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# Import iron ore price forecasting based on PSO- SVMs model

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***Abstract*—According to the nonlinear series characteristic of the price of imported iron ore, this paper proposes a support vector machines (SVMs) model for import iron ore price forecasting. But parameters of SVMs model are very difficult to determined, particle swarm optimization(PSO) algorithms are used to search these parameters and make sure the accuracy of SVMs model. Compared with autoregressive integrated moving average (ARIMA) model and BP Neural Networks, SVMs model has the highest prediction precision, and the results of SVMs model are more tally with the actual situation.**

***Index Terms—import iron ore; price forecasting; SVMs; PSO***

## I. INTRODUCTION

With the continuous development of Chinese iron and steel industry, iron ore demand keep growing. According to the customs statistics of China, iron ore imports grow up to 686.06 million tons in 2011[1].Meanwhile, in the international market, because of the sharply increase of Chinese import iron ore, iron ore price rises quickly. Steel companies should undertake large increase in raw material costs. If the iron ore price trend can be predicted accurately, it will be helpful for steel enterprise managers make the right judgment and decision making, and then reduce the purchase cost.

The factors influence import iron ore prices are iron ore supply, demand, the sea freight, import channel, political and economic policy, and so on. The price forming process is a random time-varying nonlinear process. The simulation and forecast are very difficult and complicated. According to the Platts index, iron ore quarter pricing is formed from the average of spot prices in the quarter before. So the current iron ore price is influenced by history iron ore prices. Therefore, according to the time series characteristics of iron ore prices, future iron ore prices can be forecasted.

There are many methods for time series forecasting, such as autoregressive integrated moving average model(ARIMA Model), autoregressive conditional heteroskedasticity model (ARCH Model)[2]. These models can reflected the continuity of the time series data, but difficult to capture nonlinear information. Neural network model can be used for nonlinear prediction[3,4], but there is no scientific method to determine the structure of the neural network, and it is easy to fall into the local optimal, and its generalization ability is weak. The Support Vector Machines (SVMs) was developed by Cortes and Vapnik (1995) for binary classification [5]. It is based on structural risk minimization of Machine learning method, can solve the small sample, nonlinear, high dimension and local minimum problems. It has widely applications in pattern recognition, classification and prediction [6,7,8]. In this paper, SVMs is used for iron ore price forecasting, so steel enterprise managers could make more optimal purchase decisions.

## II. THE SUPPORT VECTOR MACHINE FORECASTING MODEL

### *A. The principle of Support vector machines*

SVMs is used in the beginning for pattern recognition and classification problems. Input vector is mapped to a high dimensional feature vector space by the nonlinear mapping function, so nonlinear pattern in the feature space is converted to linear mode. According to the Structural risk minimization principle (SRM), SVMs model is used for time series prediction, make real risk minimization.

There is a training sample as：

$$Z = \left\{ (x_i, y_i) \middle| x_i \in R^n, y_i \in R, i = 1, 2, ..., m \right\} \tag{1}$$

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Where $x_i$ presents the input data and $y_i$ is the output data. Structural risk minimization is presented as:

$$R(w,\xi)=\min(\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}(\xi_i+\xi_i^*)) \tag{2}$$

The constraints are as follow:

$$\begin{aligned} & y_i-(w^T x_i+b)\le\varepsilon+\xi_i \\ & w^T x_i+b-y_i\le\varepsilon+\xi_i^* \\ & \xi_i\ge 0,\xi_i^*\ge 0 \end{aligned} \tag{3}$$

Where $w$ is a weights vector, $C$ is a punish coefficient, b is a bias term, $\varepsilon$ presents insensitive Loss, and $\xi_i$ and $\xi_i^*$ are relaxation variables. The value for $\xi_i$ and $\xi_i^*$ can be written as:

$$\xi_i^*=\begin{cases}0 & f(x_i)-y_i<\varepsilon \\ |f(x_i)-y_i|-\varepsilon & f(x_i)-y_i\ge\varepsilon\end{cases} \tag{4}$$

Using duality principle, (2) can be transformed to planning problem. And by using Lagrange coefficient method, (2) can be solved, and get the prediction function as:

$$f(x)=\sum_{i=1}^{m}(\alpha_i-\alpha_i^*)K(x,x_i)+b \tag{5}$$

Where $\alpha_i$ and $\alpha_i^*$ are Lagrange multipliers, $K(x,x_i)$ is a kernel function. In this paper, Gauss function is chose as the kernel function. It is presented as

$$K(x,x_i)=\exp\left(-\gamma|x-x_i|^2\right) \tag{6}$$

*B. SVMs parameters optimization based on PSO*

Support vector machine model's learning and generalization ability depends on the choice of parameters, such as $C$, $\varepsilon$ and $\gamma$. There are no certain provisions and methods to decide the value of these parameters. If $C$ is too large, the study accuracy will improve, but the generalization ability of the model will be poor. In contrast, the small $C$ will increase the training error, and lower the anti-interference ability. If $\varepsilon$ increases larger, support vectors number can decrease. And it will cause learning precision insufficient and owe learning. And if the value of $\varepsilon$ is too small, study accuracy will improve, but the model will be too complex, training time will increase quickly, and the study will over fitting. The bigger $\gamma$ is the faster the convergence speed will be. But the predicted value will beyond the value range sometimes. Although the error is small, it can't reflect real data.

The commonly used methods for parameters selection in SVMs are grid search and cross validation method. But these methods always have a large amount of calculation, and search time is too long. So this paper proposes a PSO algorithm as the parameters optimization method. PSO algorithm concept is simple, easy to be realized, and can search the global optimal solution [9].

Each particle represents a potential solution to the problem. In SVMs parameters optimization problem, there is a three d space. The population has n particles, and each particle can be seen as a point of the three d space. State property in the *t*th iteration of particle $j$ ($j=1,2,...,n$) can be shown by a position vector and a speed vector. Position and speed vector can be presented as $z_j^t=\left[C_j^t,\varepsilon_j^t,\gamma_j^t\right]$ and $v_j^t=\left[vC_j^t,v\varepsilon_j^t,v\gamma_j^t\right]$.The search range is between $z_L$ and $z_U$, that is $z_j^t\in(z_L,z_U)$. And $v_j^t\in[v_{\min},v_{\max}]$, where $v_{\min}$ is minimum speed, $v_{\max}$ is maximum speed. The current fitness value of particles *j* can be calculated according to the particle's position vector. Every particle and every iteration, there is a fitness value. Through comparing these fitness values, particles' individual and global optimal positions are obtained. Individual optimal position is $p_j^t=\left[pC_j^t,p\varepsilon_j^t,p\gamma_j^t\right]$, and global optimal position is $np_j^t=\left[npC_j^t,np\varepsilon_j^t,np\gamma_j^t\right]$.

In the PSO optimum process, the speed and position of particle $j$ can be updated according to the formula (7) and formula (8).

$$vC_j^{t+1}=\omega vC_j^t+c_1r_1(pC_j^t-C_j^t)+c_2r_2(npC_j^t-C_j^t) \tag{7}$$

$$C_j^{t+1}=C_j^t+vC_j^{t+1} \tag{8}$$

Where $\omega$ is the momentum factor, $r_1$ and $r_2$ are random numbers between 0 and 1. $c_1$ and $c_2$ are acceleration factors and usually equal to 2. $c_1$ can adjust step length to the individual optimal position. $c_2$ can adjust step length to the global optimal position. Adjust $c_1$ and $c_2$, can reduce the probability of particles falling into the local minimum and speed up convergence [10]. The update of $\varepsilon_j^t$ and $\gamma_j^t$ are the same of $C_j^t$.

Optimal steps using PSO method are as follows:

Step1: Set $t=0$ .Initialize each particle's position $z_j^0$ and $v_j^0$ .Set $n=20$, $t=200$, $c_1=2$, $c_2=2$, $C_j\in\left[10^{-1},10^{2}\right]$, $\varepsilon_j\in\left[10^{-4},10^{4}\right]$, $\gamma_j\in\left[10^{-2},10^{3}\right]$ and $\omega=0.6$.

Step2: Fitness function is forecasting error using SVMs, presents by (9).Calculate fitness of each particle, and determine $p_j^t$ and $np_j^t$.

$$\text{fitness}=\frac{1}{m}\sum_{i=1}^{m}\left|\frac{x_i-y_i}{x_i}\right| \tag{9}$$

Where $x_i$ is the real price, $y_i$ presents the forecasting value.

Step3: Update $vC_j^{t+1}$, $v\varepsilon_j^{t+1}$ and $v\gamma_j^{t+1}$ according to (7).

Step4: Update $C_j^{t+1}$, $\varepsilon_j^{t+1}$ and $\gamma_j^{t+1}$ according to (8).

Step5: $t=t+1$.Update fitness, $p_j^t$ and $np_j^t$.

Step6: Judge whether reaches the maximum iterative times. If it reaches the maximum iterative times, output the optimal solution .Otherwise turn to step 3.

## III. IMPORT IRON ORE PRICE FORECASTING BASED ON PSO-SVMS MODEL

The algorithms of PSO-SVMs mode is shown as Fig.1.

Step 1: Normalize original data as (10).

$$\bar{s}_i = \frac{s_i - s_{\min}}{s_{\max} - s_{\min}} \tag{10}$$

where $S$ presents the data sample , $s_{\min} = \min\{s_i, i = 1, 2, ..., m\}$ , $s_{\max} = \max\{s_i, i = 1, 2, ..., m\}$ , $\bar{s}_i$ will become a normalized version of sample $s_i$ , $\bar{s}_i \in [0,1]$ .

Step 2: Get optimal parameters using PSO algorithm.

Step 3: Train the support vector machines.

Step 4: Price forecast by SVMs.

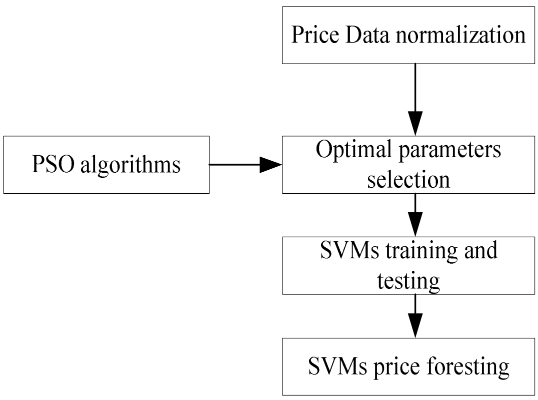


Figure 1 PSO-SVMs algorithms

## IV. CALCULATION AND ANALYSIS

According to the customs statistics in China, swing of Iron ore CIF price from2000 to 2011 is shown in the Fig. 2.

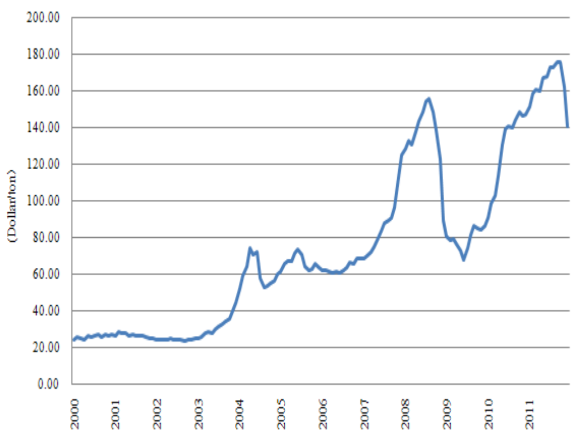


Figure 2 Import iron ore price in China

Take these 144 data as prediction samples. Use the data of six months to predict data of the seventh month. Every six months' data is the input vector, and the seventh month's data is the output vector. There are 138 input and output vectors .Take 133 sets of vectors as the training samples, and the last five vectors as a test samples. Realize PSO algorithm with MATLAB2010a, the optimal parameters is shown as Fig.3. From the Fig.3, $C$ =8.3069， $\gamma$ =5.8656， $\varepsilon$ =0.01.

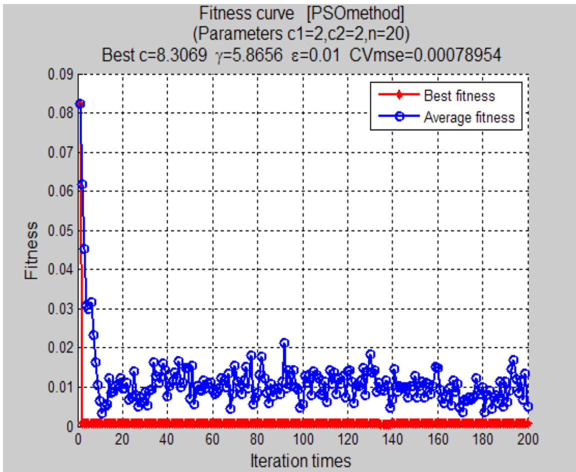


Figure 3 Optimal parameters in SVMs

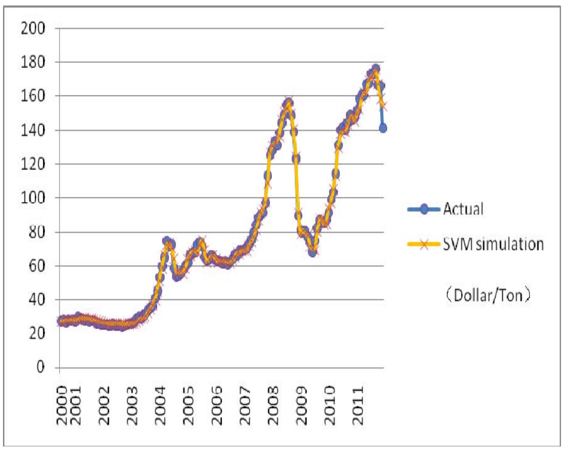


Figure 4 Comparison of actual price and simulation results

Do SVMs training and testing using libsvm toolbox in MATLAB [11]. Training simulation results are shown in Fig.4 .From the Fig.4, simulation results are basically identical with actual price. The predicted results are shown in table 1.

Using ARIMA(1,1,1) model and BP neural network model for predictiong with the same data, the results are shown in table 1.From table 1, relative error of forecasting price is control within 6% in January 2012 by these three models.All of them represent high precision, but the forecasting error of PSO-SVMs model is the smallest. Prediction results by ARIMA model have falling trend. The BP neural network predict that iron ore prices have certain fluctuation in the future four months, the price will drop in January, but has some degree of rise in February, then has a dramatically fall again in March and April. Iron ore prices will have certain

TABLE 1 Forecasting value comparison of POS-SVMs, ARIMA and BP network (Dollar/Ton)

| time | Actual | PSO-SVMs | | | ARIMA | | | BP network | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Predictive Value | Absolute Error | Relative Error（%） | Predictive Value | Absolute Error | Relative Error/% | Predictive Value | Absolute Error | Relative Error/% |
| 2011.8 | 173.37 | 173.31 | 0.06 | 0 | 176.88 | -3.51 | 2 | 178.89 | -5.52 | 3 |
| 2011.9 | 175.92 | 175.42 | 0.50 | 0 | 173.28 | 2.64 | 2 | 179.18 | -3.26 | 2 |
| 2011.10 | 175.74 | 167.35 | 8.39 | 5 | 177.64 | -1.90 | 1 | 178.23 | -2.49 | 1 |
| 2011.11 | 162.14 | 158.54 | 3.60 | 2 | 175.53 | -13.39 | 8 | 174.19 | -12.05 | 7 |
| 2011.12 | 141.24 | 154.06 | -12.82 | 9 | 153.02 | -11.78 | 8 | 158.41 | -17.17 | 12 |
| 2012.1 | 136.46 | 143.21 | -6.75 | 5 | 127.67 | 8.79 | 6 | 144.71 | -8.25 | 6 |
| 2012.2 | | 136.04 | | | 119.24 | | | 157.00 | | |
| 2012.3 | | 130.55 | | | 114.01 | | | 127.48 | | |
| 2012.4 | | 132.66 | | | 110.76 | | | 115.46 | | |

drop in the future months by PSO-SVMs model. But the range is not very big, maintain about 135 dollars per ton.

In market performance, economic crisis and the European debt crisis has continued influence Iron and Steel industry. In China, because railway investment is cut down and real estate is in regulation, steel enterprises start to reduce production. Iron ore demand will restrained, so price will fall down. ARIMA model is a linear forecast method, so it is not sensitivity to price change point. Its prediction will continue current trends, and it can only use as an auxiliary method. Rio Tinto, Rio Tin and Companhia Vale do Rio Doce (CVRD) these three iron ore giants will take corresponding measures to deal with the influence of iron ore demand falling, so iron ore prices in the next few months will not fall sharply. That means the BP neural network forecast will have big error in March and April and PSO-SVMs model results will accord with the actual situation.

## V. Conclusions

In this paper, PSO algorithm is proposed for parameters optimization in SVMs model. It can find the optimal parameters and guarantee the SVMs forecasting model's quality. Compared with ARIMA model and BP neural network model, the PSO-SVMs model has good ability catching iron ore price trend, and prediction accuracy is higher. Using PSO-SVMs model for iron ore price forecasting will support purchasing decision making.

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