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RVM Kernel Parameters Selection Method based on AIC Applied in Gold Prices

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Abstract

The relationship between the nuclear parameters and model performance is complex, which is from relevance vector machine (RVM) regression model based on Gaussian radial basis kernel function. Aiming at the problem of how to determine the kernel parameters of RVM, a method to selecting kernel parameter of RVM based on AIC criterion is proposed. Firstly, a novel of statistic Q is proposed based on "Akaike" Information Criterion (AIC), while the Q is as a fitness function. Secondly, we use the differential evolution algorithm (Differential Evolution Algorithm, DE) to find the best kernel parameter, in order to choose determine the kernel parameters. Finally, a RVM regression model mode is established and it is used in predicting gold price. Experimental results show that the prediction model has higher precision and better fitting the generalization ability than the traditional method, which demonstrates the AIC-based criteria for selecting RVM kernel parameter method is effective and feasible.

Keywords: *Radial Basis Function, Kernel Parameters, Relevance Vector Machine, Differential Evolution Algorithm, AIC Criterion, Gold Prices*

1. Introduction

Gold prices have been proven to be a low-dimensional chaotic time series [2]. Empty space reconstruction phase is the basis of chaotic time prediction, and it can tap hidden in chaotic attractors of evolution. When the phase space reconstruction, the selection of time delay (τ) and embedding dimension (m) is essential and directly affect the prediction accuracy of the subsequent gold price [3]. For the selection of the parameters τ and m, there are mainly two ideas: ①τ and *m*, respectively, solve alone. Firstly, autocorrelation method is used, mutual information method to determine τ, then with using the G-P method, pseudo-nearest neighbor method determine *m*, but only the extraction time autocorrelation linear correlation between sequences. Mutual information method is able to reflect a variety relationship of holistic systems, but these relationships are only high-dimensional phase space projection in two-dimensional space. It only reflects the independence of the two reconstructed coordinate reconstruction phase space also, but it cannot guarantee that all reconstruction overall independence. In most ways, in order to determine the best τ, you need to determine *m*, while in order to determine *m*, it needs to determine advance a fixed τ, which will inevitably lead to conflicts [4]. ②τ and *m* unity are solved. Broom head put forward as the time window method. Kim put forward the C-C method, τ and m unity solved by the relationship between τ and *m*, so that the gold price time series reconstructed more accurately reflect changes in the gold price trend. So τ , *m* is often used to solve ideological unity [5]. Advantage of the current gold price prediction algorithm is that they mainly use neural network algorithm, support vector

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machines and other algorithms [6-7], because the least squares support vector machine (LSSVM) has ability of high training speed, good generalization.

Tipping proposed relevant vector machine in 2000 (Relevance Vector Machine, RVM) [8], which is a general sparse probabilistic model framework based on Bayesian. Because its sparse model structure, the kernel function does not need to meet the complexity of the Mercer conditions and relatively low computing and other advantages. RVM method has been applied to a number of classification and prediction tasks, such as power quality disturbances classification [9], Alzheimer's disease clinical variables prediction [10], for the long-term runoff forecast [11] and so on. However, using a Gaussian kernel function RVM regression model, on the one hand because of its RVM regression model kernel parameters and performance (fitting precision, generalization ability, related to the number of vectors) complex relationship exists. It is difficult to resolve the relationship for analysis. On the other hand, due to the inevitably noisy sample data, such as statistical error, etc. So far, there is no good way to determine the kernel parameters, such as the literature [12] discussed the comparison is only appropriate the range of kernel parameters. To solve this problem, this paper based on "Akaike" Information Criterion (AIC) thought, first derive a new statistic Q. Then Q is presented to the fitness function, the use of differential evolution algorithm (DE) for kernel parameter optimization the method for determining the algorithm kernel parameters. Finally use the algorithm to establish the gold price of AIC-RVM regression model, and with MAPE-RVM regression model with mean absolute percentage error for the fitness function and the differential evolution algorithm based on support vector machine model, multidimensional gray model, wavelet neural network model and other models were compared. The results show, AIC-RVM fitting regression models has higher accuracy and better generalization ability, and it illustrates that the determination of the kernel parameters RVM method is effective.

2. Problem Model

Setting the training sample is $\{x_i, t_i\}$, $i = 1, \cdots, N$, where $x_i \in R^n$ is the input variable. n is the dimension of input variable. $t_i \in R$ is the output variable. RVM regression model of output variable t_i is as follow.

$$t_i = \sum_{j=1}^{N} \omega_j K(x_i, x_j) + \omega_0 + \varepsilon_i \ , i = 1, \cdots, N \tag{1}$$

Where $\omega = (\omega_0, \omega_1, \cdots, \omega_N)^T$ is the weight vector. $K(x, x_j)$ is the basis function, the noise $\varepsilon_i \sim N(0, \sigma^2)$, where σ^2 is variance. Assumed t_i independent of each other, the likelihood estimation of training sample $\{x_i, t_i\}$, $i = 1, \cdots, N$ can be written as:

$$p(t \mid \omega, \beta) = \left(\frac{\beta}{2\pi}\right)^{N/2} \exp\left\{-\frac{\beta}{2}\|t - \Phi\omega\|^2\right\} \tag{2}$$

where $\beta = 1/\sigma^2$, $t = (t_1, t_2, \cdots, t_N)^T$, $\Phi = (\phi_0, \phi_1, \cdots, \phi_N)$ is $N \times (N+1)$ matrix, $\phi_0 = (1, 1, \cdots, 1)^T$, $\phi_1 = (K(x_1, x_1), K(x_2, x_1), \cdots, K(x_N, x_1))^T, \cdots$, $\phi_N = (K(x_1, x_N), K(x_2, x_N), \cdots, K(x_N, x_N))^T$ is the basis vector.

Hypothesis ω meets zero mean Gaussian prior distribution. $p(\omega \mid \alpha) = \prod_{i=0}^{N} N(\omega_i \mid 0, \alpha_i^{-1})$, Where $\alpha = (\alpha_0, \alpha_1, \cdots, \alpha_N)^T$, each individual parameter α_i is only related to its weights ω_i.

The ω posterior distribution formula can be obtained by Bayesian theorem,

$p(\omega \mid t, \alpha, \beta) = N(\omega \mid \mu, \Sigma)$, where Σ is covariance matrix, μ is mean vector. And

$$A = diag(\alpha_0, \alpha_1, \cdots, \alpha_N) \tag{3}$$

$$\Sigma = \left(\beta \Phi^T \Phi + A\right)^{-1} \tag{4}$$

$$\mu = \beta \Sigma \Phi^T t \tag{5}$$

We get iterative formula, based on Bayesian evidence process to maximize the marginal likelihood $p(t \mid \alpha, \beta)$,

$$\alpha_i^{new} = \frac{1 - \alpha_i \Sigma_{ii}}{\mu_i^2}, \quad i = 0,1,\cdots,N \tag{6}$$

$$\beta^{new} = \frac{N - \sum_{j=0}^{N} \gamma_j}{\left\| t - \Phi \mu \right\|^2} \tag{7}$$

Where μ_i is the ith element of μ, Σ_{ii} is the ith diagonal element of covariance matrix Σ, $\gamma_j = 1 - \alpha_j \Sigma_{jj}$.

The formula (3) to (7) is iterated to obtain a thinning RVM model. In the specific process of the iterative calculation, we usually set a threshold value for α_i, such as 10^9. If it exceeds the threshold value, it will implement "pruning."

We selected radial basis function $K(x, x') = \exp\left(-\frac{\left\| x - x' \right\|^2}{c^2} \right)$, ($c > 0$ is the kernel parameter), as the kernel function of RVM model.

3. The Proposed Algorithm

Differential evolution algorithm (DE) is an evolutionary algorithm groups within populations through cooperation and competition between individuals to achieve the optimization problem. Its essence is that the greedy genetic algorithm has confirmed optimal thought based on real-coded. Its basic operations include mutation, crossover and a choice of three operations. Since the differential evolution algorithm (DE) has a strong global optimization features, faster convergence speed and better stability. Differential evolutionary algorithm is introduced to the kernel parameters c of RVM automatic optimization in parameter space. Among them, in the process of optimization, the selection of fitness function is the key.

3.1. Fitness Function

Training of related vector machine is to remove irrelevant points based auto-related decisions (Automatic Relevance Determination, ARD) to obtain sparse model theory. Make the number of correlation vectors obtained by the M training(that is the number of non-zero components ω_i in ω), the obtained RVM model of sparse

$$t = \Phi^* \omega^* + \varepsilon^* \tag{8}$$

Where $\Phi^* = (\phi_{i_1}, \phi_{i_2}, \cdots, \phi_{i_M})$ is the $N \times M$ matrix after Φ deleting not related to the basis vectors in model (1). $\omega^* = (\omega_{i_1}, \omega_{i_2}, \cdots, \omega_{i_M})^T$ is the vector by the components corresponding

to a non-zero in ω. $\varepsilon^* = (\varepsilon_1^*, \varepsilon_2^*, \cdots, \varepsilon_N^*)^T$, $\varepsilon_i^* \sim N(0, \frac{1}{\hat{\beta}})$, $\frac{1}{\hat{\beta}}$ is the variance σ^2 estimated value of noise ε_i, $t = (t_1, t_2, \cdots, t_N)$.

Setting $L = \frac{M}{N}$, then L can approximately represent the relevant vector proportion in the basis vector. Mak R is the correlation coefficient between output vector $t = (t_1, t_2, \cdots, t_N)$ and its prediction vector $\hat{t} = (\hat{t}_1, \hat{t}_2, \cdots, \hat{t}_N)$.

$$R^2 = \frac{\left(N\sum_{i=1}^{N} \hat{t}_i t_i - \sum_{i=1}^{N} \hat{t}_i \sum_{i=1}^{N} t_i \right)^2}{\left(N\sum_{i=1}^{N} \hat{t}_i^{\,2} - \left(\sum_{i=1}^{N} \hat{t}_i \right)^2 \right)\left(N\sum_{i=1}^{N} t_i^{\,2} - \left(\sum_{i=1}^{N} t_i \right)^2 \right)}$$ set and $SS_{eM} = \sum_{j=1}^{N} \left(t_j - \hat{t}_j \right)^2$ set are the residual sum of squares.

Lemma1. In regression model $y = \Phi_q a + \varepsilon$, where Φ_q is $N \times q$ design matrix and the first column of Φ_q is $(1,1,\cdots,1)^T$, $a = \left(a_1, a_2, \cdots, a_q \right)^T$, $\varepsilon = (\varepsilon_1, \varepsilon_2, \cdots, \varepsilon_N)^T$, $\varepsilon_i \sim N(0, \sigma^2)$, $y = \left(y_1, y_2, \cdots, y_N \right)^T$. If $(\Phi_q)^T \Phi_q$ is reversible and $a = \left((\Phi_q)^T \Phi_q \right)^{-1} (\Phi_q)^T y$, then

$\sum_{j=1}^{N} \left(y_j - \hat{y}_j \right)^2 = \left(1 - R^2 \right) \sum_{j=1}^{N} \left(y_j - \bar{y} \right)^2$, where $\bar{y} = \frac{1}{N} \sum_{j=1}^{N} y_j$, $\hat{y} = \left(\hat{y}_1, \hat{y}_2, \cdots, \hat{y}_N \right)^T$ is the prediction vector of y, R is the correlation coefficient between y and $\hat{y}$.

Lemma 2. In model (8), $\omega^* = \left((\Phi^*)^T \Phi^* + \frac{1}{\hat{\beta}} A^* \right)^{-1} (\Phi^*)^T t$, where $\frac{1}{\hat{\beta}}$ is the variance σ^2 estimated value of noise ε_i in model(1), A^* is made by A deleting the components tend to ∞.

Proof. Because of ω^* meeting (4), (5) formula, we make formula (4) into formula (5), and then we can get it.

Lemma 3. If $N \geq 4$, then it exits the positive constant δ, and C_1. For each kernel parameter $c < \delta$, which makes that the characteristic root $(\Phi^*)^T \Phi^*$ are no less than C_1.

Proof. For the first column elements of Φ^* is 1 and not all 1, respectively discuss when $c \to 0$, the limited smallest Eigen value of $(\Phi^*)^T \Phi^*$ and it can be calculated.

The following conventions $N \geq 4$, and then $\frac{1}{\hat{\beta}} \to 0$, by formula (7) we can know $\left\| t - \Phi^* \omega^* \right\| \to 0$, thereby $\min_{\beta} \left\| t - \Phi\beta \right\| \to 0$, the σ^2 maximum likelihood estimation $\frac{1}{N} (\min_{\beta} \left\| t - \Phi\beta \right\|) \to 0$. The following assumptions model (1) the variance σ^2 of noise ε_i sufficiently small.

Taking into account all the elements of the model establishment RVM thinning process usually located on a threshold value for α_i, the following assumptions the all elements of A^* does not exceed a constant C_2.

Lemma 4. In model (8), when kernel parameter c and $\frac{1}{\hat{\beta}}$ are both sufficiently small,

$$SS_{eM} \approx \left(1-R^2\right)\sum_{j=1}^{N}\left(t_j-\bar{t}\right)^2 \text{, where } \bar{t}=\frac{1}{N}\sum_{j=1}^{N}t_j \text{ .}$$

Proof. For the first column elements of Φ^* is 1 and not all 1, respectively discussed. By Lemma 1, Lemma 2 and Lemma 3 can get the lemma.

It is similar to the thought of AIC criterion. In model (8), intake $\text{AIC}=N\ln\left(SS_{eM}\right)+2M$ .From lemma 4, we can get conclusion: In model (8), when kernel parameter c and $\frac{1}{\hat{\beta}}$ are both sufficiently small, $\text{AIC}\approx N\ln\left(1-R^2\right)+2M+C$, where $C=N\ln\sum_{j=1}^{N}\left(t_j-\bar{t}\right)^2$.

Since the sample data is given, and therefore the N and C in $N\ln\left(1-R^2\right)+2M+C$ are also given. Thus $N\ln\left(1-R^2\right)+2M+C$ in the model (8) is equivalent to $\ln\left(1-R^2\right)+2\frac{M}{N}$.

Because of $\ln\left(1-R^2\right)\approx -R^2-\frac{1}{2}R^4,\left(0<R<1\right)$, so $\ln\left(1-R^2\right)+2\frac{M}{N}\approx -R^2-\frac{1}{2}R^4+2\frac{M}{N}$

$=2L-R^2-\frac{1}{2}R^4$ 。

When the statistical error of sample data is small, to take the fitness function for $Q=2L-R^2-\frac{1}{2}R^4$.

3.2. RVM Kernel Parameter Optimization Algorithm Based on AIC

Step1: Input sample data. Set the maximum iteration cycles D of DE, population size N_p, scaling factor F and crossover constant CR and set the search range parameters group c. Make iterative algebra $j=0$.

Step2: Randomly generated initial population $\alpha_s^0,(s=1,2,\cdots,N_p)$ within the scope of the parameter c setting. Using RVM obtain prediction value $\hat{t}_i$, $(i=1,2,\cdots,l)$ of t_i. Take the fitness function as $Q=2L-R^2-\frac{1}{2}R^4$. Then, we compute the fitness value of each individual. Record each individual extreme, global extremes and global extreme point.

Step3: Using mutation, crossover and selection of these three operations on the population to be updated, the new fitness value is calculated for each individual populations, and update each individual extreme, global extremes and global extreme point.

Step4: If $j<D$, then the iterative algebra $j\leftarrow j+1$, turn to step3. Otherwise, the output of the global extreme point c^*.

Step5: Establish RVM model using the parameters c^*.

In this algorithm, the vast majority are concentrated in the calculation processing of fitness, and the time complexity of the RVM trained is $O\left(N^3\right)$, so that the time complexity of the algorithm is $O\left(N_P*N^3*D\right)$.

4. Experiments and Analysis

4.1. The Experimental Data and the Environment

Previous researchs showed that the main factors causing the world price of gold short-term T (USD / troy ounce) fluctuations are: the dollar index x1, Dow-Jones index x2, crude oil prices x3 ($ / bbl), United States 30-year bond x4, euro against the dollar (one euro equivalent to USD) x5, etc[6-8]. In this paper, the world gold price April 1, 2013 to November 10, 2013 of 188 short-term factors and the main daily data (except holidays) as 188 samples of short-term price fluctuations on the world gold empirical analysis. Among them, the use of the world gold price and macroeconomic data are from the latest financial websites cn.investing.com.

Table 1. Gold Short-Term Price

D	*T*	*X1*	*X2*	*X3*	*X4*	*X5*
20130401	1600	82.89	14504	97.07	144.89	1.2849
20130402	1575.1	83.09	14589	97.19	144.49	1.2819
20130403	1552.8	82.88	14492	94.45	145.43	1.2849
…	…	…	…	…	…	…
20131108	1288	81.29	15699	94.38	131.7	1.3364
20131110	1286.8	81.41	15701	94.72	131.55	1.3346
(where D represents date)						

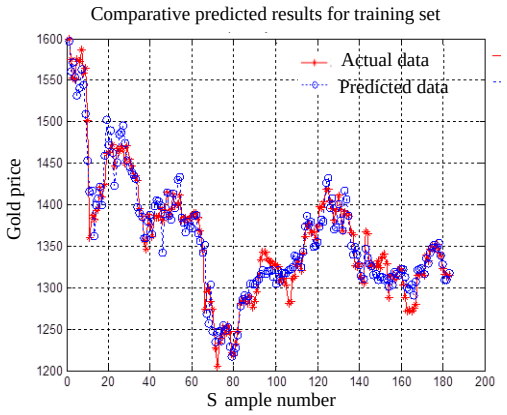

Figure 1. Comparative Predicted Results for the Gold Prices of Issues No. 1-183

For convenience, the following will be the first 1-183 samples April 1, 2013 to November 4, 2013 as the training set S, the 184-188 November 5, 2013 to November 10, 2013 in a samples as a test set T.

Using the training set S, and 2.2 kernel parameter optimization algorithm to establish RVM prediction model based on AIC(AIC-RVM), to predict the test set T. In the *matlab* environment, the use of *matlab* functions and SB2_Release_200 package can easily achieve the above algorithm. Through computer simulation, we can get the first 1-183 fitting result of the price of gold (Figure 1) and section 184-188 of the gold price forecast results (Figure 2).

Accuracy is shown in Table 1, Table 2. Visible, the prediction model has higher prediction accuracy and good generalization ability.

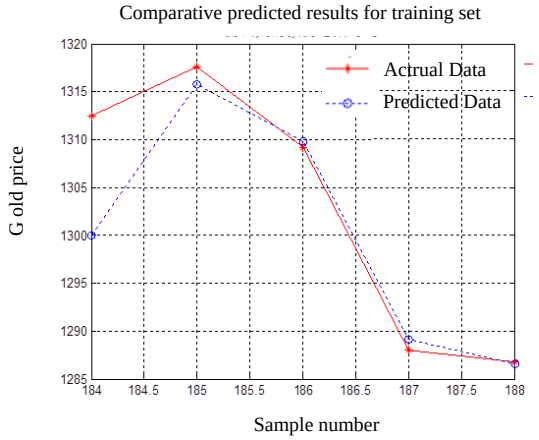

Figure 2. Comparative Predicted Results for the Gold Prices of Issues No. 184-188

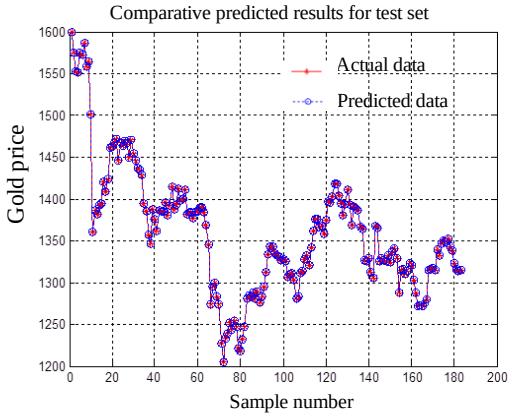

Figure 3. Comparative Predicted Results for the Gold Prices of Issues No. 1-183

4.2. Predicted Results and Analysis of Different Fitness Function

Mean absolute percentage error (MAPE) currently is usually used as the fitness function kernel parameters for RVM optimization [9] [10] literature.

The calculation formula is: $\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|t_i - \hat{t}_i|}{t_i}$, which $\hat{t}_i$ is the actual gold price of the *ith* sample, $\hat{t}_i$ is the predicted gold price of the *ith* sample. Use in the training set S in 4.1 and above MAPE as the fitness function established RVM regression model (MAPE-RVM) to predict the test set T in 4.1.

Figure 3, Figure 4 by were obtained fitting the first 1-183 result of the price of gold and section 184-188 of the gold price forecast results by MAPE-RVM model established.

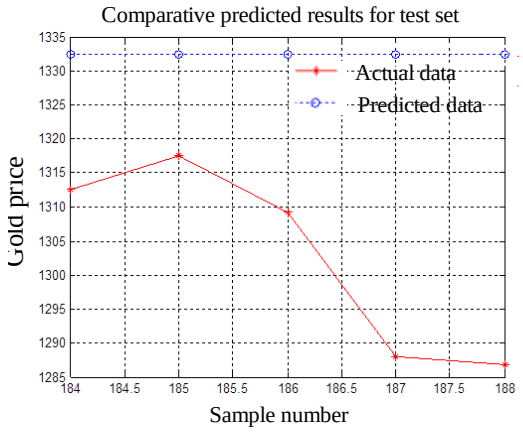

Figure 4. Comparative Predicted Results for the Gold Prices of Issues No. 184-188

From the Figure 3, we can know that the training set performance is better, but known from Figure 4 poor performance on the test set, resulting in a large error when the first 184-188 in the gold price forecast, the prediction accuracy are shown in Table 1 and table 2. Not only that, if the other samples from 1-188 in five randomly selected for testing set, the rest of the samples for the training set, MAPE-RVM model has a similar situation, like the election of the first 27, 29, 133,154,167 samples for the test set. MAPE-RVM model for the rest of the samples for the training set predictions established for the training set: the mean square error is 1.4637e-006, the average absolute error is 4.5137e-004, and the average relative error (%) is 3.3899e-005. Prediction results on the test set as follows: mean square error is 9.3404e + 003, the average absolute error is 86.1200, the average relative error (%) is 6.09. MAPE is visible to the fitness function of MAPE-RVM model to establish the first 1-188 sample space has made this performance, indicating that the model appeared over-fitting, generalization ability is poor.

4.3. Comparative Analysis of Similar Models

Compared with the accuracy prediction results of differential evolution algorithm based on support vector machine model (DE-SVR), multi-dimensional gray model (GM (1,6)) , we can see that AIC-RVM resulting prediction accuracy is better than the above model. Specific results are shown in Table 1, Table 2. With precision and prediction effect of wavelet neural network model comparison found that the wavelet neural network appeared over-fitting in predicting gold prices, generalization ability is poor. Specific results are shown in Table 2 and Table 3.

Table 2. Accuracy Comparison of Predicted Results for the Gold Prices of Issues No. 1-183

prediction method	mean square error	mean absolute error	mean relative deviation(%)
DE-SVR	578.4992	20.3887	1.50
GM(1,6)	5.7676e+004	159.2221	11.39
wavelet neural network	59.8627	4.8189	0.36
MAPE-RVM	2.9137e-005	9.9233e-004	7.4437e-005
AIC-RVM	350.9120	14.0075	1.03

Table 3. Accuracy Comparison of Predicted Results for the Gold Prices Of Issues No. 184-188

prediction method	mean square error	mean absolute error	mean relative deviation(%)
DE-SVR	1.6555e+003	37.7839	2.91
GM(1,6)	2.9994e+005	543.6824	41.78
Wavelet Neural Network	5.4895e+004	209.1826	16.06
MAPE-RVM	1.0390e+003	29.5498	2.28
AIC-RVM	32.4319	3.2694	0.25

Comprehensive above, we can know that the RVM kernel parameter optimization algorithm based on AIC (AIC- RVM) set up regression model has high precision of fitting results, good generalization ability. Its overall performance is superior to the traditional forecasting model.

5. Conclusion

When the noise variance of the sample data is small, by choosing $Q = 2L - R^2 - \frac{1}{2}R^4$ as a fitness function, we used differential evolution algorithm optimize the RVM kernel parameter to improve the fitting accuracy and increase sparse of RVM. It reduced the balance of computational complexity, and reduced the man-made interference factors in the process of fitting and over fitting to happen that improves the generalization ability of the model. We used established RVM regression model to predict the gold price. Its simulation experiments show: on the one hand, the regression model generalization ability of RVM model is stronger than the choice of the fitness function used as a mean absolute percentage error, on the other hand, the regression model prediction accuracy is better than differential evolution algorithm based on support vector machine model, multidimensional traditional forecasting model gray model. This also shows that the idea of using the AIC nuclear parameters to determine a reasonable method is an effective method.

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