



Application of a Novel Fractional Order Grey Support Vector Regression Model to Forecast Wind Energy Consumption in China

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Authors' contributions

This work was carried out in collaboration among all authors. Author JC designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors LL and LY managed the analyses of the study. Author SX managed the literature searches. All authors read and approved the final manuscript.

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Abstract

In order to achieve accurate prediction of new energy related data, a fractional grey support vector regression model based on nested cross-validation is proposed. In order to verify the superiority of the new model, China's wind energy consumption data from 2001 to 2014 were selected, and a fractional grey prediction model, a support vector regression model and a fractional support vector regression combination model were established, and wind energy consumption in China was predicted from 2015 to 2018. Numerical experimental results show that the newly proposed combined prediction model has higher prediction accuracy.

Keywords: Wind energy consumption; fractional order grey prediction model; support vector regression model; combination model.

1 Introduction

As we all know, the development of society is inseparable from the consumption of energy. At present, with the development and development of industrial technology, various energy sources are gradually used by

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human beings and consumed rapidly, and the shortage of fossil energy is becoming more serious. At the same time, the use of fossil energy has also brought a series of environmental pollution problems. Therefore, vigorously supporting and developing renewable and clean energy is the main way to solve the energy crisis of human society today. Among them, water energy, solar energy, geothermal energy, ocean energy, etc. have been continuously developed and used by people, especially wind energy, which is widespread and abundant in China. In recent years, China has vigorously developed the wind power industry and promoted the development of wind energy. Therefore, how to scientifically predict wind energy consumption with high accuracy has become the focus of our research.

At present, there are many prediction methods for new energy at home and abroad, including single models and combined models. Among them, the single prediction model mainly focuses on grey prediction [1,2,3], machine learning [4,5,6] and the traditional time series model [7,8]. Because of its simple modeling process and small amount of calculation, the grey model has been widely used in energy prediction research. Zhang et al. [9] used the GM (1,1) model to make short-term forecasts of China's coal demand. Feng et al. [10] used the optimized GM (1,1) model to forecast the per capita domestic energy consumption. With the rise of machine learning algorithms, the application trend of machine learning methods in energy prediction is also triggered. Nasr et al. [11] used the artificial neural network method to predict power consumption data effectively. Azadeh et al. [12] first proposed the application of ANN and ANOVA algorithms to predict the Power consumption related data. Wang [13] used the improved RVR model (RVR-NDM) to predict the battery life of new energy. Wang et al. [14] used the improved artificial bee colony algorithm to optimize the limit learning machine to predict the wind power.

With the rise of research on combined prediction models, more and more scholars have improved it. This method has been widely used in various energy time series predictions. Song et al. [15] proposed a novel combination model combining the advantages of BPNN, ENN, WNN and GRNN models to accurately predict wind speed. Du et al. [16] used the MOMFO method to propose a new hybrid forecasting model for predicting wind energy, which greatly improved forecast accuracy and stability. Wang et al. [17] based on the VMD method to capture and integrate data features, proposed a novel short-term wind speed nonlinear combination system, and combined with multi-objective optimization technology to improve the prediction accuracy of the model. In general, the combined prediction model has the advantages that the single prediction model does not. It can better model the energy data and make up for the low accuracy of the single prediction model.

Therefore, this paper first proposes a new fractional grey support vector regression model, which is based on nested cross validation of time series. Initially, the fractional order grey prediction model, support vector regression model and fractional order grey support regression combination model are respectively established to simulate and predict the wind energy consumption in China from 2001 to 2018. The nested cross-validation method of time series is applied to the modeling and calculation of the combined prediction model. The comparison results show that combination model has good predictive performance and can provide great help for rational utilization of new energy.

2 Predictive Model

2.1 Support vector regression

Vapnik et al. [18] proposed Support Vector Machines (SVM) in 1995. It was originally created to solve dichotomies, pattern recognition, and so on. However, with the continuous improvement of SVM theory, it can now be applied not only to classification problems, but also to regression problems. Support Vector Regression machine (SVR) [19] is a support vector machine applied to regression problems [19]. The theory of SVR was developed from SVM. Therefore, SVR also performs very well on small sample data sets. Because of its excellent data prediction ability and generalization performance, it has been widely used in various social fields.

Assume that the sample data set used for training is $S = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where $x_i = (x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(m)})^T, y_i \in R, i = 1, 2, \dots, n$. Let $X = (x_1, x_2, \dots, x_n)$ be the input space, then $Y = (y_1, y_2, \dots, y_n)$ be the output space, and each (x_i, y_i) is used as a training sample point. In order to learn that the relation between $f(X)$ and the real output Y is like the linear regression model of

$$f(x) = \omega^T x + b, \tag{1}$$

where ω is the weight coefficient vector of the hyperplane and b is the intercept vector of the hyperplane, the support vector regression problem needs to be converted into an Constrained optimization problem (2)

$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n E_\varepsilon(f(x_i) - y_i), \tag{2}$$

Where $C > 0$ is the penalty coefficient, E_ε is the ε -insensitive function, The mathematical definition is as follows

$$E_\varepsilon(e) = \begin{cases} 0, & |e| \leq \varepsilon \\ |e| - \varepsilon, & \text{others} \end{cases}, \tag{3}$$

By introducing the relaxation variables $\xi_i, \hat{\xi}_i$, the optimization problem (2) can be rewritten as the following optimization problem with constraints

$$\begin{aligned} & \min_{w,b,\xi_i,\hat{\xi}_i} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i + \hat{\xi}_i) \\ & s.t. \begin{cases} f(x_i) - y_i \leq \varepsilon + \xi_i \\ y_i - f(x_i) \leq \varepsilon + \hat{\xi}_i \\ \xi_i \geq 0, \hat{\xi}_i \geq 0, i = 1, 2, \dots, n \end{cases} \end{aligned}, \tag{4}$$

The Lagrange multiplier function of the above equation is specifically expressed as

$$\begin{aligned} & L(w, b, \alpha, \hat{\alpha}, \xi, \hat{\xi}, \mu, \hat{\mu}) \\ & = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^m (\xi_i + \hat{\xi}_i) - \sum_{i=1}^m \mu_i \xi_i - \sum_{i=1}^m \hat{\mu}_i \hat{\xi}_i \\ & + \sum_{i=1}^m \alpha_i (f(x_i) - y_i - \varepsilon - \xi_i) + \sum_{i=1}^m \hat{\alpha}_i (y_i - f(x_i) - \varepsilon - \hat{\xi}_i) \end{aligned}, \tag{5}$$

Where $\alpha_i > 0, \hat{\alpha}_i > 0, \mu_i > 0, \hat{\mu}_i > 0$ is Lagrange multipliers. Let the partial derivatives of $w, b, \xi_i, \hat{\xi}_i$, be 0, and substitute into equation (1) to obtain the following result

$$\begin{cases} w = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) x_i \\ 0 = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) \\ C = \alpha_i + \mu_i \\ C = \hat{\alpha}_i + \hat{\mu}_i \end{cases}, \quad (6)$$

Substituting in the condition (6), the dual form of Lagrange multiplier function $L(w, b, \alpha, \hat{\alpha}, \xi, \hat{\xi}, \mu, \hat{\mu})$ can be obtained as

$$\begin{aligned} \max_{\alpha_i, \hat{\alpha}_i} \sum_{i=1}^n y_i (\hat{\alpha}_i - \alpha_i) - \varepsilon (\hat{\alpha}_i + \alpha_i) - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\hat{\alpha}_i - \alpha_i) (\hat{\alpha}_j - \alpha_j) x_i^T x_j \\ \text{s.t.} \begin{cases} \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) = 0 \\ 0 \leq \alpha_i, \hat{\alpha}_i \leq C \end{cases} \end{aligned} \quad (7)$$

By substituting $w = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) x_i$ in equation (6) into equation (1), under KKT condition and Wolf theorem, the solution of support vector regression can be obtained as

$$f(x) = \sum_{i=1}^m (\hat{\alpha}_i - \alpha_i) x_i^T x + b, \quad (8)$$

Where $b = y_i + \varepsilon - \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) x_i^T x$ can be obtained from KKT condition. For the nonlinear regression problem, a suitable kernel function $\kappa(x, x_i)$ is introduced into SVR to obtain the solution of nonlinear support vector regression as

$$f(x) = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) \kappa(x, x_i) + b. \quad (9)$$

In this paper, the kernel function of RBF radial basis is selected, and the mathematical expression is

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right). \quad (10)$$

2.2 Fractional order grey prediction model

Since senior researcher Deng [20] put forward the grey system theory, the grey theory has been developed more maturely. The grey prediction model is an important part of the entire grey system theory. Among them,

the most classic grey prediction model is the GM (1,1) model. Since the model was proposed, it has attracted the interest of researchers, and actively participated in the research of optimizing and improving the GM (1,1) test model. Before Wu, the grey prediction model was still in the field of integer order accumulation. The proposal of the fractional-order FGM (1,1) model [21] successfully extended the integer-order grey prediction model to the fractional order, which greatly improved the research scope of the grey prediction model and improved the applicability of the grey prediction model. Let's make a brief introduction to the fractional grey prediction model.

Definition 1. Assume that $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3) \cdots x^{(0)}(n-1), x^{(0)}(n))^T$ is a column of non-negative vectors, and the cumulative sequence of its order r ($r - AGO, r \in R$) is $X^{(r)} = (x^{(r)}(1), x^{(r)}(2), x^{(r)}(3) \cdots x^{(r)}(n-1), x^{(r)}(n))^T$, where

$$x^{(r)}(k) = \sum_{i=1}^k \frac{\Gamma(r+k-i)}{\Gamma(k-i-1)\Gamma(r)} x^{(0)}(i), k = 1, 2, 3, \dots, n, \tag{11}$$

There is $\Gamma(n) = \int_0^\infty e^{-t} t^{n-1} dt, \Gamma(n+1) = n\Gamma(n)$, and $\Gamma(n+1) = n!$ when $n \in N$ is satisfied.

In addition, when $r = 1$, $r - AGO$ can be reduced to the most classical first-order accumulation generating sequence ($1 - AGO$), namely $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), x^{(1)}(3) \cdots x^{(1)}(n-1), x^{(1)}(n))^T$, where $x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i)$.

Definition 2. Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3) \cdots x^{(0)}(n-1), x^{(0)}(n))^T$ be a column of non-negative vectors, and its r order reduced generation sequence ($r - IAGO$) is $X^{(-r)} = (x^{(-r)}(1), x^{(-r)}(2), x^{(-r)}(3) \cdots x^{(-r)}(n-1), x^{(-r)}(n))^T$, where

$$x^{(-r)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} x^{(0)}(k-i), k = 1, 2, 3, \dots, n, \tag{12}$$

It is like $1 - AGO$. When $r = 1$, $r - IAGO$ can be reduced to first-order reduced generation operator $1 - IAGO$, namely $X^{(-1)} = (x^{(-1)}(1), x^{(-1)}(2), x^{(-1)}(3) \cdots x^{(-1)}(n-1), x^{(-1)}(n))^T$.

Definition 3. If $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), x^{(0)}(3) \cdots x^{(0)}(n-1), x^{(0)}(n))^T$ is a column of non-negative vectors and $X^{(r)}$ is as defined in definition 1 above, then the difference equation

$$x^{(r)}(k+1) - x^{(r)}(k) + az^{(r)}(k) = b, \tag{13}$$

It is called the basic form of the r order grey prediction model (abbreviated as FGM (1,1) model). Where $z^{(r)}(k) = \frac{x^{(r)}(k) + x^{(r)}(k-1)}{2}, k = 2, 3, \dots, n$, a is development coefficients, b is grey action quantities.

In particular, when $r = 1$, $x^{(r)}(k+1) - x^{(r)}(k) + az^{(r)}(k) = b$ can easily be reduced to the classical GM(1,1) model $x^{(0)}(k) + az^{(1)}(k) = b$, which is the mean GM(1,1) model.

The parameters of FGM (1,1) model can be estimated by the least square method. If the estimated value of the parameter is $\hat{u} = (\hat{a}, \hat{b})^T$, then the least square method is:

$$\hat{u} = (\hat{a}, \hat{b})^T = (B^T B)^{-1} B^T Y, \tag{14}$$

where

$$Y = \begin{bmatrix} x^{(r)}(2) - x^{(r)}(1) \\ x^{(r)}(3) - x^{(r)}(2) \\ \vdots \\ x^{(r)}(n) - x^{(r)}(n-1) \end{bmatrix}, B = \begin{bmatrix} -z^{(r)}(2) & 1 \\ -z^{(r)}(3) & 1 \\ \vdots & \vdots \\ -z^{(r)}(n) & 1 \end{bmatrix} \tag{15}$$

Definition 4. Set r -IAGO sequence $X^{(r)}$ and model parameters $u = (a, b)^T$ as described in definition 1 and definition 3 respectively, then

$$\frac{dx^{(r)}(t)}{dt} + ax^{(r)}(t) = b, \tag{16}$$

It is called the whitening differential equation of grey FGM (1,1) model with accumulative r order.

If $\hat{x}^{(0)}(1) = x^{(0)}(1)$ is the initial condition, the solution of equation (16) can be easily obtained by the constant variation method, which is called the time response function of FGM (1,1) model

$$\hat{x}^{(r)}(t) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-a(t-1)} + \frac{b}{a}. \tag{17}$$

By discretization of equation (17), the time response sequence of FGM (1,1) model is

$$\hat{x}^{(r)}(k) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-a(k-1)} + \frac{b}{a}, k = 2, 3, \dots, n-1, n. \tag{18}$$

Thus, the reduction value of the predicted value of FGM (1,1) model is

$$\hat{x}^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} \hat{x}^{(r)}(k-i), k = 2, 3, \dots, n. \quad (19)$$

2.3 Combination prediction model

Single prediction models often have their own shortcomings, but if a suitable combination method can be found and combined with the advantages of each model, a combination model with higher prediction accuracy can be obtained. This is exactly the basic idea that Bates and Granger put forward the concept of combined prediction [22]. Combinatorial prediction has become a hot topic at home and abroad. Both in theoretical research and application research of combined prediction models have achieved fruitful results. Therefore, this paper proposes a new fractional grey support vector regression model based on these foundations. The combined prediction model combines the advantages of the grey prediction model and the support vector regression model, so that it can predict small sample nonlinear time series with high accuracy. Fig. 1 below shows the combination of the newly proposed fractional grey support vector regression model (hereinafter referred to as FGM-SVR model).

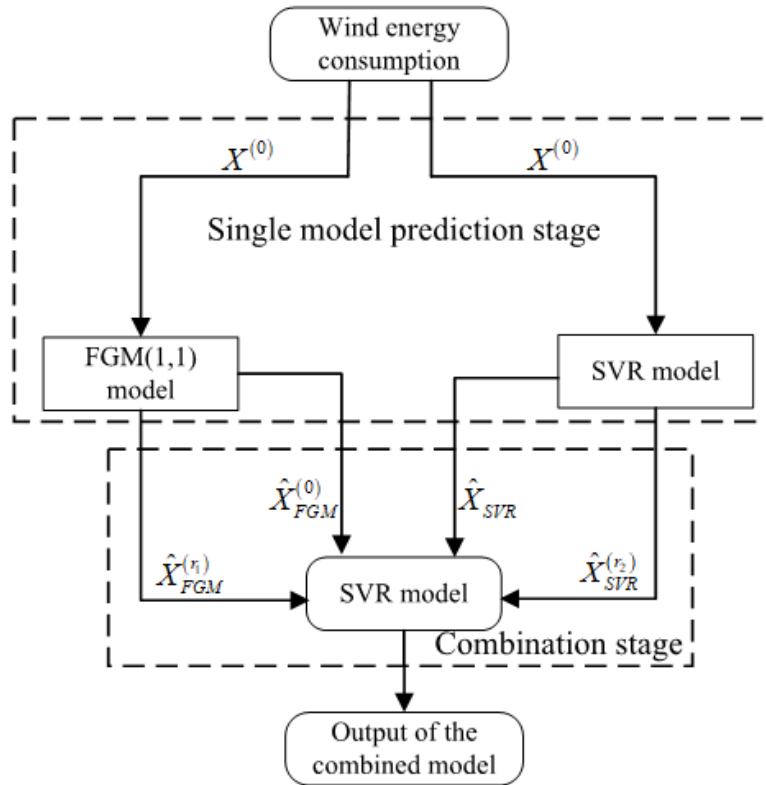


Fig. 1. Combined structure of fractional grey support vector regression model

In Fig. 1, $X^{(0)}$ is the original sample sequence of FGM (1,1) model and support vector regression model (SVR) in single prediction. $\hat{X}_{FGM}^{(0)}$ and $\hat{X}_{SVR}^{(0)}$ are the prediction sequences of FGM (1,1) model and SVR model respectively. $\hat{X}_{FGM}^{(r_1)}$ and $\hat{X}_{SVR}^{(r_2)}$ are the r_1 order and r_2 order accumulation sequences of FGM (1,1)

model and SVR model respectively. Sequence $\hat{X}_{FGM}^{(0)}$, \hat{X}_{SVR} , $\hat{X}_{FGM}^{(r_1)}$ and $\hat{X}_{SVR}^{(r_2)}$ were taken as the input and $X^{(0)}$ as the output of the SVR model to rebuild the support vector regression model. This model is the newly proposed FGM-SVR model. The hyperparameters r_1 and r_2 are obtained by nested cross-validation method of time series. The specific method is introduced in the application and analysis.

3 Application and Analysis

In order to verify the advantage of FGM-SVR model in dealing with small sample nonlinear time series, this paper uses the wind energy consumption case data of China from 2001 to 2018 to establish the FGM (1,1) model, SVR model and FGM-SVR combination model compares and analyzes the prediction performance of the three prediction models on the data set. The data of wind energy consumption from 2001 to 2018 are shown in Table 1(The following annual wind energy consumption units are million tonnes oil equivalent).

Table 1. China's wind energy consumption in new energy from 2001 to 2018

Years	Wind energy consumption	Years	Wind energy consumption	Years	Wind energy consumption
2001	0.16	2007	1.24	2013	31.95
2002	0.19	2008	2.96	2014	35.32
2003	0.23	2009	6.25	2015	42.03
2004	0.29	2010	10.10	2016	53.64
2005	0.44	2011	15.91	2017	66.75
2006	0.84	2012	21.72	2018	82.82

The data in Table 1 is divided into two sub-sequences, of which the first sub-sequence is divided into regions from 2001 to 2014. This part of data is used to build FGM (1,1) model, SVR model and FGM-SVR model. The remaining wind energy consumption data is the second subinterval, which is used to test the prediction accuracy of the three prediction models. In order to compare and analyze the three prediction models, MAPEPR (Mean absolute percentage error for the priori-sample period) and MAPEPO (Mean absolute percentage error for the post-sample period) [23] were used as the evaluation indexes of the model. The specific calculation formula is as follows

$$MAPEPR = \frac{1}{r} \sum_{t=rp+1}^{rp+r} \left| \frac{\hat{X}^{(0)}(t) - X^{(0)}(t)}{X^{(0)}(t)} \right| \times 100\%, \tag{20}$$

$$MAPEPO = \frac{1}{rf} \sum_{t=rp+r+1}^{rp+r+rf} \left| \frac{\hat{X}^{(0)}(t) - X^{(0)}(t)}{X^{(0)}(t)} \right| \times 100\%, \tag{21}$$

Where rp represents the number of original sample points not fitted by the model ($rp=1$ in FGM(1,1) model, $rp=3$ in SVR model, and $rp=0$ in FGM-SVR model), r represents the number of sample points used for fitting modeling, and rf represents the number of predicted points in the prediction model.

The optimal order of the FGM (1,1) model is obtained by minimizing the MAPEPR. The FGM-SVR model also incorporates the nested cross-validation method shown in Fig. 2 when solving the optimal orders r_1 and r_2 ., and is obtained by minimizing cross-validation MAPEPO.

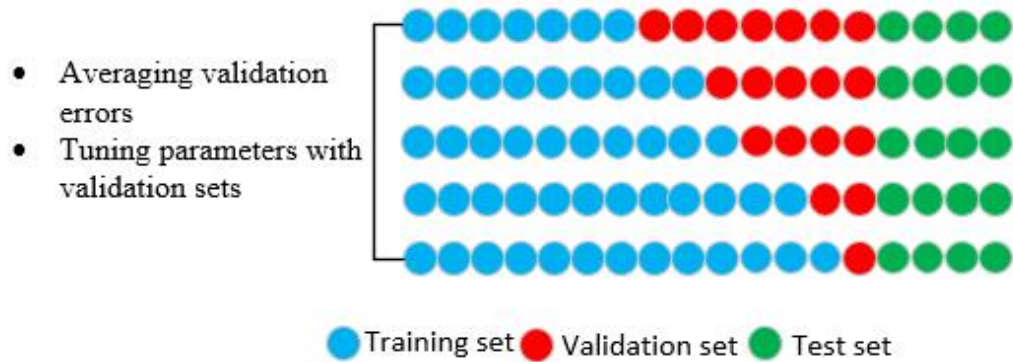


Fig. 2. Nested cross-validation

For the specific verification method in the FGM-SVR model, the last four groups of sample data are taken as the test set, and then 50%, 60%, 70%, 80%, and 90% of the remaining data are taken as the training set, and the rest as the verification set (The specific number of training set, validation set, and test set is shown in Fig. 2). The MAPEPO obtained in Fig. 2 is averaged, and then it is used as the objective function of the FGM-SVR model to solve the optimal parameters r_1 and r_2 . When solving the optimal order, the accumulation order of the FGM (1,1) model and the FGM-SVR model is set in the interval [-2,2], and the minimum MAPEPR and minimum MAPEPO are searched respectively with a step size of 0.1. By calculation, the optimal order of the FGM (1,1) model is 1.62, and the optimal order of the FGM-SVR model is -0.10 and -1.00. The modeling calculation results and model error statistics of the three prediction models are shown in Table 2 (all calculation results retain two decimal places). Fig. 3 shows the prediction effect of the three prediction models.

Table 2. Comparison of fit and error values of the three models

Years	Wind energy consumption	FGM	Relative error	SVR	Relative error	FGM-SVR	Relative error
2001	0.16	0.16	0.00	0.16	0.00	0.13	0.22
2002	0.19	0.05	0.72	0.19	0.00	0.01	0.96
2003	0.23	0.15	0.32	0.23	0.00	0.06	0.74
2004	0.29	0.27	0.05	2.04	6.07	2.31	6.99
2005	0.44	0.48	0.09	2.12	3.82	1.09	1.47
2006	0.84	0.84	0.00	2.28	1.71	1.31	0.55
2007	1.24	1.46	0.18	2.65	1.14	1.81	0.46
2008	2.96	2.55	0.14	3.26	0.10	2.54	0.14
2009	6.25	4.45	0.29	4.83	0.23	4.48	0.28
2010	10.10	7.77	0.23	8.34	0.17	8.46	0.16
2011	15.91	13.55	0.15	14.33	0.10	14.64	0.08
2012	21.72	23.63	0.09	22.54	0.04	22.71	0.05
2013	31.95	41.20	0.29	30.20	0.05	30.19	0.06
2014	35.32	71.85	1.03	34.66	0.02	37.09	0.05
MAPEPR			0.28		1.22		0.87
2015	42.03	125.31	1.98	31.83	0.24	42.26	0.01
2016	53.64	218.52	3.07	24.79	0.54	54.78	0.02
2017	66.75	381.09	4.71	19.92	0.70	78.23	0.17
2018	82.82	664.59	7.02	14.31	0.83	83.67	0.01
MAPEPO			4.20		0.58		0.05

It is obvious from Table 2 that the FGM-SVR combined model has a MAPEPO of only 4.00%, while the FGM and SVR models are as high as 419.00% and 57.00%. The FGM-SVR combined model is significantly lower than the FGM and SVR models. However, in the data fitting stage, the MAPEPR of the FGM model was 27.00%, which was lower than the SVR model and the FGM-SVR combined model. This shows that FGM model has overfitting phenomenon in the fitting stage. Fig 3 below also fully demonstrates that the FGM-SVR combination model has excellent prediction performance.

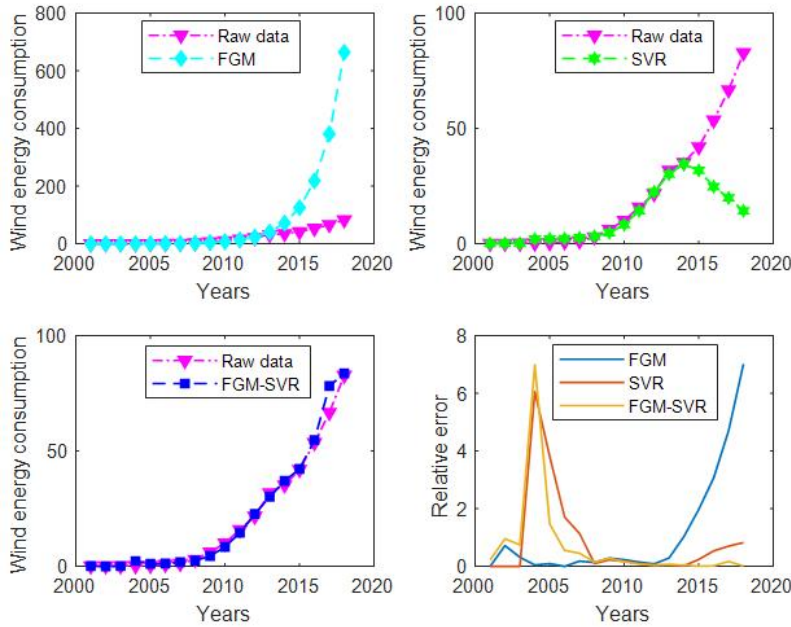


Fig. 3. Error ratios of the three models

In order to further verify the advanced nature of the combined model, the prediction effect of this model is compared with SAIGM [24] model and NGM [25] model. The results are shown in Table 3. It can be seen that the superior prediction performance of the FGM-SVR model.

Table 3. Compared with other prediction models

Years	Wind energy consumption	SAIGM	NGM	FGM-SVR
2015	42.03	39.95	103.20	42.26
2016	53.64	53.80	141.71	54.78
2017	66.75	72.12	194.44	78.23
2018	82.82	96.35	266.64	83.67
MAPEPO		0.07	1.81	0.05

4 Conclusion

The realization of high-precision prediction of new energy can make the field of new energy better developed, and the combined prediction model has more and more contributions in new energy prediction. In this paper, a new combination model is proposed, which is a fractional grey support vector regression model. The combination model combines a fractional grey prediction model and a support vector regression model, and combines their respective advantages to improve the prediction accuracy. The results show that the combined model proposed in this paper has better prediction performance than the fractional order grey

prediction model and the support vector regression model, which can predict the wind energy consumption in new energy more accurately and provide necessary feedback for the new energy field.

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Competing Interests

Authors have declared that no competing interests exist.

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