to develop a model that can be better applied to the prediction of electricity demand during COVID-19. In this work, COVID-19-related factors are considered in the model design, and the applicability of factors as model inputs is discussed. In the model design, ICEEMDAN is utilized as a data preprocessing tool, MOGWO is used to optimize the SVM, and the accuracy and stability are considered. Thus, the work is innovative in that it discusses the adaptability of various factors related to COVID-19 in the model application. Besides, the proposed prediction model takes into account both accuracy and stability. The main contributions of this paper are as follows:

1) A hybrid model is proposed to predict the daily electricity demand during the COVID-19 pandemic.
2) The proposed model is compared with benchmark models regarding prediction accuracy and stability.
3) The influences of the denoising method and optimizer on prediction are discussed.
(4) The applicability of factors related to COVID-19 as inputs to the prediction model is discussed.

(5) The results of one-step ahead, two-step ahead, and three-step ahead predictions are compared.

The rest of this paper is organized as follows. Section 2 introduces the relevant theories and implementation of the proposed model. Section 3 describes the collected data and prediction steps. Section 4 gives the prediction results. Section 5 discusses four critical issues related to this work. Finally, the primary conclusions and future works are summarized in Section 6.

2. Methods

The proposed in this paper, ICEEMDAN-MOGWO-SVM, is a hybrid model with the structure of "data cleaning method-optimizer-basic prediction model". The relevant theories associated with the different methods are introduced in this section.

2.1. Improved complete ensemble empirical mode decomposition with adaptive noise

Data decomposition breaks down the raw data into multiple datasets but does not distort the original data. The decomposed data is usually smoother, which is helpful for the execution of prediction. ICEEMDAN is a method that appeared in 2014 [24], and its predecessors include EMD, EEMD, CEEMDAN, and so on [25]. EMD is an adaptive signal time-frequency processing method suitable for nonlinear signals. It can decompose complex signals into a finite number of IMFs, and each IMF contains local characteristic signals of different time scales of the original signal; EEMD is developed based on EMD to overcome the mode mixing problem; CEEMDAN eliminates the noise involved in the reconstructed signal by adding white noise, and improves the efficiency of EEMD; ICEEMDAN is another innovation based on CEEMDAN, it has high efficiency and can avoid the generation of spurious modes. Its implementation process is as follows:

(1) Perform $l$ times EMD decomposition on the original signal:

$$s^{(l)} = s + \lambda_0 E_1 w^{(0)}$$

where $s$ is the original signal; $E_k(\cdot)$ is the $k$-th mode component generated by EMD; $w^{(0)}$ is Gaussian noise; $s^{(l)}$ is noise added signal; $\lambda$ is noise amplitude.

(2) Calculate the first residue and the first mode:

$$r_1 = M\{s^{(0)}\}$$

$$IMF_1 = s - r_1$$

where $r_k$ is the $k$-th residue; $IMF_k$ is the $k$-th mode; $M(\cdot)$ is local average of signal.

(3) Calculate the second residue and the second mode:

$$r_2 = M\{r_1 + \lambda_1 E_2 w^{(0)}\}$$

$$IMF_2 = r_1 - M\{r_1 + \lambda_1 E_2 w^{(0)}\}$$

(4) Calculate the $k$-th residue and the $k$-th mode:
\[ r_k = M \left\{ r_{k-1} + \lambda_{k-1} E_k \left[ W^{(i)} \right] \right\} \]  
(6)

\[ \overline{M} F_k = r_{k-1} - r_k \]  
(7)

(5) Repeat step (4) until the termination condition of decomposition is satisfied.

2.2. Multi-objective grey wolf optimizer

MOGWO is developed based on the grey wolf optimizer (GWO) [26]. GWO is a meta-heuristic algorithm inspired by the hunting behavior of wolves [27]. Each wolf in the population can be regarded as a solution to the problem. The optimal solution, optimal solution, suboptimal solution, and other solutions correspond to the wolf swarm’s four levels. When wolves find their prey, they approach them. Its position equations are:

\[ \{ \bar{J} = | \overline{M} \cdot \overline{L}_p(p) - \overline{L}_w(p) | \} \]

\[ \overline{L}_w(p + 1) = \overline{L}_p(p) - \overline{N} \cdot \bar{J} \]  
(8)

where \( \bar{J} \) is the distance between the wolf and prey; \( \overline{M} \) and \( \overline{N} \) are coefficient vectors; \( \overline{L}_p \) and \( \overline{L}_w \) are the position vectors of the prey

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**Table 1**

Studies related to energy demand prediction in the past two years.

| Reference | Prediction target | Model | Factors considered | Models for comparison |
|-----------|-------------------|------|-------------------|-----------------------|
| [5]       | Energy demand in Iran | A hybrid model combines scenario analysis and Bayesian approach | Historical energy demand, primary energy production, population, GDP, natural gas price, gasoline price | – |
| [6]       | Energy demand in Ireland | Covariance matrix adaptation evolutionary strategy | Historical energy demand | PSO, DE, BP, MA, RWF, LR |
| [7]       | Electricity demand in India | LSTM | Historical electricity demand considering cluster analysis | ANN, RNN, SVM, SVM, SSA-SVM, SSA-LSSVM, ARIMA |
| [8]       | Electricity demand in New South Wales and Singapore | VMD-SSA-SVM | Historical electricity demand | FAR-LSTM, FAR, CNN, LSTM, MLP, AR, SAR, LightGBM |
| [9]       | Natural gas demand in Germany | FAR-CNN | Historical natural gas demand | – |
| [10]      | Energy demand in China | ADL-MIDAS | Historical energy demand | – |
| [11]      | Residential natural gas demand | LR, KM, KMM, TRM, TLM, TNM | Historical maximum daily demand, weather | – |
| [12]      | Energy demand in Basilicata and Italy | Regression analysis | End user-related factors | – |
| [13]      | Load demand | SWPT--HHO--FNN | Historical load demand, date attribute, weather | PSO-ANN, PSO-LSSVM, BP |
| [14]      | Energy demand | ARIMA-ANN-PSO-SVM | Historical energy demand | ARIMA, ANN, PSO-SVM |
| [15]      | Building energy demand | Engineering simulation | Factors related to building energy | – |
| [16]      | Heating demand | ANN with an online learning method | Historical heating demand, air temperature | Thermal model, LR, SVM, Huber regressor, orthogonal matching pursuit, SGD regressor, decision tree regression, random forest |
| [17]      | Electricity demand | ANN, MARS, MLR, ARIMA | Historical electricity demand, climate | – |
| [18]      | Energy load | VMD-LSTM | Historical energy load | SVM, RNN, DBN, EMD-LSTM |
| [19]      | Natural gas demand | ARIMA, MLP, ANN, ELM | Historical natural gas demand, weather, biogas production, date attribute, electricity price, gas price, solar radiation | – |
| [20]      | Electricity demand | AFD-FFT-SCA-SVM | Historical electricity demand | RWF, ARMA, SVM, SCA-SVM, AFD-SCA-SVM, SPA-SCA-SVM, BP, ELM |
| [21]      | HVAC system energy demand | Takagi-Sugeno fuzzy-NN | Historical HVAC energy demand, weather | RLF |
| [22]      | Electricity demand of fans | ANN | Historical electricity demand | SVM |
| [23]      | Electricity demand | CB-PAA-PI | Historical electricity demand | Holt-Winters seasonal model, seasonal naive model |
and grey wolf, respectively; $p$ is the current iteration.

GWO keeps the best three solutions, and continuously updates the position of the grey wolf by the following formula to find the best solution:

\[
\begin{align*}
J_a &= \frac{L_a}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
J_b &= \frac{L_b}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
J_g &= \frac{L_g}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
L_1 &= \frac{L_a}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
L_2 &= \frac{L_b}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
L_3 &= \frac{L_g}{C_1} \left( \frac{p}{L_w} \right)^\frac{1}{C_0}, \\
L_{p}(p+1) &= \frac{1}{3} \left( L_1 + L_2 + L_3 \right)
\end{align*}
\]

where $a$, $b$ and $g$ are grey wolves of different levels.

MOGWO has two changes compared to GWO [26]. First, the update method has changed, and an archive is introduced to store the current best individual. After each iteration, the new individual generated is compared with the individual in the archive. In addition, to avoid too many similar individuals, all individuals are grouped according to the distance of the objective function value. Secondly, the selection mechanism of the leader wolf has changed. That is, using roulette to directly select the leader wolf in the archive, solving the problem that it is difficult to directly determine three non-dominant solutions through Pareto method. The probability of each hypercube can be calculated by Eq. (11). More information can be found in the literature [26].

\[
P_i = L_i^{-c}
\]

where $c$ is a constant; $L_i$ is the number of Pareto optimal solutions; $P_i$ is the probability of the hypercube.

2.3. Support vector machine

SVM is one of the most popular machine learning models. It has a strong statistical foundation and is very suitable for small samples. Related theories can refer to the literature [28]. SVM has a wide range of applications in energy [29], environment [30], hydrology [31], and economy [32]. It is not only used as a target model for research, but also as a benchmark model. In regression problems, the training set can be defined as [33]:

\[
\left\{ (x_j, y_j) | x_j, y_j \in \mathbb{R}^n, j = 1, 2, \cdots, n \right\}
\]

where $x_j$ and $y_j$ are input and output, respectively.

The specific form of the SVM model is:

\[
f(x) = \sigma^T \phi(x) + c
\]

where $\sigma$ is weighted vector; $\phi(x)$ is nonlinear mapping function; $c$ is the constant term.

![Fig. 3. Datasets of electricity demand and three COVID-19-related factors.](image)

Table 2

| Dataset | Unit | Data amount | Maximum | Minimum | Mean | Standard deviation |
|---------|------|-------------|---------|---------|------|-------------------|
| ED      | MWh  | 118         | 12,283,918 | 8,518,041 | 9893992.51 | 843837.09         |
| DI      | –    | 118         | 48,529 | 0 | 12016.01 | 13542.94         |
| DD      | –    | 118         | 4928 | 0 | 728.02 | 991.41             |
| GRSI    | –    | 118         | 73.57 | 0 | 40.53 | 31.36              |
is deviator.

In the SVM model, the penalty factor and the kernel width are two hyperparameters that affect the prediction performance. Many scholars use optimizers to optimize the original SVM model. For example, Fan et al. [34] utilized WOA, BA, and PSO to optimize SVM to predict solar radiation; Zhang et al. [35] employed CS to optimized SVM to predict short-term electricity load; Li et al. [36] used MOMVO to optimize LSSVM to predict air quality indicator.

3. Empirical analysis

In this section, the validity of the proposed model is verified through a case study. Considering that the United States is the second-largest energy-consuming country in the world, and is the most affected in this pandemic (as of May 29, 2020, the number of infected people accounts for about 30% of the world), the case study is set up for the daily electricity demand of the United States.

3.1. Data collection and description

In this work, the daily electricity demand data of the United States come from EIA (https://www.eia.gov/). Since the proposed model considers the impact of COVID-19, data on the number of daily infections, the number of daily deaths, and GRSI are collected. The data for these three factors are derived from Our World In Data (https://ourworldindata.org/). It is worth noting that GRSI is an indicator of the degree of lockdown proposed by Oxford University after the outbreak [37]. It is a comprehensive indicator of nine factors, as shown in Fig. 2. Its total score is 100, and the higher the score, the stricter the lockdown. The horizons of the four types of data are daily, from January 19 to May 15, 2020 (see Fig. 3). Their statistical description is shown in Table 2.

| Dataset | Raw data | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 |
|---------|----------|------|------|------|------|------|------|
| Maximum | 12,283,918 | 498434.6 | 529416.8 | 261793.4 | 176162.7 | 739302.2 | 10,188,100 |
| Minimum | 8,518,041 | -487,111 | -487,698 | -214,320 | -170,305 | -225,773 | 9,110,830 |

| Fig. 4. Overall prediction system.

Table 3
Ranges of the raw dataset and decomposed datasets.

(2) Data normalization

| Dataset | Raw data | IMF1 | IMF2 | IMF3 | IMF4 | IMF5 | IMF6 |
|---------|----------|------|------|------|------|------|------|
| Maximum | 12,283,918 | 498434.6 | 529416.8 | 261793.4 | 176162.7 | 739302.2 | 10,188,100 |
| Minimum | 8,518,041 | -487,111 | -487,698 | -214,320 | -170,305 | -225,773 | 9,110,830 |
3.2. Prediction system

3.2.1. Overall system

As shown in Fig. 4, the prediction system includes three parts: (1) data collection, (2) data preprocessing, and (3) optimization and prediction. The details of data collection are described in Section 3.1. The rest parts are described in Section 3.2.2.

3.2.2. Prediction steps

(1) Data decomposition

ICEEMDAN is used to decompose the raw data into multiple IMFs, so that the decomposed data can be in smaller ranges (smaller fluctuation ranges), as shown in Fig. 4 and Table 3. According to the related theory of ICEEMDAN, the termination of decomposition needs to satisfy the condition that the last IMF has less than three local extrema. However, for some data, the termination condition may not be met, so the maximum number of decompositions is set to 5000. If 5000 decomposition times still do not meet the condition, the decomposition is terminated. In the end, the raw dataset is broken down into six IMFs.

(4) Denormalization and addition

Because the dimensions of datasets may be different, to eliminate the influence of dimensions and improve the accuracy and speed of prediction, normalization is executed using the following equation:

\[ \text{Normalized value} = \frac{\text{Actual value} - \text{Minimum value}}{\text{Maximum value} - \text{Minimum value}} \]

Table 4

| Model          | Reason for being selected | Theories   | Applications |
|----------------|----------------------------|------------|--------------|
| NSGAII-SVM     | NSGA-II is a classic multi-objective optimizer. It adopts fast non-dominated sorting and elite strategy. | [40]        | [41]         |
| WOA-SVM        | WOA is one of the most popular meta-heuristic optimizers that has appeared in recent years. | [42]        | [43]         |
| PSO-SVM        | PSO is a classic meta-heuristic optimizer. | [44]        | [45]         |
| SVM            | The most primitive SVM model. | [28]        | [33]         |
| RBFNN          | One of the most popular neural network models. | [46]        | [47]         |

Fig. 5. The optimization and training processes of MOGWO-SVM.

Fig. 6. The principle of one-day ahead prediction.
dn = \frac{dr - d_{min}}{d_{max} - d_{min}} \tag{14}

where $dn$ is normalized data at interval [0,1]; $dr$ is raw data, respectively; $d_{min}$ and $d_{max}$ are minimum and maximum of the raw data, respectively.

(3) Optimization and prediction

After ICEEMDAN completes the decomposition and normalization, the decomposed data is input into the model for optimization and training operations. These two operations are performed in the training set and are synchronized. That is, the training of SVM and the optimization of SVM are carried out at the same time. When the optimization is completed, the training of SVM is also terminated, as shown in Fig. 5. In the conventional optimization (single-objective optimization) problem, scholars usually establish one objective function to minimize the prediction error in the training set. Because the multi-objective optimization adopted in this paper considers both prediction accuracy and stability, two objective functions are established:

$$
\min = \begin{cases} 
\text{ObjAcc} = \text{MAPE}_{\text{training}} = \frac{1}{S_t} \sum_{k=1}^{S_t} \frac{|A_k - P_k|}{A_k} \\
\text{ObjSt} = \text{std}(A_k - P_k)
\end{cases}
$$

where $\text{ObjAcc}$ and $\text{ObjSt}$ are the objective functions for prediction accuracy and stability, respectively; $\text{MAPE}_{\text{training}}$ is the MAPE in the training set; $S_t$ is the sample size of the training set; $A_k$ and $P_k$ are the actual and prediction values at time $k$; $\text{std}$ is the population standard deviation.

The SVM optimized by MOGWO is output from the training set and imported into the test set for prediction. Therefore, before optimization and prediction, the data set needs to be segmented. In this work, the ratio of the training set to test set is 7:3. Besides, the one-day ahead prediction is performed in this case study (see Fig. 6), and the relevant theories are shown in the literature [38].

Since the prediction is performed in the normalized datasets, denormalization processing is required to convert them into real values after the prediction is completed. The equation for denormalization is [39]:

$$
p_i = (1 - p_n)d_{min} + p_n d_{max} \tag{16}
$$

where $p_i$ is real prediction value; $p_n$ is normalized prediction value.

Because the prediction is made in each IMF after being
Fig. 8. The relative error of the prediction. (a) ICEEMDAN-MOGWO-SVM; (b) NSGAII-SVM; (c) WOA-SVM; (d) PSO-SVM; (e) SVM; (f) RBFNN.
decomposed, according to the principle of ICEEMDAN, the final prediction result is the sum of the prediction results in each IMF:

\[ P_f = \sum_{m=1}^{c} p_{IMF_m} \]  

(17)

where \( P_f \) is the final prediction result; \( p_{IMF_m} \) is prediction results in each IMF; \( c \) is the number of IMFs decomposed from the raw data.

(5) Error analysis

Three commonly used error metrics are used to measure the prediction performance: MAE, RMSE, and MAPE. Their expressions are as follows:

\[ MAE = \frac{1}{Z} \sum_{t=1}^{Z} |R_t - P_t| \]  

(18)

\[ RMSE = \sqrt{\frac{1}{Z} \sum_{t=1}^{Z} (R_t - P_t)^2} \]  

(19)

\[ MAPE = \frac{1}{Z} \sum_{t=1}^{Z} \left| \frac{R_t - P_t}{R_t} \right| \times 100\% \]  

(20)

where \( R_t \) and \( P_t \) are the real and prediction values at time \( t \), respectively; \( Z \) is the sample size.

3.3. Benchmark models

To highlight the advantages of the proposed model, this paper defines NSGAII-SVM, WOA-SVM, PSO-SVM, SVM, and RBFNN as the benchmark model for comparison. Of the five models, four are based on SVM, and RBFNN is a classic neural network model. The theory and application of these models and the reasons for choosing them are shown in Table 4.

4. Prediction results

4.1. Prediction accuracy

Fig. 7 shows the prediction results of each model in the test set from the time series. It reveals that the prediction results of the proposed model are basically consistent with the actual values, while the prediction results of WOA-SVM and PSO-SVM are consistent with the actual values in the overall trend. The prediction results of the other three models deviate greatly from the actual values. Such conclusions can also be obtained from Table 5. MAE, RMSE, and MAPE for the proposed model are 45134.7 MWh, 54865.1 MWh, and 0.49%, respectively, which are lower than other benchmark models. MAPEs for WOA-SVM and PSO-SVM are 2.24% and 2.99, respectively. MAPEs for NSGAII-SVM, SVM, and RBFNN are 7.28%, 5.62%, and 5.26%, respectively. It can be concluded that the proposed model has the highest prediction accuracy among the evaluated models.

4.2. Prediction stability

Fig. 8 shows the relative errors of every point for six models in the test set. It indicates that the relative errors of the proposed model are all around \( Y = 0 \), the maximum value is 1.06%, and the minimum value is −0.21%. Compared with the proposed model, the distributions of relative error points for benchmark models are more chaotic, and relative error the ranges are larger. STDRE is employed to evaluate the stability of the prediction comprehensively, it can be implied from Fig. 9 that the STDRE of the proposed model is 0.389%, which is much lower than other models. It indicates that the prediction stability of the proposed model is the best among the evaluated models.

5. Discussions

5.1. DM test

Although some error indicators can reflect the difference in prediction accuracy of the models, the results obtained may be misleading because some of the difference in accuracy is caused by the data’s feature. Therefore, using a DM test can further measure the difference in accuracy between the models [48]. Suppose the two competing models are \( M_1 \) and \( M_2 \), respectively, and the true series is \( y_t \). The prediction result of the first model is \( y_t^{M_1} \), and the prediction result of the second model is \( y_t^{M_2} \), then their prediction
The null hypothesis $H_0$ and the alternative hypothesis $H_1$ are:

$$H_0 : E[SL(e_1^t)] = E[SL(e_2^t)]$$

$$H_1 : E[SL(e_1^t)] \neq E[SL(e_2^t)]$$

where $SL$ is loss function of the square error.

DM test statistics are calculated according to Eq. (24):

$$DM = \frac{\sum_{t=1}^{q} |SL(e_1^t) - SL(e_2^t)|}{\sqrt{\nu^2/q}}$$

where $\nu^2$ is an estimation of the variance of $|SL(e_1^t) - SL(e_2^t)|$.
Table 6 shows that the proposed model's accuracy level is very different from the benchmark model, so it further proves that the proposed model is far superior to the benchmark model in prediction accuracy.

5.2. The impact of the denoising method and optimizer

The model proposed in this paper is developed based on SVM by introducing a denoising method and optimizer. In this section, the influences of the denoising method and the optimizer on the original model are further discussed. Thus, two other models are considered: MOGWO-SVM and ICEEMDAN-SVM. Table 7 implies that MAPE of SVM can be reduced by about 9.4% when SVM is combined with ICEEMDAN, and 72.2% when MOGWO is combined with SVM. Similar rules can be found in STDRE. They indicate that the multi-objective optimizer is better than the noise reduction method in improving the prediction performance of the original SVM. The same conclusion can be obtained by comparing ICEEMDAN-SVM, MOGWO-SVM, and ICEEMDAN-MOGWO-SVM. Nevertheless, the denoising method is still vital in some problems that require high accuracy and stability. As shown in Fig. 10, after the introduction of ICEEMDAN in MOGWO-SVM, the prediction accuracy and stability are greatly improved on the original basis.

5.3. COVID-19-related input variables

In the case study, ED is the predicted target, and the three factors of DI, DD, and PRSI are considered. Correlation analysis (to improve the reliability of the results, three correlation coefficients are used, as shown in Eqs. 25–27) proves that these three factors are indeed closely related to ED, as shown in Table 8.

![Image](image_url)
$$\text{SCC} = 1 - \frac{6 \times \sum_{i=1}^{N} |R(X_i) - R(Y_i)|^2}{N^3 - N}$$  \hspace{1cm} (26)$$

$$\text{KCC} = \frac{2(n_c - n_d)}{N \times (N - 1)}$$  \hspace{1cm} (27)$$

where $\text{cov}(X, Y)$ is covariance between $X$ and $Y$; $\sigma_X$ and $\sigma_Y$ are the standard deviation of $X$ and $Y$, respectively; $N$ is number of samples; $R(X_i)$ and $R(Y_i)$ are the ranking of $X_i$ and $Y_i$ in their respective column vectors; $n_c$ and $n_d$ are the number of concordant pairs and discordant pairs, respectively.

Filtering input variables is critical in prediction. Excess or missing factors may make the prediction model perform poorly. In this section, six more cases are set up to explore the influence of the COVID-related factors on the prediction results, as shown in Table 9. Fig. 11 and Table 10 imply that when ED and DI are considered in the model input, its prediction accuracy and stability are the highest. However, according to the correlation analysis, the correlation between GRSI and ED is the strongest, which indicates that the factors with strong correlation as the input of the model do not mean the best prediction results. For the prediction of electricity demand in the United States during the COVID-19 pandemic, the prediction accuracy ranking of models considering different factors is shown in Fig. 12.

5.4. One-step ahead vs. multi-step ahead prediction

In the practical application of daily electricity demand prediction, if managers can predict more days, the benefits for management are more significant [49]. Thus, this paper additionally examines the performance of the proposed model in two-day ahead and three-day ahead predictions. As shown in Fig. 13, the MAPE for the two-day ahead prediction is 2.06%, and the MAPE for the three-day ahead prediction is 1.86%. Although their performance is not as good as one-day ahead prediction, the prediction accuracy is still about 2%, indicating that the proposed model not only has high accuracy in one-step prediction, but also has great application potential in multi-step prediction. In practical applications, single-step prediction results and multi-step prediction results can be combined to measure the future short-term electricity consumption. If the forecast result is higher than the planned consumption, a policy to restrict electricity use can be introduced.

5.5. Considerations of real-world applications

The test of real-world data indicates that the model proposed in this work can be used to predict the daily electricity consumption in a pandemic. In the real-world applications, the real-time prediction can be carried out by establishing a prediction system. The system includes three modules: input module, model training module, and prediction module. Note that the prediction assumes that there is no significant change in energy policy.

The model proposed in this paper can be used as a power system management tool, which has the following practical or energy policy-oriented functions:

1. It can predict the electricity demand during the pandemic, and the power sector can reasonably allocate the power resources according to the prediction results (such as one-step ahead, two-step ahead, and three-step ahead), so as to ensure the security of power supply during the pandemic;
2. The supply and demand of electricity determine the price, and accurate forecasting of electricity consumption can make prices more reasonable. On the other hand, price setting can balance the relationship between supply and demand, and can also help the government to better formulate policies;
3. During the pandemic, the performance of renewable energy power generation is more outstanding and more flexible, and accurate electricity consumption forecasts are conducive to the integration of renewable energy and the power system.
6. Conclusions and future works

In this work, a hybrid model combines ICEMDAN, MOGWO, and SVM is presented to predict daily electricity demand during the epidemic. Taking the daily electricity demand in the United States as a case study, the analysis results indicate that the proposed model has higher prediction accuracy and stability than the other five benchmark models. DM test further proved the superiority of the proposed model. In addition, this paper discusses several key issues and draws some valuable conclusions:

(1) In the prediction scenario of electricity demand in the United States, the multi-objective optimizer improves the prediction performance of SVM most significantly.

(2) When the external factor considered by the model is DI, the accuracy and stability of the model are the highest; however, DI is not the most correlated factor with ED, indicating that the most correlated factor as the input of the model does not mean the best prediction accuracy.

(3) The proposed model not only performs well in one-day ahead prediction, but also has high accuracy in two-day ahead and three-day ahead predictions. Therefore, the proposed model has a higher potential in multi-step prediction although the prediction performance is not as good as one-step prediction.

The model proposed in this paper aims to be able to accurately predict electricity demand during the COVID-19 pandemic or major global events. Although it has been proved by practice that the proposed model can already obtain high prediction accuracy and stability, there are still some aspects worthy of further study. Thus, future works are summarized as follows:

(a) The prediction is made in each IMF, and the final result is obtained by summing up all the results. However, direct addition may not be the best way. Therefore, follow-up research may consider using other result processing methods or developing new denoising methods.

(b) In future work, more external factors can be considered as input to the model and test their rationality.

CRediT author statement

Hongfang Lu: Conceptualization, Methodology, Data curation, Writing – original draft. Xin Ma: Investigation, Methodology, Writing- Reviewing and Editing. Minda Ma: Writing- Reviewing and Editing

Declaration of competing interest

Authors declare that there is no conflict of interest due to the publication of this paper.

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