The International Journal of Engineering and Science (IJES)
|| Volume || 7 || Issue || 9 Ver.II || Pages || PP 27-35 || 2018 ||
ISSN (e): 2319 – 1813 ISSN (p): 23-19 – 1805

SVM and Reserve Capacity Price Based Wind Speed Forecasting For North China Power Grid

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ABSTRACT

As the rapidly growth of wind farms in North China power grid, the wind speed prediction becomes more important for the dispatching center. The peak regulation and wind power consumption need better wind forecasting accuracy. In this paper a wind speed forecasting method based on interpolation is proposed. With the training data, support vector machines(SVM) prediction model is build, however, the prediction accuracy is decided by training data size. Thus, the polynomial interpolation is involved to increase the training data. Based on the real data of North China power grid, the simulation shows that this method can provide better prediction accuracy especially when the wind speed changes abruptly. This paper presents the reserve capacity price for the new energy power price which can reflect the effect of new energy power fluctuation on the real time reserve capacity.

KEY WORDS: *wind speed prediction, peak regulation, training data, support vector machines, reserve capacity price*

Date of Submission: 25-08-2018 Date of acceptance: 08-09-2018

I. INDUCTION

In recent years, many efforts have been devoted to forecast the wind speed and generated power in wind farm, and a variety of models have been proposed. These mainly include auto-regressive moving average (ARMA)[1][2]、chaotic time series [3]、neural network [1][4][5]、support vector machines (SVM)[4]、Kalman filter [8]、spatial correlation Model [9]。The errors of forecasting result are about 10%~30% in different models, and it depend on the predicting period and the characteristic of wind speed in the predicting place. In general, the predications have higher accuracy with shorter predicting period and wind speed slowly changed, and vice versa [10].

Support Vector Machines (SVM) is a very powerful machine learning method, which is developed by Vapnik on the foundation of the statistical learning theory[11][12]。Compared with the traditional neural network model, SVM, which is based on the theory of structural risk minimization, has stronger generalization ability, and provides a better approach to solve a series of problems such as nonlinearity, high dimension, local minimum and so on[13].

However, there are always some difficulties when we predict the wind speed with SVM model, as described in the following.

(1). In the original prediction method base on the SVM model, SVM model is constructed with the training data of one day, a few days or even one year ago. Therefore, the forecasting results has bad accuracy and reliability when the wind speed changes significantly in a sudden moment during the predicting period.

(2). The establishment of SVM model need a certain amount of training data, and thus the training of SVM model is constrained by sampling period of measured wind speed.

(3) The period of training data used in the SVM model is fixed, and can not be adjusted according to the demands for the prediction. This problem will reduce the accuracy of the model.

For resolving the problems above, the method of wind speed prediction which can give the forecasting results with one observation period ahead is studied with an example of measured data of wind speed in a wind farm of north China. Furthermore, a dynamic SVM model based on interpolation is proposed in this paper. In the proposed model, the SVM model is established firstly with the training data of measured wind speed of a certain period, and then forecast the wind speed of next period on the same day with the measured data, which can shorten predicting period and avoid the error caused by the abrupt change of wind speed. Moreover, polynomial interpolation is used in the series of measured wind speed in the model, which enlarges the number of the training sample of SVM and increases the precision of prediction

The cost of coal-power plants are rised because of the nondeterminacy of new energy power output. The new energy power plants cause a lot of problems, both in safety and power quality[14]-[17]. Moreover, the electric power ancillary services are limited by new energy power output fluctuation. Thus, the real time reserve capacity reserve capacity price is adopted to analysis the affect of new energy power output. In this paper, not only the adjust cost allowance of the traditional coal power plants can be considered, but new energy power plants operation can be affected by the market price.

II. PRINCIPLE OF THE PREDICATION ALGORITHM OF SUPPORT VECTOR REGRESSION

The objective of a regression is to approximate a function g(x) from a given training set, $G=(x_i, y_i)_{i=1}^{n}$, obtained from g with noise. In the regression of SVM, the input data x is mapped into a high dimension feature space firstly, and then a liner regression is performed to estimate the regressive function f(x) in the feature space[11] **:**

$$F = \{f \mid f(x) = w^T\Phi(x) + b, w \in R^n\} \quad (1.1)$$

where Φ(x) is a nonlinear function, w is the function coefficient vector, and b is a real constant named "threshold value".

In order to make above function f(x) flat, the minimum value of w can be determined though minimizing its Euclidean Norm. If the training data (x_i, y_i) can be fitted linearly under the precise ε, the problem of determining the coefficients w and b can be written as a convex optimization problem as follows,

$$\min \frac{1}{2}\|w\|^2 \quad (1.2)$$

s.t.

$$\begin{cases} y_i - w^T x_i - b \le \varepsilon \\ w^T x_i + b - y_i \le \varepsilon \end{cases} \quad (1.3)$$

Where $\|w\|^2$ describes the complexity of the function f. In order to estimate the function f, a loss function called Vapnik's ε-insensitive function is introduced as follows:

$$|\xi|_\varepsilon = \begin{cases} 0, & |\xi| \le \varepsilon \\ |\xi| - \varepsilon, & \text{other} \end{cases} \quad (1.4)$$

Where the function ξ is given as

$$\xi = y - f(x) \quad (1.5)$$

Obviously, one can see that the deviations less than ε in above insensitive function are not considered to be errors, which increases the robustness of the resgression.

The slack variables $\zeta_i \ge 0$ and $\zeta_i^* \ge 0$ can be introduced when the coefficients w and b cannot be estimated by the function f under the accuracy ε. This problem can be transformed into the constrained optimization problem:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \quad (1.6)$$

s.t.

$$\begin{cases} y_i - w^T x_i - b \le \varepsilon + \zeta_i \\ w^T x_i + b - y_i \le \varepsilon + \zeta_i^* \\ \xi_i \ge 0 \\ \xi_i^* \ge 0 \end{cases}$$

where i=1,2,…,n, and C(C>0) is regularization constant and called "penalty factor", which determines the trade-offs between training errors and model complexity.

In order to solve above problem, Lagrange multipliers can be introduced to the equations. The optimization problem can then be written as its dual form:

$$\min_{\alpha\alpha^*}\left\{\frac{1}{2}[(\alpha,(\alpha^*)^T]\begin{bmatrix} Q & -Q \\ -Q & Q \end{bmatrix}\begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix} + [\varepsilon I^T + y^T \quad \varepsilon I^T - y^T]\begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix}\right\} \quad (1.7)$$

s.t.

$$\begin{bmatrix} I^{\mathrm{T}} & -I^{\mathrm{T}} \end{bmatrix}\begin{bmatrix} \alpha \\ \alpha^* \end{bmatrix} = 0, \quad \alpha, \alpha^* \in [0, C]$$

where : $Q_{i,j} = \Phi^T(x_i)\Phi(x_j)$, $I = [1, \ldots, 1]^T$, α and α^* are the Lagrange multipliers.

The parameter α can be obtained by solving the quadratic optimization. Meanwhile, the coefficient w can also be solved which is given as,

$$w = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*)\Phi(x_i) \tag{1.8}$$

The real constant b can be calculated with the condition of KKT （Karush-Kuhn-Tucker） ,which can be witten as

$$b = y_j + \varepsilon - \sum_{i}^{l} (\alpha_i - \alpha_i^*) K(x_j, x_i) \tag{1.9}$$

Therefore, the regressive function f(x) can be described as

$$f(x) = \sum_{i}^{l} (\alpha_i - \alpha_i^*) K(x, x_i) + b \tag{1.10}$$

where $K(x, x_i) = \Phi^T(x)\Phi(x_i)$ is a kernel function that meets the Mercer condition. The function can implements the nonlinearization of the algorithm although its concrete forms of the nonlinear transformation is not known .

III. FORECASTING MODEL OF SVM BASED ON THE DYNAMIC INTERPOLATION

3.1 Basic frame of the forecasting model

The regressive predicting model of SVM needs a large number of training data to train the model. At present, the measured wind speed of one day or few days before are commonly used as the training sample [4][6], and the sample transfers accordingly as the time goes on. In general, the wind speeds of certain wind farm are measured in every ten minutes, and thus the number of the measured data during one day is no more than 144. Therefore, there are not enough sample to train the SVM model, lead to the decrease of the precision of prediction. In addition, the distribution of wind speed differs significantly in different seasons and weather conditions. When the SVM model is trained with the previous day's data or the data of a few days ago, the reliability of the trained model will be greatly induced if the wind speed changes frequently and drastically in recent days or even in the same day.

In this paper, a modified SVM model based on dynamic interpolation is proposed, which can improve the reliability and precision of the SVM model for predicting wind speed remarkably. In this model, measured wind speeds of a certain time period during a day are used to train the SVM model, and then to predict the data tendency of another time window of the same day, which decreases the time internal between the sample data and predicting data. Moreover, the training sample is expanded by polynomial interpolation with given sample. The detailed procedure of the improved SVM model for predicting the wind speed is described as follows.

In this paper, the data of the average wind speed in every ten minutes of a wind farm is given with certain height of the fan, temperature and air pressure. The sample involved in above model consists of input vector matrix S, training vector matrix T, objective vector matrix D, which can be defined as follows :

1) Input vector matrix S, i.e., S=[s_1, s_2, …, s_n], is composed of the historical measured wind speed of time i=1, 2, …, n before the predicting time.
2) Training vector matrix T , i.e., T=[t_{11}, $t_{12, \ldots,}$ t_{1j}, $t_{2,}$ $t_{21, \ldots,}$ t_{nj}], t_{nj}=s_i, is made up of the wind speed obtained by interpolation. In the modified model, j-1 points are interpolated between the adjacent two sample points of measured wind speed, as shown in fig.2. As indicated in fig.2, the curve of the relation between the wind speed and the time are fitted with given measured data at the time of t=t_n, t_{n+1}, …, t_{n+k}, and then the wind speeds at the time of t=t_{n1}, t_{n2}, …, t_{ni}, …, t_{nj} can be obtained by interpolation with the fitted curve. The training data of SVM model consists of the given measured wind speed and the interpolated wind speed.
3) Objective vector matrix D, i.e., D=[d],f

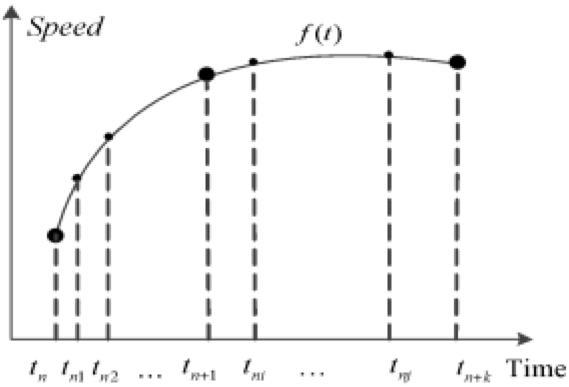

Fig.1 Trainning data interpolation

3.2 Interpolation of training data

Interpolation and data fitting are effective means of mathematical analysis, which can be used to determine some parameters for a function or find its approximate function with high similarity to known data. It can also be used to analyze characteristics reflected by some data. At present, polynomial interpolation and are commonly used methods of interpolation [7].

Polynomial interpolation[7] are most commonly used functional interpolation. In general, unique polynomial meeting certain conditions of interpolation polynomial can be determined, if we choose n-order polynomial as the function $\phi(x)$. From the perspective of geometry, a cure of n-order polynomial can be found which goes through the known n+1 points. At present, there are two commonly used forms of polynomial interpolation, one is the Lagrange interpolation polynomial, the other is the Newton interpolation polynomial.

To avoid the problem of large fluctuations that may occur in high order spline high-order spline interpolation [7], the theory of subdivision interpolation （low-order） is used which can improve the degree of approximation between given data and interpolation result. For example, piecewise linear interpolation is an effective way to approximate given function. However, the interpolation result of piecewise linear interpolation has poor smoothness. In order to improve the smoothness of the interpolation results, a global piecewise linear interpolation named cubic spline interpolation is proposed, in which one family curves are obtained by solving three-moments equations. In the interpolation process of the measured wind speed, different methods of interpolation can be used as described in [7].

The flow diagram of the SVM model based on dynamic interpolation for predicting the wind speed is shown in fig.3. As is described above, the given sample of measured wind speed is processed by interpolation, and the training data for SVM is expanded consisting of the given data and the interpolated result. Then the property and objective matrix of the SVM model are received from the training sample, and the trained SVM model is obtained subsequently. Moreover, for better forecasting the wind speed of next time-period, the trained SVM model will be updated when we get new measured data.

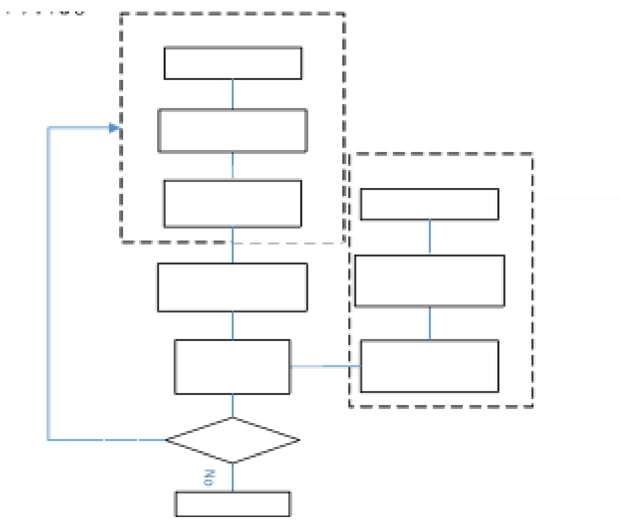

Fig.2 SVM model for wind speed prediction based on dynamic interpolation

IV. RESERVE CAPACITY PRICE

As metioned in [18] , new energy power price is as followed:

$$c^{w} = c^{w0} + c^{wv} \qquad (1)$$

Where c^{w0} is the price of fixed cost for new energy plant opertating, c^{wv} is the floating price of effection cost which can reflect the environmental protection effect on power grid.

Real time reserve capacity means that thethermal power unit has the output adjustment ability when the load and new energy units output changes, meanwhile, the thermal unit can track the AGC order based on the frequency change. Therefore, the real-time reserve capacity price of new energy units should be determined by the real-time adjustment of reserve capacity.

Assume that the thermal unit i's output at the moment t is $p_i^h p_i^h$, thus, the maximum and minimum value at t+1 are as follows:

$$p_{i.\max}^{hn} = \min\left\{p_{i.\max}^{h}, p_i^h + v_i^h \times \Delta T\right\} \qquad (22)$$

$$p_{i.\min}^{hn} = \max\left\{p_{i.\min}^{h}, p_i^h - v_i^h \times \Delta T\right\} \qquad (23)$$

While, the v_i^h is the adjustment rate of unit i(MW/min); ΔT is the time interval between t and t+1.
Thus, the adjustment margin of power system is a close interval:

$$\left[\sum_i^N p_{i.\min}^{hn}, \sum_i^N p_{i.\max}^{hn}\right] = \left[P_{i.\min}^{hn}, P_{i.\max}^{hn}\right] \qquad (24)$$

While, the load increase at t+1 is ΔP^L, the output increase of new energy is ΔP^w.

As shown in Fig.3, take the two thermal power units for example, U is the thermal power unit operation area considering formula (24). M and N are the diagonal vertex of area U which represent the maximum and minimum adjustment value of thermal power unit.

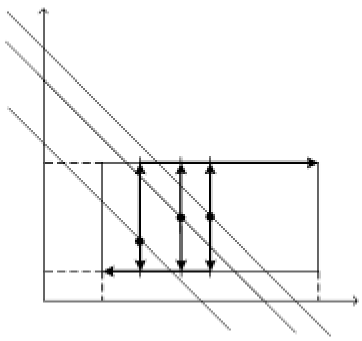

Fig3.The optimal point of power gererating unit as variation of load and new energy

At the time of t+1, the thermal power unit operate at the point A, the real-time reserve capacity is the sum of $s_1 + s_2$ and $s_3 + s_4$. The total length of s_1, s_2, s_3, s_4 is $P_{i.\max}^{hn} - P_{i.\min}^{hn}$.

At the time of t+1, assumed that $\Delta P^w = 0$, thus, the thermal power unit is operating at the point B in area U, the real-time reserve capacity is the sum of $s_1' + s_2'$ and $s_3' + s_4'$.

If the $\Delta P^w \neq 0$, then the thermal power unit is operating at the point C in area U, the real-time reserve capacity is the sum of $s_1'' + s_2''$ and $s_3'' + s_4''$.

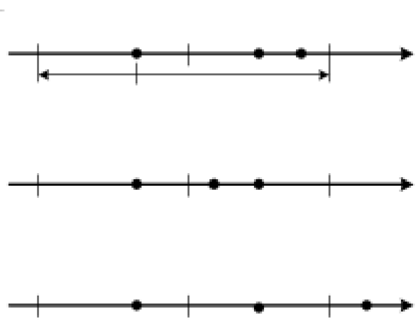

Fig4. Variation of up-and-down spinning reserve brought by new energy unit

From the Fig.4, it is clearly that the thermal power unit operates at the point O(the middle of $\overline{MN}$) is reasonable at anytime. The reverse capacity is $\frac{1}{2}(P_{i.\max}^{hn} - P_{i.\min}^{hn})$. Meanwhile, if point C is closer to the O than point B, it means the new energy unit output is increasing. Vice versa, the new energy unit output is decreasing.

The worst situation is that point C is out of $\overline{MN}$, which means the thermal power unit cannot afford the disturbance of new energy power, the system reverse capacity is negative. At this situation, the only solution is staring more thermal power units or shut down the load, otherwise, the frequency will fall.

In conclusion, the reserve capacity price of new energy resources should follow these principles:

1) If point C coincides with point O, then the reserve capacity price is most expensive(positive number);
2) If point C is between point O and B, then the reserve capacity price is positive;
3) If point C coincides with point B, then the reserve capacity price is zero;
4) If point C is far from point O than point B, then the reserve capacity price is negative;
5) If point C is out of $\overline{MN}$, the reserve capacity price and penalty factor make the price curve steeper;

When the point B coincides with M or N, the reserve capacity which caused by load fluctuation is zero. Meanwhile, the adjustment amount of coal-power plant is maximum. Thus, the price at point O can be decided by coal-power plants average cost gradient(price/kWH) in unit interval. Otherwise， if point B does not coincides with M or N, then the price at point O reduces proportionally.

1. SIMULATION RESULTS AND DISCUSSION

In this paper, we quantified the predicted results with the APE(absolute percentage error) and the MAPE(mean absolute percentage error). These parameters can be defined as follows：

$$E_{APE} = \frac{W_R - W_F}{W_R} \times 100\% \qquad (1.11)$$

$$E_{MAPE} = \frac{1}{N}\sum E_{APE} \qquad (1.12)$$

Where W_R is measured wind speed, and WR is predicted wind speed, N is the size of the training sample.

1.1. Traning model day by day

Training by the real wind speed data of day t, the forecast wind speed of day t+1 can be acquired. And the forecast wind speed of day t+2 can be acquired as the same.

1) When the wind speed changing smoothly(day t+1)

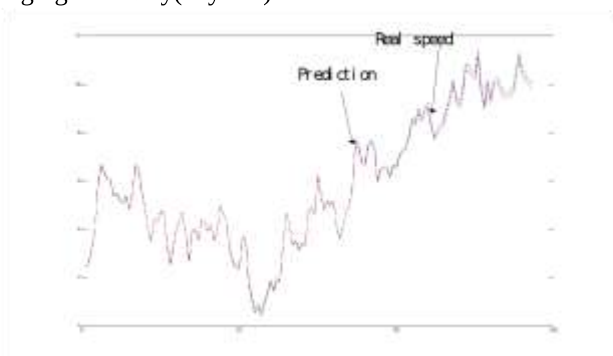

Fig.5 Daily wind speed prediction when wind speed changing smoothly

In the simulation, the MAPE of the daily wind prediction result is 2.22%(wind speed changes smoothly).
Fig.2 shows that when the wind speed changing smoothly, the daily wind speed prediction model has a high forecast accuracy.
2) When the wind speed changing abruptly(day t+2)

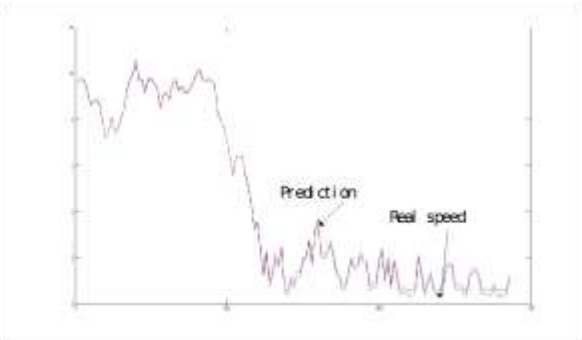

Fig.6 Daily wind speed prediction when wind speed changing abruptly

When the wind speed changing, the MAPE of the daily wind speed prediction result reduces to 17.46%.
Fig.3 shows that when the wind speed changing abruptly, the forecast accuracy of the daily wind speed prediction model reduces a lot.

1.2. Training model period by period（method of interpolation）
As there only 36 real sample data for the simulation, the data is not enough for hourly the SVM training model. For enhance the forecast accuracy, the three-polynomial interpolation is adopted to rose the training data from 36 to 351. With those 351 wind speed data, the SVM training model can be acquired.
The hourly wind speed prediction results of day t+2 are as in Fig.4 to Fig.6(wind speed changing abruptly).

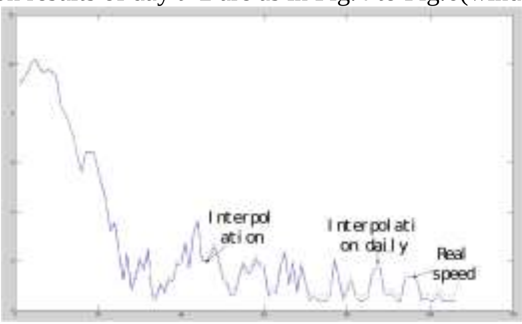

Fig.7 The prediction results of tow prediction model when wind speed changes abruptly

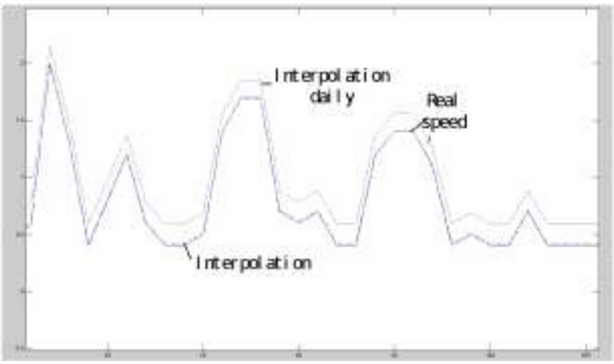

Fig.8 The prediction results of tow prediction model when wind speed changes abruptly(fractionated gain figure)

From the results, it is clear that when the wind speed changing smoothly, the forecast accuracy is almost the same. However, when the wind speed changing abruptly the hourly forecast model has a much better accuracy than the daily forecast model.

Table.1 Prediction results and APE of different model

Time	Real speed (m/s)	Daily model		Hourly model with dynamic interpolation	
		Forecat speed (m/s)	APE (%)	Forecat speed (m/s)	APE (%)
6:00	9.4	9.33	0.69	9.39	0.12
6:10	9.7	9.63	0.76	9.69	0.14
6:20	10.1	10.02	0.84	10.08	0.17
6:30	10.2	10.11	0.86	10.18	0.18
6:40	9.8	9.72	0.78	9.79	0.15
6:50	9.7	9.63	0.76	9.69	0.14
7:00	9.8	9.72	0.78	9.79	0.15
7:10	9.7	9.63	0.76	9.69	0.14
7:20	9.5	9.43	0.71	9.49	0.13
7:30	8.3	8.27	0.41	8.30	0.01
…	…	…	…	…	…
22:10	1.1	1.27	15.61	1.10	0.40
22:20	0.4	0.59	47.92	0.42	3.79
22:30	0.5	0.69	37.77	0.51	2.72
22:40	0.4	0.59	47.92	0.42	3.79
22:50	0.4	0.59	47.92	0.42	3.79
23:00	0.7	0.88	26.16	0.71	1.51
23:10	0.4	0.59	47.92	0.42	3.79
23:20	0.4	0.59	47.92	0.42	3.79
23:30	0.4	0.59	47.92	0.42	3.79
23:40	0.4	0.59	47.92	0.42	3.79
23:50	1.1	1.27	15.61	1.10	0.40
MAPE		17.46%		2.3%	

The results in table 1 shows that the forecast accuracy reduces when the wind speed changing abruptly, however, hourly model reduces much smaller than the daily model.

The optimization objective of real-time reserve capacity price is to minimize the coal consumption of the whole system thermal power unit. Assumed η_2 =0.005, thus the price in positive and negative peak load operation is shown as figure 9.

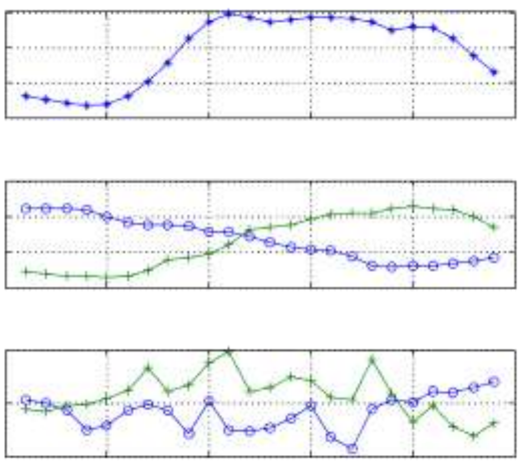

Fig9.correlation curve of new energy reserve capacity cost

In figure 9, the comparison load change rate and wind power generation change rate can be seen that when the wind power and the load are in the same direction, the power price of the spare capacity is positive and the reverse is negative. In other words, wind power and load change in the same direction to help thermal power units peak, the standby capacity price is positive. Otherwise, wind power and load change in reverse, coal-power units need to increase the adjustment intensity, the standby capacity price is negative. The absolute value of electricity price reflects the strength of peak load adjustment and reverse peak adjustment.

V. CONCLUSION

In this paper , the real-time reserve capacity price of electric power is presented. The pricing method based on real-time dispatching is also be given in this paper. Moreover, the simulation results shows that the real-time reserve capacity price can reflect the peaking load influence caused by new energy plants in each period. At the present or future electric power price institution, the pricing method presented in this paper can be directively.

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