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# Forecasting seasonal variations in electricity consumption and electricity usage efficiency of industrial sectors using a grey modeling approach



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## ARTICLE INFO

### Article history:

Received 4 October 2020

Received in revised form

22 December 2020

Accepted 20 January 2021

Available online 24 January 2021

### Keywords:

Electricity consumption

Seasonal fluctuation

COVID-19 impact

Grey prediction

## ABSTRACT

The aim of this research is to forecast seasonal fluctuations in electricity consumption, and electricity usage efficiency of industrial sectors and identify the impacts of the novel coronavirus disease 2019 (COVID-19). For this purpose, a new seasonal grey prediction model (AWBO-DGGM(1,1)) is proposed: it combines buffer operators and the DGGM(1,1) model. Based on the quarterly data of the industrial enterprises in Zhejiang Province of China from the first quarter of 2013 to the first quarter of 2020, the GM(1,1), DGGM(1,1), SVM, and AWBO-DGGM(1,1) models are employed, respectively, to simulate and forecast seasonal variations in electricity consumption, the added value, and electricity usage efficiency. The results indicate that the AWBO-DGGM(1,1) models can identify seasonal fluctuations and variations in time series data, and predict the impact of COVID-19 on industrial systems. The minimum mean absolute percentage errors (MAPEs) of the electricity consumption, added value, and electricity usage efficiency of industrial enterprises separately are 0.12%, 0.10%, and 3.01% in the training stage, while those in the test stage are 6.79%, 4.09%, and 2.25%, respectively. The electricity consumption, added value, and electricity usage efficiency of industrial enterprises in Zhejiang Province will still present a tendency to grow with seasonal fluctuations from 2020 to 2022. Of them, the added value is predicted to increase the fastest, followed by electricity consumption.

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## 1. Introduction

### 1.1. Background and motivation

Forecasting energy consumption in the course of economic activity is important for a country to cope with climate change and ensure sustainable economic growth [1]. Electricity is a high-quality secondary energy and its consumption dominates the energy consumption structure. Industrial enterprises play a leading role in electricity consumption and the electricity consumption of industrial sectors is closely related to their economic growth. Forecasting the electricity consumption and added value of industrial enterprises is related to the understanding of the reliability

of the economic growth rate of industrial sectors. Moreover, there is a practical need for governments to forecast electricity demand and analyze the constraints of various factors in economic planning. According to the data released by Zhejiang Provincial Bureau of Statistics (<http://tj.zj.gov.cn/>), the output value of industrial enterprises in the province is growing rapidly: the total added value of industrial enterprises in Zhejiang Province increased from 1158.4 billion yuan in 2013 to 1824.6 billion yuan in 2019, with an average annual growth rate of 6.74%. Strongly driven by the growth of industrial production, the electricity consumption of industrial enterprises also shows a trend of rapid growth. In 2019, the electricity consumption of industrial enterprises reached  $3.2345 \times 10^{11}$  kW h, accounting for 75.4% of the total electricity consumption. It can be seen from Figs. 1 and 2 that the electricity consumption and added value of industrial enterprises in Zhejiang Province show seasonal and cyclical fluctuations. The outbreak of the novel coronavirus disease 2019 (COVID-19) in early 2020 has a significant effect on the electricity consumption and added value of industrial enterprises.

The research expands the prediction method for energy

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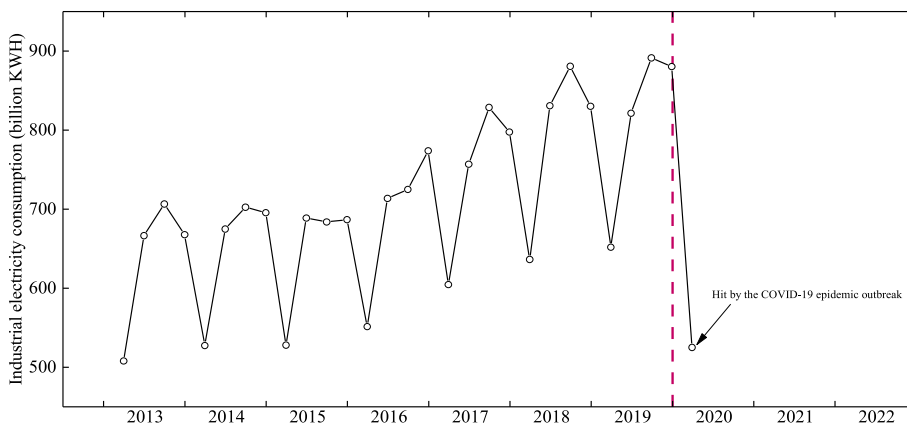


Fig. 1. Quarterly electricity consumption data: industrial enterprises in Zhejiang Province from 2013 to 2020.

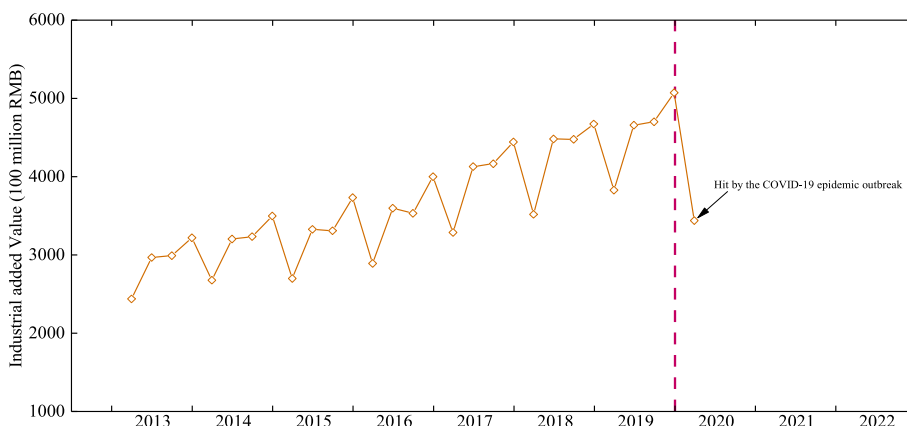


Fig. 2. Quarterly added value data: industrial enterprises in Zhejiang Province from 2013 to 2020.

consumption in conventional scenarios and the improved method is not only suitable for prediction of energy consumption of seasonal time series with structural breaks under the influences of unconventional events, but also can predict energy consumption in conventional scenarios. To verify the practicability and effectiveness of the model, the quarterly data about electricity consumption, added value, and electricity usage efficiency of the industrial enterprises in Zhejiang Province of China from 2013 to 2020 are used. This conforms to the modeling requirement of the grey system for a small sample size and poor information, so the model performs well in predicting the seasonal and periodic data in the industrial system. In addition, it also considers the significant influences of an external impact, that is, the COVID-19 pandemic, on the accuracy of the model.

1.2. Literature review

The electricity usage efficiency of industrial sectors reflects the relationship between their added value and electricity consumption. Its improvement is of significance to the upgrading of the structure of industry and realizing the high-quality development of industrial sectors in China; however, because the electricity consumption and economic output of industrial enterprises are affected by many factors, such as urbanization, climate, price and government policy intervention [2], they show certain characteristics of seasonal variations, making them difficult to forecast. Scientifically, reasonably forecasting and mastering seasonal variations in electricity consumption, economic added value and

electricity usage efficiency of industrial sectors are the important bases for the layout, policy and development planning of electricity industry in the future. In recent years, scholars have investigated the forecasting of electricity consumption. The studies focus on models based on traditional statistical methods, such as an autoregressive integrated moving average (ARIMA) model [3,4], a multivariate regression model [5–7] and an error correction model [8]. Furthermore, with the development of artificial intelligence and big data technology, machine learning methods have attracted the attention of many scholars. The models based on big data and machine learning methods include support vector machine (SVM) [9–11], artificial neural networks (ANNs) [12], nonlinear autoregressive neural networks (NARNNs) [13] and Quantile Regression Neural Network (QRNN) [14], which are widely used in the such forecasts. In addition, some scholars use evolutionary algorithms, such as the particle swarm optimization (PSO) algorithm [15] and genetic algorithm [16] to optimize the model parameters, thus improving forecast accuracy. These models have provided good energy forecasts, albeit with certain shortcomings; for example, the strongly explanatory models based on the traditional statistical methods can only make predictions under strict assumptions, and the forecast effects are unsatisfactory. The models based on machine learning have strong predictability at the cost of interpretability and need a lot of data for repeated training and testing, with a high complexity therein. For these reasons, some scholars begin to use hybrid models for forecast. By combining with the traditional machine learning methods and econometric models, Fan et al. [17] constructed a new hybrid forecasting model, namely a

model integrating empirical mode decomposition (EMD), support vector regression (SVR), PSO, autoregression (AR), and generalized autoregressive conditional heteroskedasticity (GARCH). The model is used to forecast electricity consumption data in New South Wales. In view of the low robustness of traditional statistical methods and machine learning methods in predicting the non-linear electricity demand, Bedi and Toshniwal [18] built a deep learning model considering the long-term dependence of historical data. They used clustering and long short-term memory (LSTM) network for prediction and the results indicate that the model is practicable and effective.

The grey forecasting model was first proposed by Professor Deng Julong in the 1980s [19]. Compared with other forecasting methods, the grey forecasting model has obvious advantages when used on incomplete information and small sample data. It is widely used in many fields, such as economy, energy, and agriculture due to its outstanding performance [20–22]. From different research perspectives including optimization of background values [23,24], model parameters [25–27] and initial conditions [28], as well as accumulative generation method [29–31], some scholars have expanded the research scope of the grey model (GM) and improved its forecast accuracy. In recent years, many scholars have found that the traditional GM with a linear structure has been unable to provide accurate forecasts of energy consumption, so a lot of scholars have extended the traditional model to adapt to the data with non-linear characteristics. Jia et al. [32] corrected the GM(1,1) model through use of Markov chains and verified the accuracy of the model by forecasting coal consumption of Gansu Province, China from 1999 to 2018. Ayvaz et al. [33] forecast greenhouse gas emissions in the regions including Turkey by establishing discrete grey models (DGMs) with rolling and non-rolling mechanisms. Luo et al. [34] optimized the parameters of a discrete grey polynomial model through the PSO algorithm. Ma & Liu [35] developed a time-delayed polynomial grey model (TDPGM(1,1)) to forecast natural gas consumption in China. Nguyen et al. [36] filtered the errors by Fourier series, so that the non-linear grey Bernoulli model (NGBM) can be applied in different situations in the case of data fluctuation and information uncertainty. By extending the traditional integer-order buffer operators to fractional-order operators, Wu et al. [37] revealed the internal relationship between the strengthening and weakening buffer operators and verified the effectiveness of the model through six cases. Based on the grey modeling technique and forward difference method, Wu et al. [38] built a new fractional-order multivariate grey model (GM( $a,n$ )). Wei et al. [39] expanded the DGM(1,1) model and used the data adaptive selection algorithm to optimize the model structure, which shows favorable robustness. By adopting the variable weight buffer operator of perfect information, He et al. [40] predicted the production and sales of new-energy vehicles in China and favorably reflected the non-stationary characteristic of the production and sales data. In addition, considering that a single model cannot readily forecast the trends in the development of a system, some scholars have combined the GM with other models to build hybrid forecasting models. By combining the residual modification model with ANNs, Hsu & Chen [41] proposed an improved GM(1,1) model. Combining the NGBM with the capital intensity model, Zheng et al. [42] established a hybrid model that can forecast changes of capital intensity, to forecast the capital intensity of new energy industry in China. By using the mean GM(1,1) and grey Verhulst model, Katani [43] forecast the total energy consumption in Ghana. Instead of the least squares method for parameter estimation in the traditional GM(1,1) model, Moonchai & Chutsagulprom [44] used Kalman filtering to estimate parameters of the model. By introducing the association rules of the machine learning in the multivariable GM for the first time, Ma et al. [45] studied the linear relationship

between each variable and the carbon emission to good effect.

For the forecasting of time series data with the characteristics of seasonal fluctuation, the traditional GM cannot identify seasonal variations, showing low accuracy, therefore, some scholars improved the grey forecasting model by using different methods, so that it can forecast seasonal time series: these can be classified into two categories: one is based on a group modeling method. Wang et al. [46] firstly proposed a data grouping approach based on the grey modeling method DGGM (1,1). Based on this, they proved that the new model is applicable to time series data with the characteristics of seasonal fluctuation based on quarterly data pertaining to hydropower generation in China. Wang et al. [47] proposed a grey forecasting model based on data grouping and buffer operators through the genetic algorithm to optimize the parameters of the model, which accurately forecasts seasonal fluctuation of residential solar energy consumption in the United States. The other category is a new grey forecasting model established by combining time series with the GM. Wang et al. [48] combined the GM with seasonal fluctuation in time series and applied the adaptive learning mechanisms into the new model, leading to a high forecast accuracy. Xu et al. [49] built a GM-autoregressive moving average (ARMA) model based on the Hodrick-Prescott (HP) filter method to forecast energy consumption under different application situations. Due to non-linear and seasonal characteristics of time series data pertaining to short-term traffic flow, Xiao et al. [50] performed cyclic truncation and generation on the original series to weaken the random disturbance of the original series. The empirical results show that the model has good adaptability and stability for the traffic volume data with the characteristics of seasonal variations. Wang et al. [51] constructed a grey forecasting model based on the cumulative generation operators of seasonal factors, namely a seasonal grey model (SGM(1,1)), and optimized by using the PSO algorithm. This model accurately forecasts seasonal fluctuation of electricity consumption of primary industry in China. In the subsequent studies, Wang et al. introduced seasonal factors with dynamic adjustment into the GM. The new model can effectively identify dynamic changes to such seasonal adjustment factors and improve forecast accuracy [52]. Carmona-Benítez and Nieto [53] improved the damp trend grey model (DTGM) and constructed a grey forecasting model that can obtain dynamic changes and seasonal fluctuations of time series, namely a seasonal damp trend grey forecasting model (SDTGM). Zhou et al. [54] introduced the seasonal fluctuation factor into the NGBM(1,1) to build a new SGM and obtained good forecast results of air quality in Shanghai City, Hangzhou City (Zhejiang Province), Nanjing City (Jiangsu Province), and Hefei City (Anhui Province), China.

### 1.3. Contribution and organization

The main innovations in this study are as follows:

- (1) In view of existing problems with traditional statistical methods, machine learning methods, and grey prediction models, the present research combined the buffer operators with the DGGM(1,1) model. In this way, a new DGGM(1,1) model based on average weakening buffer operators (AWBO-DGGM(1,1)) is proposed. The model can accurately predict seasonal time series and decrease influences of external impacts on the prediction accuracy. Then, this study simulates and forecasts quarterly data of the electricity consumption, economic output, and electricity usage efficiency of industrial enterprises in Zhejiang Province using the DGGM(1,1) model and the AWBO-DGGM(1,1) model. Moreover, the effectiveness and applicability of these grey forecasting methods have been verified.

- (2) Previous studies mainly focused on the relationship between the electricity consumption and economic growth of the whole society. This study explored the development trends of the electricity consumption, economic output, and electricity usage efficiency of industrial enterprises in Zhejiang Province. This can better reflect the quality of development of industry and the economy in Zhejiang Province for saving energy, reducing consumption and product cost, and increasing profits.
- (3) The sudden outbreak of the COVID-19 epidemic in 2020 has seriously affected the electricity consumption, economic output, and electricity usage efficiency of industrial enterprises in Zhejiang Province and the external impacts weaken the forecast accuracy of the DGGM(1,1) model. By using the AWBO-DGGM(1,1) model, we investigate the development of the electricity consumption, added value and electricity usage efficiency of industrial enterprises in Zhejiang Province from 2020 to 2022 under the impacts of the COVID-19 epidemic. Moreover, their future development trends are forecast.

The remainder of the research is arranged as follows: Section 2 introduces the method for establishing the AWBO-DGGM(1,1) model. Section 3 forecasts the quarterly data of the electricity consumption, added value, and electricity usage efficiency of industrial enterprises in Zhejiang Province using the GM(1,1) model, DGGM(1,1) model, SVM model, and AWBO-DGGM(1,1) models. The conclusions and future work are summarized in Section 4.

## 2. Models and methods

### 2.1. AWBO-DGGM(1,1) model

The traditional GM(1,1) model is suitable for the time series data with exponential growth and little fluctuation, however, for variable data including the electricity consumption, added value, and electricity usage efficiency of industrial enterprises characterized by seasonal fluctuations, the relative forecasting error is large. Based on the group modeling, the DGGM(1,1) model can better simulate and forecast time series data with seasonal fluctuations [46]. Furthermore, the outbreak of the COVID-19 epidemic has affected the electricity consumption and economic output of industrial enterprises in China. It is difficult to forecast the external impacts on the system itself using the DGGM(1,1) model, the data of the system cannot reflect the real changes therein. The AWBO-DGGM(1,1) model can eliminate the interference of shock waves on behavior series of the system to some extent, restore the original data and improve the forecast accuracy, therefore, the AWBO-DGGM(1,1) model is established as follows:

Firstly, the original time series data are grouped according to seasonal characteristics, that is, the original data are divided into four groups by quarters:

$$x^{(0)}(s) = (x^{(0)}(s, 1), x^{(0)}(s, 2), \dots, x^{(0)}(s, n)) \quad s = 1, 2, 3, 4 \quad (1)$$

By introducing the first-order weakening buffering operator into the grouped data, the series of the first-order weakening buffering operator can be obtained:

$$X^{(0)}D = x^{(0)}(s)d = (x^{(0)}(s, 1)d, x^{(0)}(s, 2)d, \dots, x^{(0)}(s, n)d) \quad s = 1, 2, 3, 4 \quad (2)$$

where,  $D$  denotes the AWBO and its series can act many times.  $X^{(0)}D$  represents the first-order weakening buffer operator;  $X^{(0)}D^2 =$

$X^{(0)}DD$  denotes the second-order weakening buffer operator [55].

$$x^{(0)}(s, k)d = \frac{1}{n - k + 1} (x^{(0)}(s, 1) + x^{(0)}(s, 2) + \dots + x^{(0)}(s, n)), \quad k = 1, 2, \dots, n; s = 1, 2, 3, 4$$

Thereafter, the grouped data in the buffer series are used as basic data upon which to build the GM(1,1) model, that is, an accumulated generating operation (AGO) is performed on the new basic data  $x^{(0)}(s)d = (x^{(0)}(s, 1)d, x^{(0)}(s, 2)d, \dots, x^{(0)}(s, n)d)$  to generate an AGO series  $x^{(1)}(s)d$ .

$$x^{(1)}(s)d = (x^{(1)}(s, 1)d, x^{(1)}(s, 2)d, \dots, x^{(1)}(s, k)d) \quad (3)$$

where,  $x^{(1)}(s, k)d = \sum_{i=1}^k x^{(0)}(s, i)d, k = 1, 2, \dots, n; s = 1, 2, 3, 4$ .

Therefore, the grey differential equation of the established AWBO-DGGM(1,1) model is expressed as follows:

$$x^{(0)}(s, k)d + az^{(1)}(s, k)d = b, k = 2, 3, \dots, n; s = 1, 2, 3, 4 \quad (4)$$

where, the mean series is  $z^{(1)}(s, k)d = 0.5x^{(1)}(s, k)d + 0.5x^{(1)}(s, k - 1)d$ .

In accordance with the grey differential equation, the corresponding whitening differential equation can be obtained as follows:

$$\frac{dx^{(1)}(s)d}{dt} + ax^{(1)}(s, t)d = b \quad (5)$$

where,  $t, a$ , and  $b$  indicate the time series, development coefficient, and grey action quantity, respectively.

According to the least squares method, two parameters  $a, b$  can be obtained and expressed as follows:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (6)$$

where,  $B$  and  $Y$  are separately expressed as follows:

$$B = \begin{bmatrix} -\frac{1}{2} [x^{(1)}(s, 1)d + x^{(1)}(s, 2)d] & 1 \\ -\frac{1}{2} [x^{(1)}(s, 2)d + x^{(1)}(s, 3)d] & 1 \\ \vdots & \vdots \\ -\frac{1}{2} [x^{(1)}(s, n - 1)d + x^{(1)}(s, n)d] & 1 \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(s, 2)d \\ x^{(0)}(s, 3)d \\ \vdots \\ x^{(0)}(s, n)d \end{bmatrix} \quad (7)$$

Finally, the time response formula of the model can be obtained:

$$\hat{x}^{(1)}(s, t + 1)d = \left[ x^{(0)}(s, 1)d - \frac{b}{a} \right] e^{-at} + \frac{b}{a}, s = 1, 2, 3, 4 \quad (8)$$

After an inverse accumulated generating operation (IAGO), the forecast value of the basic series  $x^{(0)}(s)d$  can be obtained:

$$\hat{x}^{(0)}(s, t + 1)d = \hat{x}^{(1)}(s, t + 1)d - \hat{x}^{(1)}(s, t)d, t = 1, 2, \dots, n - 1; s = 1, 2, 3, 4 \quad (9)$$

Finally, the forecast values attained by modeling the four groups of quarterly data are integrated into a continuous time series, namely,

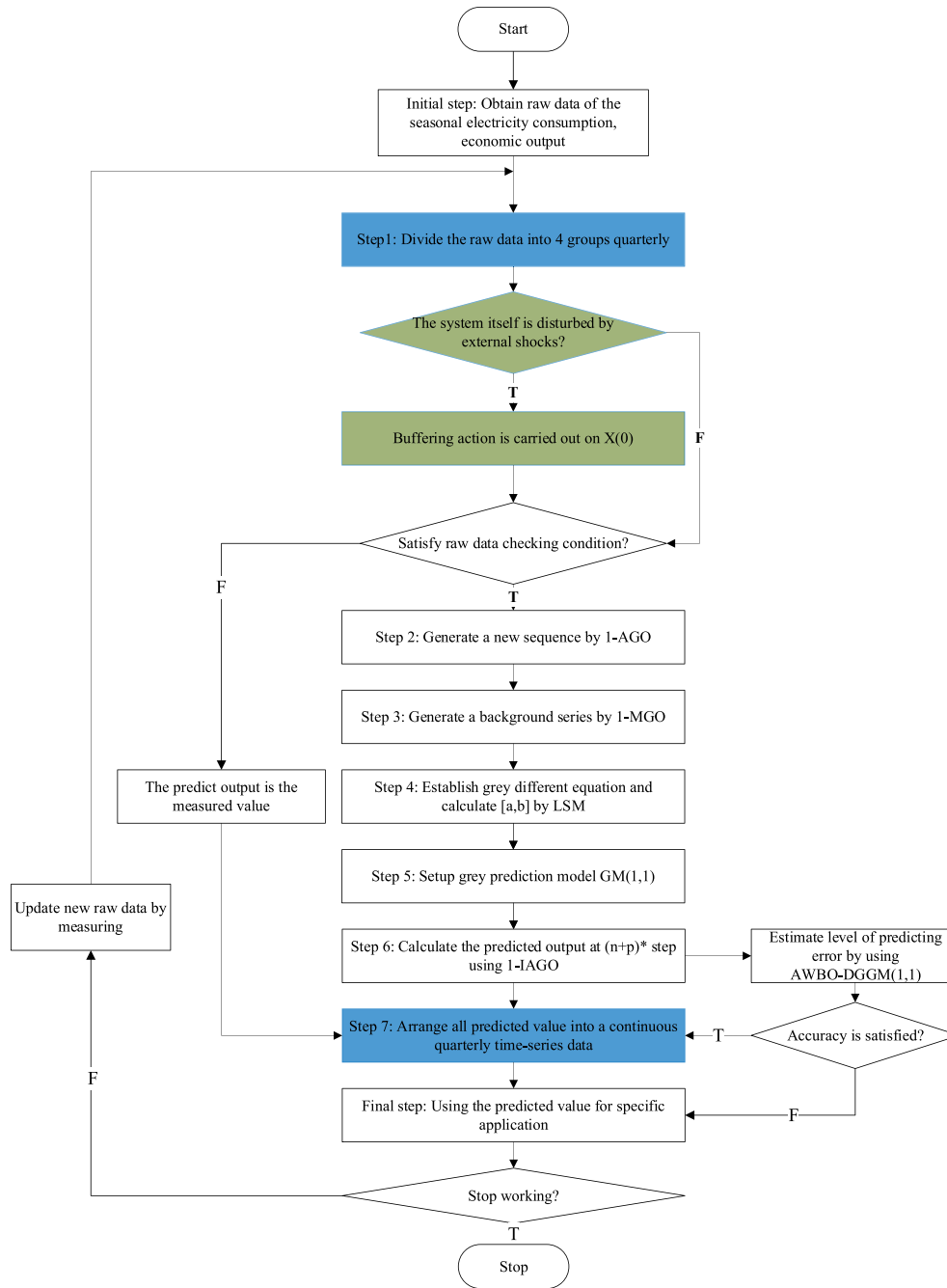


Fig. 3. Modeling process of the AWBO-DGGM(1,1).

Table 1  
The MAPE criterion for model examination.

MAPE (%)	Forecasting ability	MAPE (%)	Forecasting ability
<10	Excellent	20–50	Reasonable
10–20	Good	>50	Incorrect

$$\hat{x}^{(0)}(s, t + 1)d = \begin{pmatrix} \hat{x}^{(0)}(1, 1)d, \hat{x}^{(0)}(2, 1)d, \hat{x}^{(0)}(3, 1)d, \hat{x}^{(0)}(4, 1)d \\ \vdots \\ \hat{x}^{(0)}(1, n)d, \hat{x}^{(0)}(2, n)d, \hat{x}^{(0)}(3, n)d, \hat{x}^{(0)}(4, n)d \end{pmatrix} \quad (10)$$

It is worth noting that it is the classic average weakening buffer operator that is used in the research, however, in the case that the system is impacted by other events, buffer operators in other forms, such as the variable weight buffer operator, can be constructed to weaken or eliminate influences of external disturbance on the system. By using buffer operators in different forms, the model can always predict changes to the system under different impacts.

The DGGM(1,1) model based on the first-order AWBO is known as the 1-AWBO-DGGM(1,1) model, while that based on the second-order AWBO is called the 2-AWBO-DGGM(1,1) model. The modeling process is shown in Fig. 3.

2.2. Model-performance metrics

In this study, the root-mean-square error (RMSE), mean absolute error (MAE), average percent error (APE), and mean absolute percentage error (MAPE) are selected to compare accuracies of different models. The smaller the values thereof, the greater the accuracy [46,48].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_{real} - Y_{forecast})^2} \tag{11}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_{real} - Y_{forecast}| \tag{12}$$

$$APE = \left| \frac{Y_{real} - Y_{forecast}}{Y_{real}} \right| \times 100\% \tag{13}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{Y_{real} - Y_{forecast}}{Y_{real}} \right| \times 100\% \tag{14}$$

where,  $Y_{real}$  and  $Y_{forecast}$  denote the real values and forecast values, respectively. The equivalent evaluation criteria for forecast with the MAPE are listed in Table 1.

Industrial electricity consumption	$a$	$b$	Time response formula
Group 1	-0.053	470.089	$\hat{x}^{(1)}(1, t + 1) = 9426.415e^{0.0527(t-1)} - 8919.58$
Group 2	-0.053	604.269	$\hat{x}^{(1)}(2, t + 1) = 11916.92e^{0.053(t-1)} - 11410.1$
Group 3	-0.067	593.963	$\hat{x}^{(1)}(3, t + 1) = 9306.312e^{0.0675(t-1)} - 8799.48$
Group 4	-0.050	631.050	$\hat{x}^{(1)}(4, t + 1) = 13009.43e^{0.05(t-1)} - 12502.6$

3. Empirical analysis

Accurate forecast of the electricity consumption, economic output, and electricity usage efficiency of industrial enterprises have great practical significance for optimizing industrial layout, improving energy efficiency and building an environmentally friendly and resource-conserving society. Based on the quarterly data pertaining to electricity consumption and added value of industrial enterprises in Zhejiang Province from 2013 to 2020, we forecast the electricity consumption, economic output, and electricity usage efficiency of industrial enterprises. Firstly, the original data are divided into a training set and a test set, that is, the data from the first quarter of 2013 to the fourth quarter of 2018 are regarded as the training set, while those from the first quarter of 2019 to the first quarter of 2020 are used as the test set. Based on this, the traditional GM(1,1) model, DGGM(1,1) model and SVM model are built, analyzed, and compared. Secondly, considering the external impacts and influences caused by the COVID-19 epidemic, the AWBOs are introduced into the original data to generate new basic data and then the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models are separately established. Finally, by using the DGGM(1,1) model and AWBO-DGGM(1,1) models, an out-of-sample forecast is conducted on the electricity consumption, economic

output, and electricity usage efficiency of industrial enterprises from 2020 to 2022.

3.1. Forecasting the electricity consumption of industrial enterprises

According to the modeling, the traditional GM(1,1) model is directly built using the quarterly data of the electricity consumption of industrial enterprises from 2013 to 2018 as the training set, to forecast the electricity consumption from the first quarter of 2019 to the first quarter of 2020. The forecast values are compared with the actual data. The parameters and time response function of the GM model are demonstrated as follows:

The parameters and time response function for the electricity consumption of industrial enterprises are shown as follows:

$$\hat{\alpha} = \begin{bmatrix} a \\ b \end{bmatrix} = [-0.0124, 600.036] \tag{15}$$

$$\hat{x}^{(1)}(t) = 48860.23e^{0.0124(t-1)} - 48353.4 \tag{16}$$

Based on the modeling at the core of the DGGM(1,1) model, data in the training set are divided into four groups according to the seasonal characteristics. By using the least squares method, the parameters and time response function of the model are calculated as follows:

The SVM is a learning algorithm based on the statistical learning theory. It was first applied to supervised classification problems and then popularized to include use in prediction problems involving regression. At present, the SVM has become an important means of predicting non-linear time series and features high robustness and accuracy in prediction of small sample data [18]. In the current research, the SVM is used as a comparative model for prediction. The SVM model is debugged and then used for simulation and prediction adopting the LIBSVM toolbox in the MATLAB™ R2016b. The embedded dimension of the SVM model is four and the radial basis is used as the kernel.

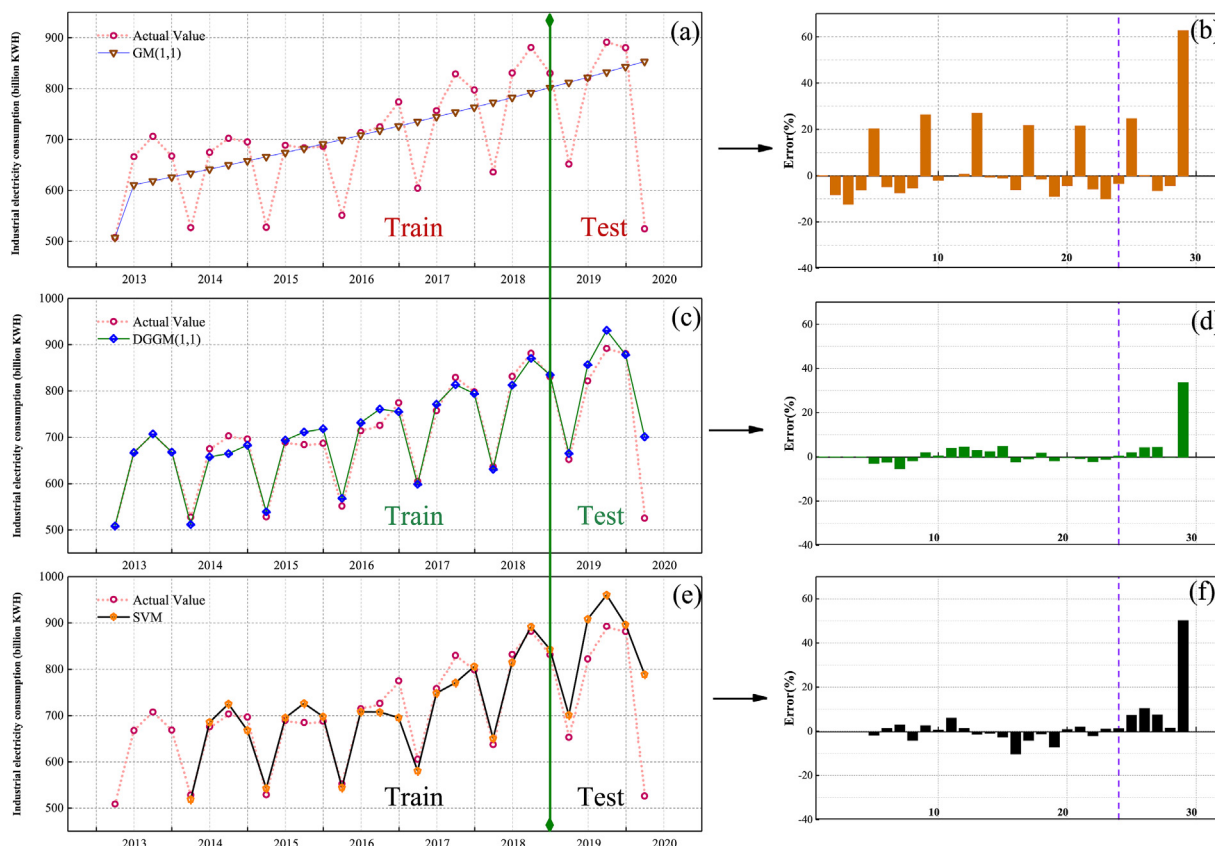
The actual values and forecast values obtained by the GM(1,1), DGGM(1,1), and SVM models and comparison of errors are illustrated in Table 2 and Fig. 4.

As shown in Table 2 and Fig. 4, compared with the traditional GM(1,1) and SVM model, the DGGM(1,1) model can better forecast seasonal fluctuation of the electricity consumption of industrial enterprises, with a small error therein. The maximum absolute percentage error, maximum APE of the GM(1,1), DGGM(1,1) and SVM models in the training set separately are 27.06%, 5.42%, and 10.34%; however, in the test set, the errors of three models for the first quarter of 2020 are 62.77%, 33.56%, and 50.22%, respectively.

The DGGM(1,1) model has achieved good forecast results,

**Table 2**  
Forecast results of the electricity consumption using the GM(1,1), DGGM(1,1), and SVM models.

Time	Actual value	GM(1,1)		DGGM(1,1)		SVM	
		Forecast value	APE (%)	Forecast value	APE (%)	Forecast value	APE (%)
2013Q1	506.83	506.83	0.00	506.83	0.00	—	—
2013Q2	665.76	610.10	8.36	665.76	0.00	—	—
2013Q3	705.79	617.72	12.48	705.79	0.00	—	—
2013Q4	666.98	625.43	6.23	666.98	0.00	—	—
2014Q1	526.39	633.24	20.30	510.13	3.09	516.72	1.84
2014Q2	674.18	641.15	4.90	656.76	2.58	683.85	1.43
2014Q3	701.81	649.16	7.50	663.75	5.42	723.23	3.05
2014Q4	694.90	657.26	5.42	681.78	1.89	666.14	4.14
2015Q1	526.96	665.47	26.28	537.73	2.04	540.59	2.59
2015Q2	688.14	673.78	2.09	692.48	0.63	693.43	0.77
2015Q3	683.20	682.19	0.15	710.10	3.94	724.45	6.04
2015Q4	686.00	690.71	0.69	717.07	4.53	695.67	1.41
2016Q1	550.38	699.34	27.06	566.83	2.99	542.21	1.48
2016Q2	713.08	708.07	0.70	730.15	2.39	706.34	0.95
2016Q3	724.39	716.91	1.03	759.69	4.87	705.48	2.61
2016Q4	773.51	725.86	6.16	754.19	2.50	693.50	10.34
2017Q1	603.72	734.93	21.73	597.51	1.03	578.40	4.19
2017Q2	756.44	744.10	1.63	769.86	1.77	746.77	1.28
2017Q3	828.44	753.39	9.06	812.74	1.90	768.99	7.18
2017Q4	797.19	762.80	4.31	793.24	0.50	804.22	0.88
2018Q1	635.59	772.33	21.51	629.84	0.90	648.58	2.04
2018Q2	830.51	781.97	5.84	811.73	2.26	813.42	2.06
2018Q3	880.60	791.73	10.09	869.49	1.26	890.27	1.10
2018Q4	829.90	801.62	3.41	834.30	0.53	841.12	1.35
<b>Test set</b>							
2019Q1	651.10	811.63	24.66	663.93	1.97	699.19	7.39
2019Q2	821.00	821.76	0.09	855.87	4.25	906.68	10.44
2019Q3	891.20	832.03	6.64	930.21	4.38	958.84	7.59
2019Q4	880.20	842.41	4.29	877.49	0.31	894.60	1.64
2020Q1	524.00	852.93	62.77	699.86	33.56	787.17	50.22

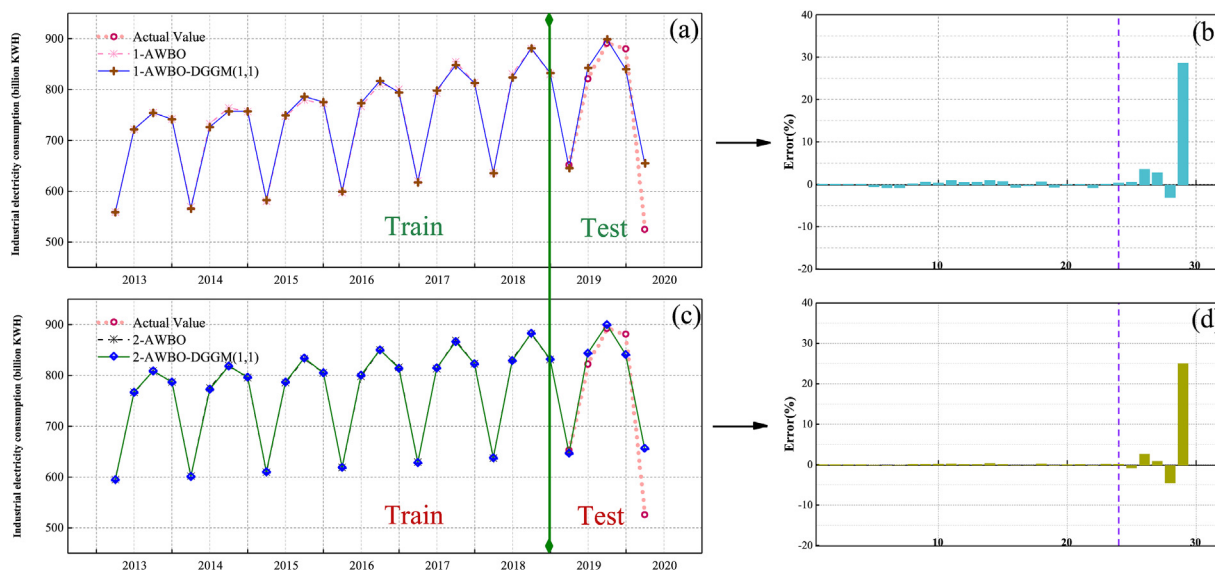


**Fig. 4.** The forecast results and error of the electricity consumption of industrial enterprises: (a) the results using the GM(1,1), (b) the error using the GM(1,1), (c) the results using the DGGM(1,1), (d) the error using the DGGM(1,1), (e) the results using the SVM, (f) the error using the SVM.



**Table 3**  
Forecast results of the electricity consumption using the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models.

Time	Actual value	1-AWBO-DGGM(1,1)			2-AWBO-DGGM(1,1)		
		$\chi^{(0)}D$	Forecast Value	APE (%)	$\chi^{(0)}D^2$	Forecast value\	APE (%)
2013Q1	506.83	558.31	558.31	0.00	592.98	592.98	0.00
2013Q2	665.76	721.35	721.35	0.00	765.25	765.25	0.00
2013Q3	705.79	754.04	754.04	0.00	807.19	807.19	0.00
2013Q4	666.98	741.41	741.41	0.00	785.50	785.50	0.00
2014Q1	526.39	568.61	565.41	0.56	599.92	599.51	0.07
2014Q2	674.18	732.47	725.93	0.89	774.03	771.63	0.31
2014Q3	701.81	763.69	756.87	0.89	817.82	817.15	0.08
2014Q4	694.90	756.30	756.99	0.09	794.32	795.16	0.11
2015Q1	526.96	579.16	582.14	0.51	607.74	608.43	0.11
2015Q2	688.14	747.04	749.19	0.29	784.43	785.34	0.12
2015Q3	683.20	779.16	786.14	0.90	831.36	832.87	0.18
2015Q4	686.00	771.65	775.19	0.46	803.82	803.91	0.01
2016Q1	550.38	596.56	599.36	0.47	617.27	617.48	0.03
2016Q2	713.08	766.68	773.19	0.85	796.89	799.30	0.30
2016Q3	724.39	811.14	816.53	0.66	848.75	848.88	0.02
2016Q4	773.51	800.20	793.83	0.80	814.55	812.76	0.22
2017Q1	603.72	619.66	617.09	0.41	627.62	626.67	0.15
2017Q2	756.44	793.48	797.96	0.56	811.99	813.50	0.19
2017Q3	828.44	854.52	848.10	0.75	867.56	865.21	0.27
2017Q4	797.19	813.55	812.92	0.08	821.72	821.70	0.00
2018Q1	635.59	635.59	635.34	0.04	635.59	636.00	0.06
2018Q2	830.51	830.51	823.52	0.84	830.51	827.96	0.31
2018Q3	880.60	880.60	880.89	0.03	880.60	881.84	0.14
2018Q4	829.90	829.90	832.47	0.31	829.90	830.75	0.10
<b>Test set</b>							
2019Q1	651.10		654.13	0.47		645.46	0.87
2019Q2	821.00		849.90	3.52		842.67	2.64
2019Q3	891.20		914.95	2.67		898.80	0.85
2019Q4	880.20		852.49	3.15		839.89	4.58
2020Q1	524.00		673.48	28.53		655.07	25.01



**Fig. 5.** The forecast results of the electricity consumption of industrial enterprises: (a) the results using the 1-AWBO-DGGM(1,1), (b) the error using the 1-AWBO-DGGM(1,1), (c) the results using the 2-AWBO-DGGM(1,1), (d) the error using the 2-AWBO-DGGM(1,1).

however, due to the impact of the COVID-19 epidemic on the electricity consumption of industrial enterprises in the first quarter of 2020, the year-on-year growth rate of the electricity consumption in the first quarter of 2020 is  $-19.52\%$ . Both the GM(1,1) model, DGGM(1,1) model and SVM model cannot obtain good forecast results, with a large error therein, therefore, using the quarterly data of the electricity consumption of industrial enterprises in

Zhejiang Province from 2013 to 2018 as the basic data, this study acquires new basic data by introducing the first-order and second-order AWBOs. The series of first and second-order AWBOs and forecast results are summarized in Table 3 and a comparison of their errors is given in Fig. 5.

According to Table 3 and Fig. 5, the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models have a smaller error. In the training set,

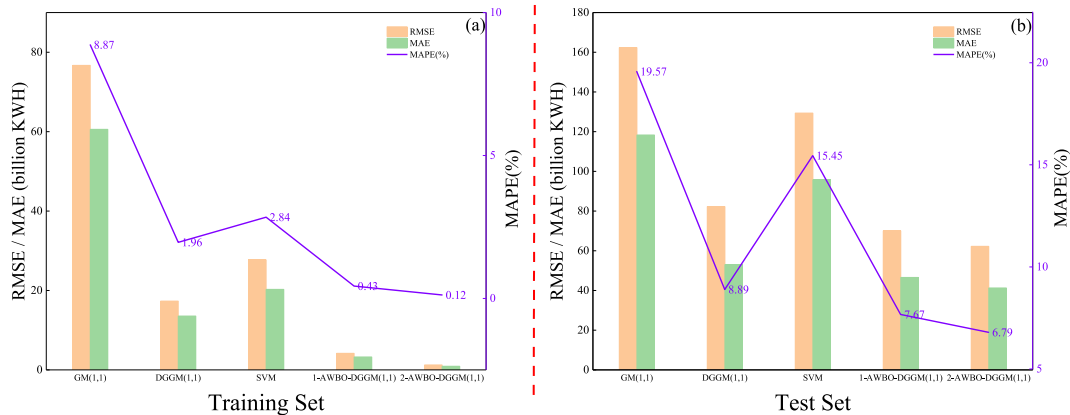


Fig. 6. Comparison of performance evaluation of the five models: (a) Training set (b) Test set.

**Table 4**  
Accuracy comparison of models for electricity consumption of industrial enterprises.

Training set	RMSE	MAE	MAPE (%)
GM(1,1)	72.79	55.77	8.62
DGGM(1,1)	17.32	13.56	1.96
SVM	27.71	20.28	2.84
1-AWBO-DGGM(1,1)	4.17	3.26	0.43
2-AWBO-DGGM(1,1)	1.25	0.91	0.12
Test set			
GM(1,1)	166.67	117.44	19.69
DGGM(1,1)	82.26	53.05	8.89
SVM	129.38	95.80	15.45
1-AWBO-DGGM(1,1)	70.03	46.58	7.67
2-AWBO-DGGM(1,1)	62.23	41.26	6.79

SVM models are built using the quarterly data of the added value of industrial enterprises from 2013 to 2018 as the training set. The models are used to forecast the added value from the first quarter of 2019 to the first quarter of 2020 and the forecast values are compared with the actual data. The parameters and the time response functions of the GM model are shown as follows:

① GM(1,1) forecasting

$$\hat{\alpha} = \begin{bmatrix} a \\ b \end{bmatrix} = [-0.0211, 2713.859] \quad (17)$$

$$\hat{\chi}^{(1)}(k) = 131033.2e^{0.0211(k-1)} - 128604 \quad (18)$$

② DGGM(1,1) forecasting

the error is less than, or equal to 5%, however, in the test set, the maximum absolute percentage errors incurred by the 1-AWBO-

Added value of industrial enterprises	a	b	Time response formula
Group 1	-0.077	2274.742	$\hat{\chi}^{(1)}(1, t + 1) = 31900.05e^{-0.077(t)} - 29471.1$
Group 2	-0.092	2676.692	$\hat{\chi}^{(1)}(2, t + 1) = 31675.37e^{0.092(t)} - 29246.4$
Group 3	-0.092	2670.327	$\hat{\chi}^{(1)}(3, t + 1) = 31583.47e^{0.092(t)} - 29154.5$
Group 4	-0.076	3098.954	$\hat{\chi}^{(1)}(4, t + 1) = 43392.49e^{0.076(t)} - 40963.5$

DGGM(1,1) and 2-AWBO-DGGM(1,1) models for data in the first quarter of 2020 separately are 28.53% and 25.01%, which are smaller than that of the DGGM(1,1) model, so their forecast accuracy is higher.

As shown in Table 4 and Fig. 6, the RMSE, MAE and MAPE of the 2-AWBO-DGGM(1,1) model are the smallest in the training and test sets, representing the highest forecast accuracy. MAPEs are 0.12% and 6.79%, respectively. MAPEs of the GM(1,1), DGGM(1,1), SVM, and 1-AWBO-DGGM(1,1) models separately are 8.62%, 1.96%, 2.84%, and 0.43% in the training set, while those in the test set are 19.69%, 8.89%, 15.45%, and 7.67%, respectively.

3.2. Forecasting the added value of industrial enterprises

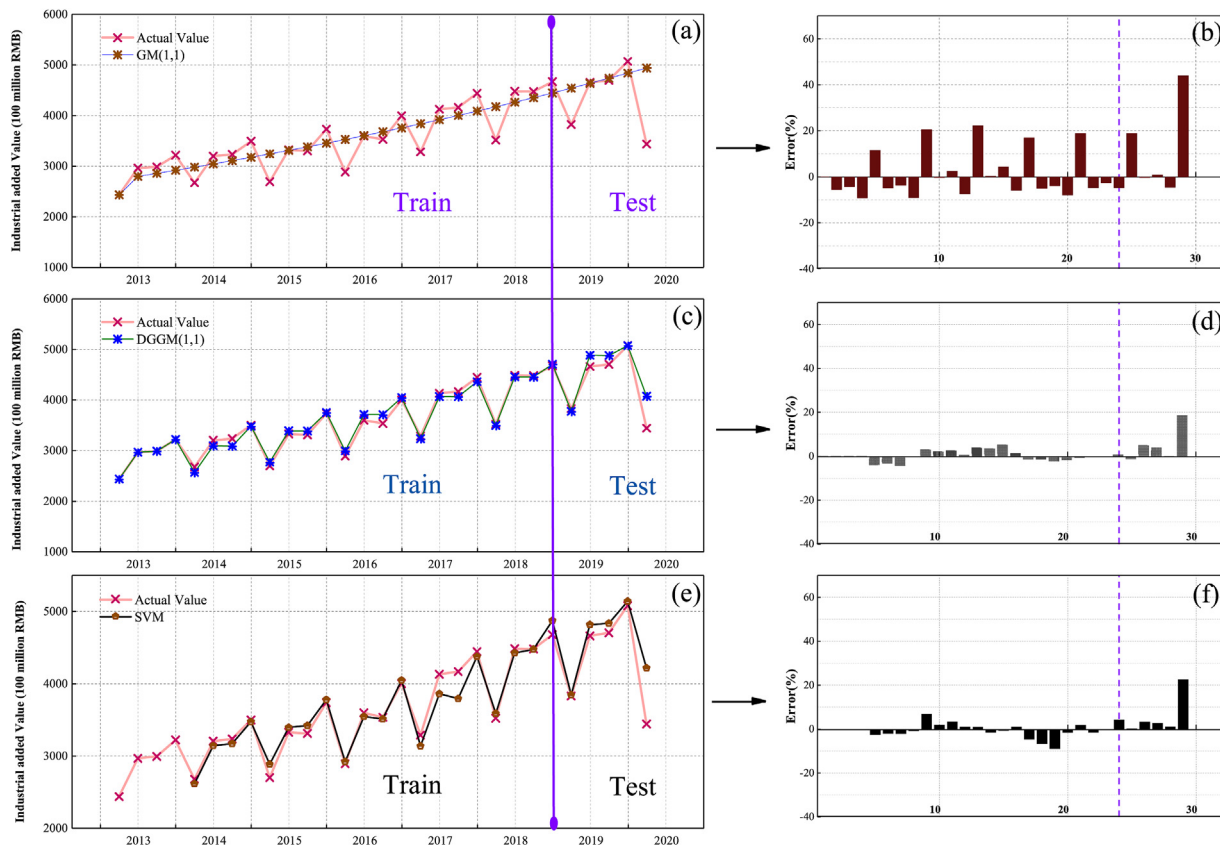
Similar to the modeling process for the electricity consumption of industrial enterprises in Section 4.1, the GM(1,1), DGGM(1,1), and

③ The SVM model

The SVM model is debugged and then used for simulation and prediction using the LIBSVM toolbox in the MATLAB™ R2016B. The embedded dimension of the SVM model is four and the kernel is a radial basis, respectively (see Fig. 7).

The actual values and predicted values obtained using the GM(1,1), DGGM(1,1), and SVM models established based on the quarterly data of the added value of industrial enterprises and comparison results of errors are demonstrated in Table 5 and Fig. 7, respectively.

It can be seen from Table 5 and Fig. 7 that the DGGM(1,1) model can better identify the seasonal fluctuation of the added value of industrial enterprises, with small errors therein. The maximum



**Fig. 7.** Forecast results of the added value of industrial enterprises: (a) the results using the GM(1,1), (b) the error using the GM(1,1), (c) the results using the DGGM(1,1), (d) the error using the DGGM(1,1), (e) the results using the SVM, (f) the error using the SVM.

absolute percentage errors of the GM(1,1), DGGM(1,1) and SVM models separately are 22.24%, 4.99%, and 9.02% in the training set. In the test set, the errors of the three models for data in the first quarter of 2020 are 43.90%, 18.48%, and 22.64%, respectively.

However, due to the influences of the COVID-19 epidemic on the economic output of industrial enterprises in the first quarter of 2020, the year-on-year growth rate of the added value in the first quarter is  $-10.20\%$ . The GM(1,1), DGGM(1,1), and SVM models cannot obtain good forecast results and show large errors. As a result, we use quarterly data pertaining to the added value of industrial enterprises in Zhejiang Province from 2013 to 2018 as the basic data and introduced first and second-order AWBOs, thus obtaining new basic data. The series of first and second-order AWBOs and forecast results are shown in Table 6 and the comparison of errors is demonstrated in Fig. 8.

As shown in Fig. 8, the 1-AWBO-DGGM (1, 1) and 2-AWBO-DGGM(1, 1) models have smaller errors and the errors in the training set are smaller than 1%. In the test set, the maximum absolute percentage errors of the two models for data in the first quarter of 2020 are 11.1% and 6.68%, which are significantly smaller than those of the GM (1, 1), DGGM (1, 1), and SVM models, indicating a higher forecast accuracy.

In Table 7, the RMSE, MAE, and MAPE of the 2-AWBO-DGGM (1, 1) model are the smallest in the training set. Its MAPE is 0.1%, while those of the other four models are 7.36%, 1.79%, 2.70%, and 0.38%, respectively. In the test set, the 1-AWBO-DGGM (1, 1) model shows the highest forecast accuracy and the smallest RMSE, MAE, and MAPE. Its MAPE is 4.09%, while those of the GM (1, 1), DGGM (1, 1), SVM, and 2-AWBO-DGGM (1, 1) models are 13.70%, 5.72%, 6.05%, and 4.55%, respectively (see Fig. 9).

### 3.3. Forecasting the electricity usage efficiency of industrial enterprises

The electricity usage efficiency of industrial enterprises, a single general element, is defined as the ratio of the added value to the electricity consumption of industrial enterprises. In accordance with Sections 3.1 and 3.2, the forecast values of quarterly data of the electricity consumption and added value of industrial enterprises can be calculated using the GM(1,1), DGGM(1,1), SVM, 1-AWBO-DGGM(1,1), and 2-AWBO-DGGM(1,1) models, thus obtaining the forecast value of the electricity usage efficiency. As shown in Fig. 10(a), compared with the GM(1,1) model, the DGGM(1,1) model and the SVM model can more accurately identify the seasonal fluctuations in electricity efficiency. It can be observed from Fig. 10(b) and (c) that the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models can better fit the seasonal growth trends of the electrical efficiency. It can be seen from Fig. 10(d) that, the MAPEs of the five models in the training set are 3.67%, 3.44%, 2.69%, 3.02%, and 3.01%, respectively, while those in the test set are 5.03%, 2.25%, 7.25%, 2.91%, and 2.93%, respectively. Although the SVM model has the highest prediction accuracy in the training set, its prediction accuracy in the test set is much lower than that of the other models. The rates of growth of electricity consumption and added value of industrial enterprises did not follow the internal growth trend due to the epidemic in the first quarter of 2020. The actual value of electricity usage efficiency increased in the first quarter of 2020.

### 3.4. Out-of-sample forecast

Based on the test results of the models in Sections 3.1, 3.2, and

**Table 5**  
Forecast results of the added value of industrial enterprises using the three models.

Time	Actual value	GM(1,1)		DGGM(1,1)		SVM	
		Forecast value	APE (%)	Forecast value	APE (%)	Forecast value	APE (%)
Training set							
2013Q1	2428.96	2428.96	0.00	2428.96	0.00	—	—
2013Q2	2958.88	2794.50	5.56	2958.88	0.00	—	—
2013Q3	2983.91	2854.09	4.35	2983.91	0.00	—	—
2013Q4	3212.48	2914.96	9.26	3212.48	0.00	—	—
2014Q1	2669.25	2977.13	11.53	2559.74	4.10	2603.42	2.47
2014Q2	3196.24	3040.62	4.87	3086.59	3.43	3134.27	1.94
2014Q3	3226.98	3105.47	3.77	3082.65	4.47	3161.11	2.04
2014Q4	3490.51	3171.70	9.13	3471.65	0.54	3465.12	0.73
2015Q1	2690.35	3239.34	20.41	2765.14	2.78	2875.63	6.89
2015Q2	3319.84	3308.42	0.34	3382.41	1.88	3385.24	1.97
2015Q3	3301.72	3378.98	2.34	3378.33	2.32	3411.86	3.34
2015Q4	3728.02	3451.04	7.43	3744.47	0.44	3770.43	1.14
2016Q1	2883.41	3524.64	22.24	2987.02	3.59	2911.49	0.97
2016Q2	3590.70	3599.81	0.25	3706.58	3.23	3537.21	1.49
2016Q3	3526.39	3676.58	4.26	3702.37	4.99	3505.36	0.60
2016Q4	3994.08	3754.99	5.99	4038.74	1.12	4039.78	1.14
2017Q1	3280.13	3835.07	16.92	3226.71	1.63	3129.65	4.59
2017Q2	4124.39	3916.86	5.03	4061.82	1.52	3852.72	6.59
2017Q3	4161.00	4000.39	3.86	4057.50	2.49	3785.48	9.02
2017Q4	4438.94	4085.71	7.96	4356.13	1.87	4369.41	1.57
2018Q1	3513.65	4172.84	18.76	3485.63	0.80	3579.64	1.88
2018Q2	4478.84	4261.84	4.85	4451.11	0.62	4417.14	1.38
2018Q3	4474.62	4352.73	2.72	4446.68	0.62	4468.67	0.13
2018Q4	4669.50	4445.56	4.80	4698.46	0.62	4866.98	4.23
<b>Test set</b>							
2019Q1	3823.00	4540.37	18.76	3765.32	1.51	3836.84	0.36
2019Q2	4655.03	4637.20	0.38	4877.71	4.78	4808.60	3.30
2019Q3	4696.89	4736.09	0.83	4873.20	3.75	4826.79	2.77
2019Q4	5071.74	4837.10	4.63	5067.70	0.08	5132.94	1.21
2020Q1	3433.06	4940.26	43.90	4067.46	18.48	4210.21	22.64

**Table 6**  
Forecast results of the added value of industrial enterprises using the two models.

Time	Actual value	1-AWBO-DGGM(1,1)			2-AWBO-DGGM(1,1)		
		$\chi^{(0)}D$	Forecast value	APE (%)	$\chi^{(0)}D^2$	Forecast value	APE (%)
Training set							
2013Q1	2428.96	2910.96	2910.96	0.00	3191.08	3191.08	0.00
2013Q2	2958.88	3611.48	3611.48	0.00	4012.84	4012.84	0.00
2013Q3	2983.91	3612.44	3612.44	0.00	4010.49	4010.49	0.00
2013Q4	3212.48	3922.25	3922.25	0.00	4297.55	4297.55	0.00
2014Q1	2669.25	3007.36	2987.96	0.65	3247.10	3245.39	0.05
2014Q2	3196.24	3742.00	3721.13	0.56	4093.11	4090.88	0.05
2014Q3	3226.98	3738.14	3712.78	0.68	4090.10	4089.00	0.03
2014Q4	3490.51	4064.21	4066.75	0.06	4372.61	4376.95	0.10
2015Q1	2690.35	3091.89	3112.02	0.65	3307.04	3311.46	0.13
2015Q2	3319.84	3878.44	3898.07	0.51	4180.89	4185.60	0.11
2015Q3	3301.72	3865.93	3892.12	0.68	4178.09	4184.27	0.15
2015Q4	3728.02	4207.63	4214.01	0.15	4449.71	4450.58	0.02
2016Q1	2883.41	3225.73	3241.22	0.48	3378.76	3378.87	0.00
2016Q2	3590.70	4064.64	4083.43	0.46	4281.70	4282.51	0.02
2016Q3	3526.39	4054.00	4080.13	0.64	4282.15	4281.77	0.01
2016Q4	3994.08	4367.51	4366.60	0.02	4530.41	4525.45	0.11
2017Q1	3280.13	3396.89	3375.79	0.62	3455.27	3447.66	0.22
2017Q2	4124.39	4301.62	4277.61	0.56	4390.23	4381.67	0.19
2017Q3	4161.00	4317.81	4277.22	0.94	4396.22	4381.53	0.33
2017Q4	4438.94	4554.22	4524.72	0.65	4611.86	4601.58	0.22
2018Q1	3513.65	3513.65	3515.95	0.07	3513.65	3517.85	0.12
2018Q2	4478.84	4478.84	4481.01	0.05	4478.84	4483.12	0.10
2018Q3	4474.62	4474.62	4483.83	0.21	4474.62	4483.62	0.20
2018Q4	4669.50	4669.50	4688.57	0.41	4669.50	4678.99	0.20
<b>Test set</b>							
2019Q1	3823.00		3661.92	4.21		3589.47	6.11
2019Q2	4655.03		4694.09	0.84		4586.93	1.46
2019Q3	4696.89		4700.43	0.08		4588.08	2.32
2019Q4	5071.74		4858.35	4.21		4757.71	6.19
2020Q1	3433.06		3813.96	11.10		3662.54	6.68

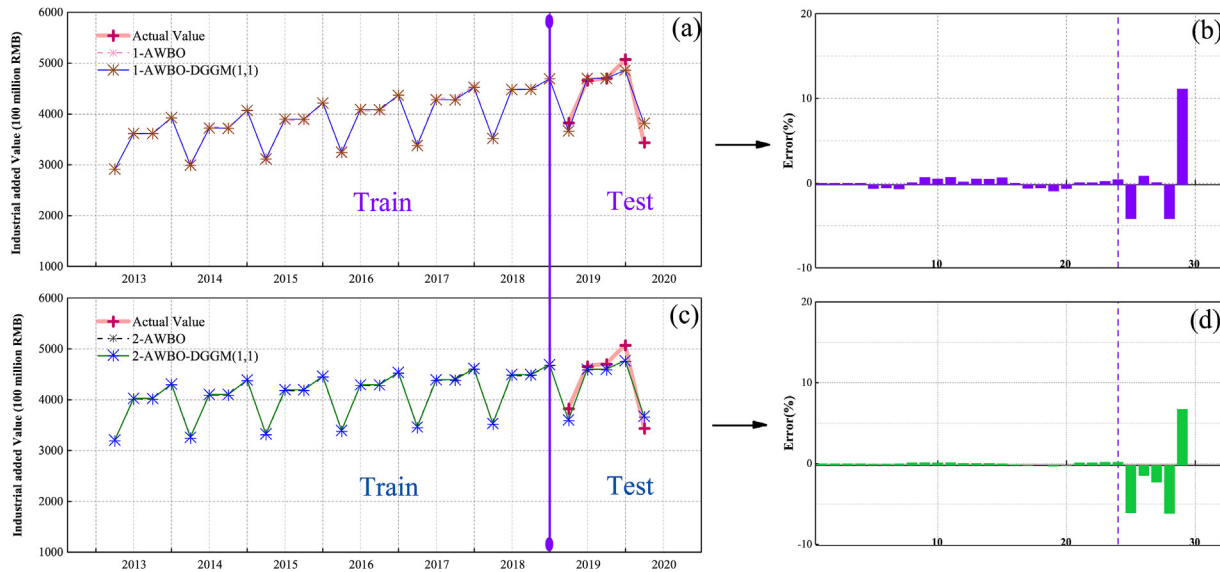


Fig. 8. Forecast results of the added value of industrial enterprises: (a) the results using the 1-AWBO-DGGM(1,1), (b) the error using the 1-AWBO-DGGM(1,1), (c) the results using the 2-AWBO-DGGM(1,1), (d) the error using the 2-AWBO-DGGM(1,1).

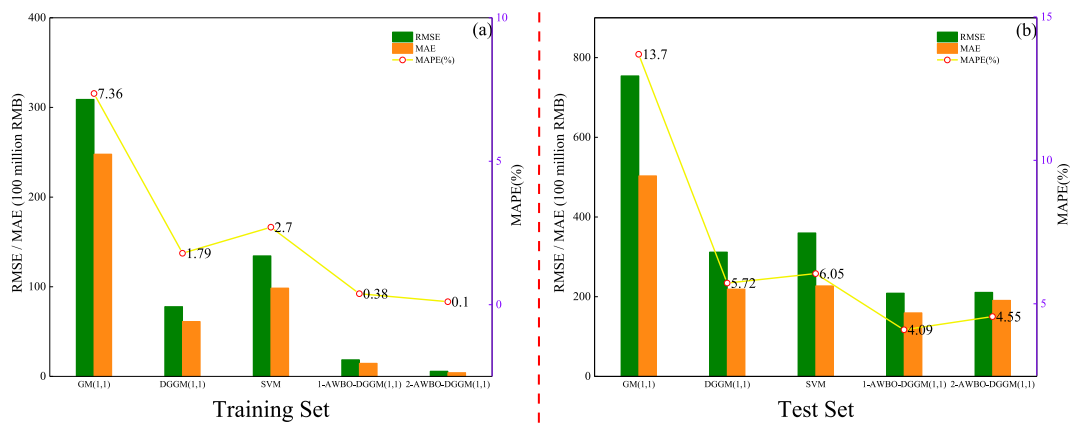


Fig. 9. Comparison of performance evaluation of the models: (a) Training set (b) Test set.

3.3, we forecast the electricity consumption, added value, and electricity usage efficiency of industrial enterprises by selecting the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models. By taking the quarterly electricity consumption and added value of industrial enterprises data from 2013 to 2019 as the in-sample data, the data from 2020 to 2022 are forecast. Table 8 and Fig. 11 show the forecast and actual values and comparison of results. Model-1 and Model-2 separately represent the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models.

Based on the forecast results using the models in Table 8 and Fig. 11, the electricity consumption, added value, and electricity usage efficiency of industrial enterprises are predicted to continue a seasonal growth trend in 2020-2022. The annual growth rates of electricity consumption from 2020 to 2022 using the 1-AWBO-DGGM(1,1) model are, separately, -1.26%, 7.18% and 2.47%, while those obtained through the 2-AWBO-DGGM(1,1) model are -2.74%, 5.44%, and 1.08%, respectively. Similarly, the annual growth rates of the added value of industrial enterprises forecast by the 1-AWBO-DGGM(1,1) model are 1.37%, 6.92%, and 3.86%. Moreover, the annual growth rates obtained by the 2-AWBO-DGGM(1,1) model are -0.57%, 4.40%, and 1.79%, respectively. The electricity usage efficiency of industrial enterprises in Zhejiang Province grows

Table 7 Accuracy comparison of the models for the added value of industrial enterprises.

Training set	RMSE	MAE	MAPE (%)
GM(1,1)	308.98	247.84	7.36
DGGM(1,1)	77.86	61.16	1.79
SVM	134.42	98.45	2.70
1-AWBO-DGGM(1,1)	18.54	14.57	0.38
2-AWBO-DGGM(1,1)	5.75	4.16	0.10
Test set	RMSE	MAE	MAPE (%)
GM(1,1)	754.08	503.25	13.70
DGGM(1,1)	311.92	219.03	5.72
SVM	360.10	227.13	6.05
1-AWBO-DGGM(1,1)	208.86	159.60	4.09
2-AWBO-DGGM(1,1)	210.85	190.79	4.55

constantly and it is at its highest in the first quarter, followed by that in the fourth quarter, while it is lowest in the third quarter. According to the prediction results of the 1-AWBO-DGGM(1,1) model, the annual average electricity usage efficiency of industrial enterprises in the province in 2020, 2021, and 2022 is predicted to be 5.7, 5.78, and 5.86; while that predicted using the 2-AWBO-

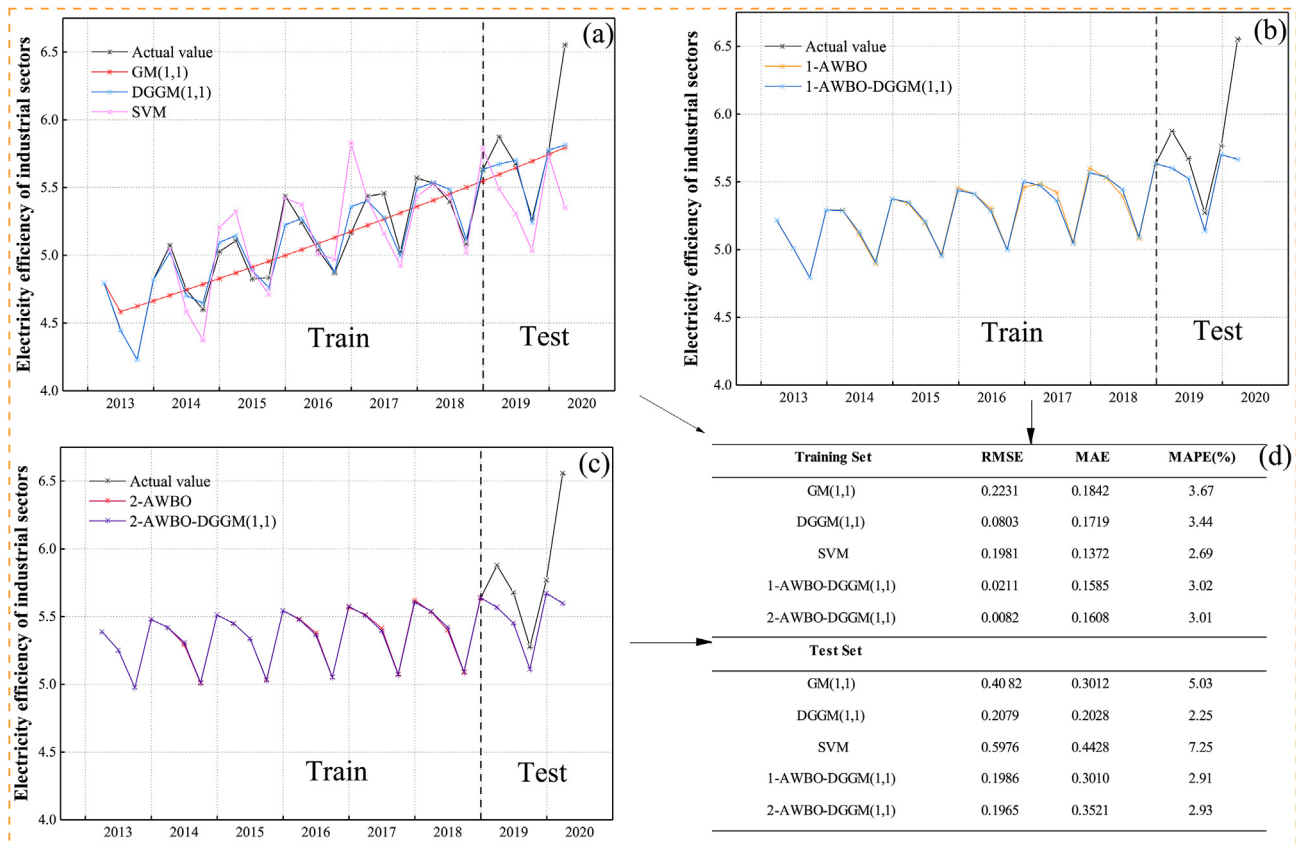


Fig. 10. Forecast results of the electricity efficiency: (a) the results using the GM(1,1), DGGM(1,1) and SVM models; (b) the results using the 1-AWBO-DGGM(1,1) model; (c) the results using the 1-AWBO-DGGM(1,1) model; (d) RMSE, MAE and MAPE using the models.

Table 8

Forecast results of industrial enterprises from the second quarter of 2020 to the fourth quarter of 2022 using the two models.

Time	Forecast value					
	Industrial electricity consumption		Industrial added value		Electricity usage efficiency	
	Model-1	Model-2	Model-1	Model-2	Model-1	Model-2
2020Q2	849.47	833.62	4883.27	4754.20	5.75	5.70
2020Q3	928.16	906.90	4928.77	4798.83	5.31	5.29
2020Q4	900.98	890.13	5251.18	5157.39	5.83	5.79
2021Q1	687.30	667.16	4139.32	3976.42	6.02	5.96
2021Q2	867.50	840.70	5068.11	4832.51	5.84	5.75
2021Q3	954.17	917.34	5124.10	4882.98	5.37	5.32
2021Q4	923.58	901.17	5444.11	5249.89	5.89	5.83
2022Q1	703.75	674.25	4308.70	4055.86	6.12	6.02
2022Q2	885.92	847.84	5259.95	4912.11	5.94	5.79
2022Q3	980.90	927.90	5327.16	4968.61	5.43	5.35
2022Q4	946.75	912.35	5644.14	5344.05	5.96	5.86

DGGM(1,1) model is 5.67, 5.71, and 5.76, respectively.

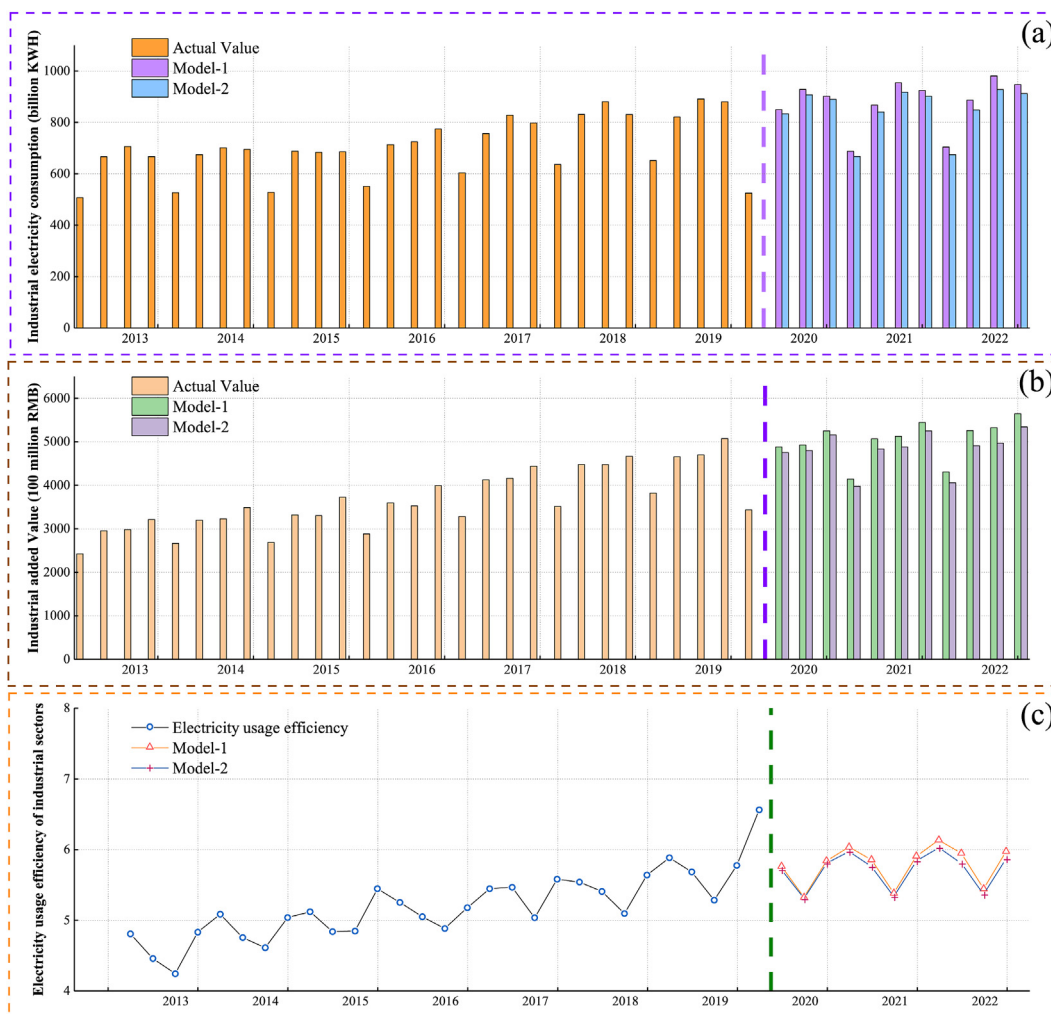
#### 4. Conclusion and future work

##### 4.1. Conclusion

This study uses the 1-AWBO-DGGM(1,1) model and the 2-AWBO-DGGM(1,1) model to the forecast for industrial enterprises. Based on the quarterly data of relevant variables in Zhejiang Province, the seasonal variations in the electricity consumption, added value, and electricity usage efficiency of industrial

enterprises are simulated and forecast. The results demonstrate that these two models can identify seasonal variations in such data and accurately forecast the impacts of the COVID-19 epidemic on industry and economy, thus obtaining a high forecast accuracy overall.

- (1) Either the electricity consumption or the added value of industrial enterprises shows significant characteristics of seasonal fluctuation, which increases the difficulties in forecast. Compared with the traditional GM(1,1) model and machine learning method (SVM model), the DGGM(1,1) model established based on grouping has better predictability, and can forecast seasonal fluctuations in electricity consumption and the added value of industrial enterprises.
- (2) Affected by the COVID-19 epidemic, indices including the electricity consumption and economic output of industrial enterprises show an abnormal tendency to decline. Due to the decrease of forecast accuracy, it is difficult for the traditional DGGM(1,1) model to reveal accurately those changes to the added value and electricity consumption: however, the 1-AWBO-DGGM(1,1) and 2-AWBO-DGGM(1,1) models established by introducing AWBOs into the original data effectively weaken the impacts of the external events on the system, strengthen adaptability to the data, and improve forecast accuracy. When forecasting the electricity consumption, the 2-AWBO-DGGM(1,1) model presents an extremely high forecast accuracy. When forecasting the added value, the 1-AWBO-DGGM(1,1) model shows better adaptability.



**Fig. 11.** Forecast results of industrial enterprises from the second quarter of 2020 to the fourth quarter of 2022 using the two models: (a) Industrial electricity consumption; (b) Industrial added value; (c) Electricity usage efficiency.

(3) Based on the forecast of the electricity consumption, added value, and electricity usage efficiency of industrial enterprises in Zhejiang Province in the short-term using these models, they maintain stable seasonal growth trends and the added value rises the fastest. As the energy industry in Zhejiang Province enters the period of structural optimization and adjustment, the proportion of traditional fossil energy continues to decline, while that of clean energy consumption constantly increases. The forecast results show that when the impact of the COVID-19 epidemic is taken into consideration, the electricity consumption of industrial enterprises in Zhejiang Province will reach  $3.36234 \times 10^{11}$  to  $3.51732 \times 10^{11}$  kW h, with a year-on-year increase of 1.08%–2.47%.

#### 4.2. Future work

Just like the grey prediction model, the traditional statistical methods assume that the variable system to be predicted is stable, therefore, when the system is subject to external impact, it inevitably, and significantly, influences the accuracy of predictions made using the model. The proposed mechanism will be introduced into

the multiple regression model in future research to solve prediction problems in areas related to energy consumption.

#### Credit author statement

Hai-Bao Chen: Investigation; Methodology; Software; Supervision; Writing - original draft. Ling-Ling Pei: Data curation; Formal analysis; Conceptualization; Visualization; Writing - review & editing. Yu-Feng Zhao: Methodology; Conceptualization; Writing - original draft; Writing - review & editing.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgement

The authors are grateful to the editors and the anonymous reviewers for their insightful comments and suggestions. This research is supported by the National Natural Science Foundation of China (Grant No. 71801190; 71571157).

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