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Prediction of NOx Emissions from Coal-Fired Boilers Based on Support Vector Machines and BP Neural Networks

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ABSTRACT

The BP neural network and support vector machine (SVM) are respectively employed using operation test data to establish models describing the NOx emission characteristics of a coal-fired boiler with the assistance of the intelligent MATLAB toolbox. The momentum method is employed to improve existing problems within the BP neural network, and to choose the optimal kernel function of the SVM prediction model and the corresponding parameters c and g. The maximum error of the prediction model of the improved BP neural network is 9.85% with an average error of 4.2%; the maximum error of the SVM prediction model after parameter optimization simulation is 4.57% with an average error of 2.15%. Results indicate that both modelling methods demonstrate improved accuracy and generalization. Finally, quantitative comparison analysis of the simulation and prediction results of the two models indicate that the supporting vector machine model is greatly superior to the neural network model in terms of computing speed, fit and generalizability while requiring fewer thermal state data samples from boiler operation.

INTRODUCTION

As the environment continues to deteriorate, greater attention is being devoted to energy conservation and environmental protection. Coal-fired power plants consume large amounts of coal; simultaneously, rapid economic development results in the gradual increase of coal consumption and greater emission of nitrogen oxides, which greatly harms the environment through the resultant acid rain and light chemical smoke (GB 2011). Therefore, powerplants assign great importance to the nitrogen oxide emissions. Since NOx formation factors are extremely complex, it is difficult to control and predict NOx emissions. Actual production often requires the commissioning and grouping of real boilers to introduce new operational modes and reduce subsequent NOx emissions, but this method is extremely effortful and imprecise in its determination of best working conditions (Lin 2006). With the rapid development of computer technology, artificial intelligence technology has made great achievements in the prediction of boiler NOx emissions. More accurate predictions of NOx emissions and power plant boiler combustion optimization based on an RBF neural network model not only improve boiler efficiency, but also reduce NOx emissions (Bao 2013). An & Song (2008) used the support vector machine (SVM) algorithm to establish the NOx and boiler efficiency prediction model for coal-fired boilers. Thus, NOx emissions and boiler efficiency are predicted via multi-objective optimization by using the genetic algorithm. Wu & Zhu (2002) and Peng (2011) determined the NOx emission characteristics of a boiler according to a neural network model and verified the model by using an artificial neural network of nonlinear dynamics and self-learning characteristics. Zhao & Wang (2008) created a model to predict NOx emission response characteristics based on kernel principal component analysis in combination with the support vector regression machine and mechanism models. The researches mentioned above is all based on a single-modelling approach without the use of additional methods to establish a control model. For neural network models, the structure is more complex and generalizability is weak, resulting in input and output data with great impact on the predicted result, among other problems. All previous research mentioned above has developed NOx modelling predictions; however, most methods require extensive programming efforts in order to determine combustion characteristics with the use of a predictive modelling algorithm. The effect of the application often depends on the programming ability of the researching and the understanding of the model; however, the professional MATLAB intelligent toolbox can help professional researchers avoid numerous complications of intelligent modelling algorithms in order to focus on the areas of expertise related to the research object and create a targeted boiler combustion prediction model. For example, Lv & Liu (2012) and Lv & Peng (2011) used the MATLAB toolbox to create an RBF neural network, which is used to optimize boiler efficiency and NOx emissions. Results demonstrate that this method is not only easily programmable but demonstrates high prediction accuracy. He (2013) and Wang & Zhang (2013) used the MATLAB toolbox to create a model, resulting in a decrease of predication error from 6% to 3.4%, and strengthening the generalizability of the model.

In this paper, the MATLAB neural network toolbox is used in combination with the BP neural network and the support vector machine (SVM) algorithm, respectively, to create two different predictions of NOx emissions from a coal-fired boiler. The results are compared and the two respective models are analysed.

STUDY DESCRIPTION

A 660 MW ultra-super-critical coal-fired boiler is a variable pressure direct current boiler with 2060t/h, 26.15MPa, 605°C/603°C. The studied boiler includes a single reheat, balanced ventilation, an open layout, solid-state slagging, a steel frame and a full suspension ∏ -type structure, and is categorized as DG2060/26.15-II2. This coal mill system consists of a medium-speed mill which directly blows positive pressurized cold primary air. Each boiler is equipped with six coal mills. In combustion mode, the boiler uses opposed wall combustion and an eddying flow combustor. One coal mill corresponds to one layer of the combustor, while decorating a layer of over-fire air nozzle on both of the front and back wall.

The combustor system is arranged in both the front and back walls. The system uses a hedging combustor and a swirl combustor; the wind and pulverized coal air flow are sprayed from the pulverized coal combustors and over-fire air into the furnace. Each combustor creates a separate fire within the furnace.

The combustor layout is depicted in Fig. 1. Both the front and back wall consists of three layers; each layer has six combustors. Additionally, both the front and back wall contain a layer of over-fire air nozzle; each layer contains two side over-fire air nozzles and six over-fire air nozzles. Every pulverized coal combustor has a small oil gun of 250 kg/h (mechanical atomization), which is used to ignite the oil gun and the pulverized coal combustor and maintain the stable combustion of the pulverized coal combustor. The centre of each combustor is located in the middle of the front or back wall, and has a 3300 kg/h initial oil gun (steam atomization), and twelve oil guns in total.

Each coal mill consists of one layer, and there are a total of six combustors. The relationship between the combustor and the coal mill is shown in Fig. 2.

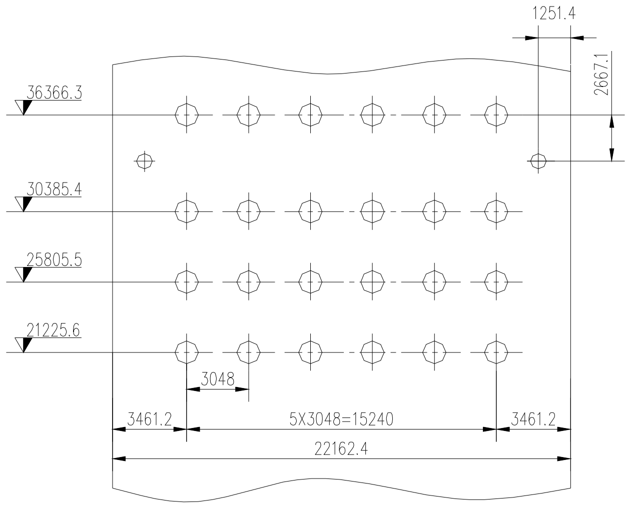

Fig. 1: Combustor layout.

MODELLING OF NOx EMISSIONS

The MATLAB 2013b neural network toolbox is used to establish a BP neural network model and a support vector machine model for the prediction of NOx emissions from a coal-fired boiler (Chen 2013, Shi & Wang 2011).

Modelling of the BP Neural Network

Six of the boiler's coal mills are chosen for analysis, representing a total of 23 input parameters, including coal feed, secondary air damper opening, furnace outlet O_2, etc. The output parameter represents the predicted concentration of NOx emissions. Sorting of the sample is extremely difficult; therefore the model is established with a fixed coal load. There are 64 groups of data representing normal operation conditions of 500 MW; 56 data groups are used as training data, and the remaining eight data groups are used as test data to verify the fit and generalizability of the network. Detailed data are presented in Tables 1 and 2.

Using the Feed forwardnet function of the neural network rather than the old Newff function allows the completion of the input and output layer dimension with the train function; its convergence speed is fast, and it demonstrates a higher accuracy than the Newff function. Over-adaptation is possible during the training of the neural network in which the very small sample error in the training set differs significantly from the potentially great error in new sample data; thus, the network lacks new sample generalizability (Zhou 2013). In order to avoid the above situation, data are normalized prior to the neural network prediction, meaning that all data are converted to numbers in the range of [0,1], thus eliminating differences in orders of magnitude between

The Front Wall

The	CFU1	CFU2	CFU3	CFU4	CFU5	CFU6	Pulverizer E
Left	CFM1	CFM2	CFM3	CFM4	CFM5	CFM6	Pulverizer D
Wall	CFD1	CFD2	CFD3	CFD4	CFD5	CFD6	Pulverizer C

The Back Wall

The	CBU6	CBU5	CBU4	CBU3	CBU2	Pulverizer B	The
Right	CBM6	CBM5	CBM4	CBM3	CBM2	Pulverizer F	Left
Wall	CBD6	CBD5	CBD4	CBD3	CBD2	Pulverizer A	Wall

Fig. 2: The relationship between combustor and mill.
(Note: C represents the combustor, F represents a front wall combustor, B represents a back wall combustor, U indicates UPPER, M indicates middle, and D indicates down).

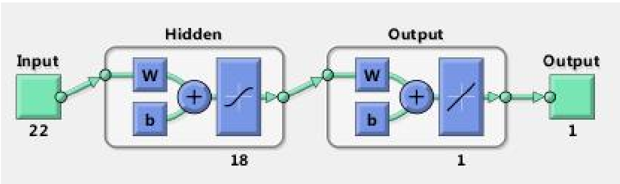

Fig. 3: BP neural network model.

dimensional data. The BP neural network model is used to compare predicted and actual values of NOx emission concentration, and a comparison graph representing the actual and predicted values of training set data. The number of hidden layer nodes are repeatedly adjusted by the Feed forwardnet function; results indicate that the BP neural network achieves its best prediction results when the number of hidden layer nodes is equal to 18. The neural network model is shown in Fig. 3.

Simulation and prediction of the BP neural network: Simulation and prediction results of the BP neural network are shown in Fig. 4, training sample error and test sample error are shown in Fig. 5. As shown in Fig. 4, most of the BP neural network simulation values coincide with training values; some simulation values are close to training values, indicating that the network demonstrates a better fit. Fig. 5 shows the error between training values and simulation values, with a maximum error of 9.85%, smallest minimum error of 0.95%, and an average error of 4.2%.

Modelling of Support Vector Machines

In order to compare the SVM model with the BP neural network model, both are assigned identical input and output data, as shown in Table 1, 23 input parameters and an output parameter which can be used to predict the concentration of NOx emissions.

The Libsvm toolbox is used to model SVM (Lin & Lin 2013), it is a simple and efficient SVM pattern recognition and regression software package, developed by professor Lin Zhiren in Taiwan University. It provides numerous default parameters which result in relatively small parameter adjustment, and provides a cross-validation feature. The training function is model = svmtrain (trainy, trainx, ['ibsvm_options']); the prediction function is [predict, accuracy]= svmpredict (testy, testx, model, ['libsvm_options']). There is no general model used internationally to choose parameters and kernel function parameters when SVM is used for regression prediction, so the SVM algorithm parameters are typically chosen by experience, experimental contrast, broad searches or with the assistance of a software package which can provide cross-validation. In this model, "svmtrain", the penalty parameter c and kernel function g are chosen by cross-validation, which adopts the mean error of the array as the best parameter. The error is identified by the training set corresponding to the given c and g with the K-CV method in the libsvm box, which options the optimized parameters c=0.616 and g=3.4. In order to avoid excessive adaptation and improve new sample generalizability, data is normalized prior to the neural network prediction.

SVM model simulation and prediction: The simulation and prediction results of the SVM model are shown in Fig. 6, training sample error and test sample error are shown in Fig. 5. As shown in Fig. 6, most BP neural network simulation values coincide with training values; a few values are near the training values, indicating that the proposed network demonstrates a better fit. Fig. 7 shows error between training values and simulation values, with a maximum error of 4.57%, a minimum error of 0.21%, and an average error of 2.15%.

Comparative Analysis of two Model Types

Both, the BP neural network and SVM can be used to determine non-linear regression; however, they are based on different theoretical bases, and different return mechanisms. SVM is based on the theory of structural risk minimization, and is generally agreed to represent stronger generalizability than neural networks. In order to compare the prediction results achieved by the two respective models, the following three evaluation indicators are introduced:

1. Mean absolute relative error and maximum absolute relative error

$$M=\frac{1}{N}\sum\frac{|V_p-V_r|}{V_r} \quad ...(1)$$

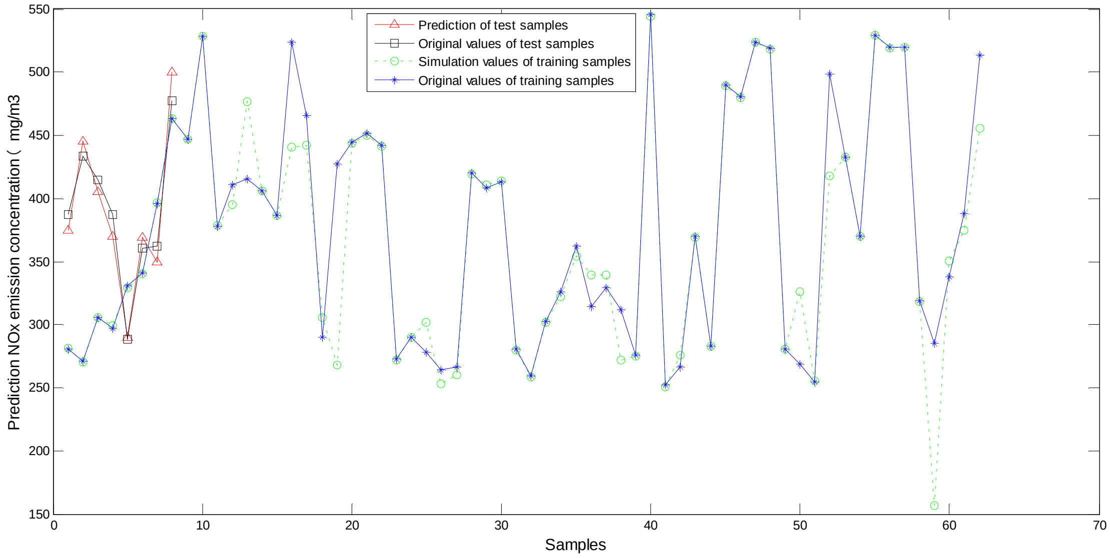

Fig. 4: BP neural network prediction results.

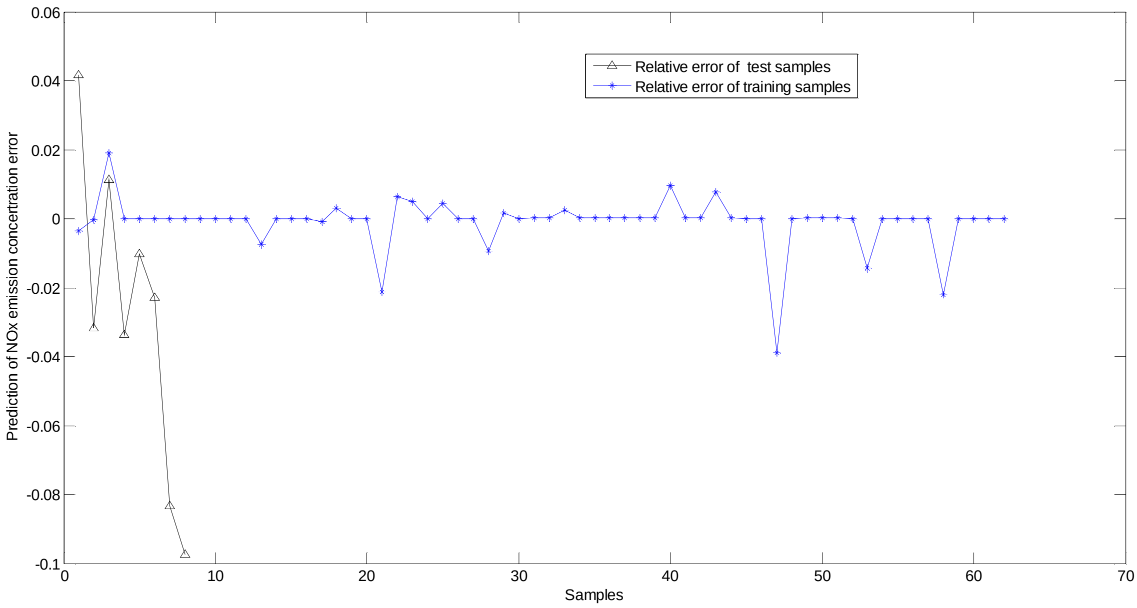

Fig. 5: Relative error of BP neural network prediction.

$$ME = \max\left|\frac{V_p - V_r}{V_r}\right| \quad ...(2)$$

2. Training sample training time
3. Speed of convergence
4. Fault tolerance

For the comparison, the fault tolerance of the two proposed models, five groups of inaccurate training samples are selected, which form a new training sample. BP model simulation and SVM results which reflect the new training sample are shown in Fig. 8 and Fig. 9, respectively. The accuracy of the BP neural network simulation model degrades, and most simulation data points deviate from actual values. However, there is almost no difference between the revised SVM simulation results and results of the original sample simulation. Comparison indicates that the SVM model is vastly superior to the BP neural network model in terms of fault tolerance.

According to the four evaluation indicators introduced by Peng Wang-shu (Peng 2013), a comparison between the

Table 1: Experimental data samples.

Working condition	Load (MW)	Furnace outlet O_2	Coal feed (t/h)						Secondary air damper opening (%)			
			A	B	C	D	E	F	A/R	A /L	B/R	B/L
1	500	9.096	43.6	42.2	37.8	42.6	49.3	42.2	98.1	98.9	50.5	49.7
2	500	8.606	45.6	43.9	39.3	44.9	51.3	36.8	98.1	98.9	50.4	49.8
20	500	8.008	48.7	40.4	36.9	40.1	30.9	42.5	98.1	99.1	88.1	94.5
48	500	8.446	42.6	35.9	47.4	46.4	36.79	46.8	98.7	99.6	88.7	98.5
62	500	8.117	46.0	42.2	44.2	49.7	47.5	47.0	98.7	99.5	91.7	99.9

Table 2: Experimental data samples.

Working condition	Secondary air damper opening (%)								Over-fire air (%)				NOx emission concentration (mg·m^{-3})
	C/R	C/L	D/R	D/L	E/R	E/L	F/R	F/L	A1	A2	B1	B2	
1	6.6	75.3	6.6	99.8	98.8	98.4	74.6	75.2	30.24	30.2	49.3	50.3	480.7
2	6.6	75.3	6.6	99.9	98.7	98.4	74.6	75.2	30.2	30.2	49.4	50.3	471.1
20	6.6	59.8	6.6	99.9	99.2	98.4	40.2	40.5	69.9	70.4	39.7	40.5	444.3
48	6.6	59.8	6.6	99.9	99.0	70.5	49.7	50.1	75.4	75.7	58.9	60.6	518.7
62	99.1	20.5	9.9	99.2	99.9	99.2	64.8	65.3	70.3	70.4	49.3	50.2	563.6

Note:R-Right;L-Left.

Table 3: Evaluation index of BP neural network and support vector machine models.

Evaluation index	BP neural network model	SVM model
M	1.45	0.83
ME	4.2	2.15
Training samples learning time	Long	Short
Speed of convergence	Slow	Fast
Optimality	Local	Global
Fault tolerance	Poor	Good

BP and the SVM is shown in Table 3. The analysis of SVM and BP neural network simulation prediction results in the following conclusions:

1. The SVM model simulation and prediction demonstrate high accuracy.
2. The SVM model demonstrates improved calculation speed.
3. The SVM model demonstrates greater generalizability and fault tolerance than the BP neural network model.

CONCLUSION

NOx formation in a coal-fired boiler is a very complicated process, and is influenced by the type of boiler, the mode of combustion, coal type, the air-coal ratio, mode of air distribution, furnace temperature, uniformity of distribution and other factors, in addition to complex coupling relationships among various factors. Thus, there exists no accurate function model to describe NOx formation in coal-fired boilers. A BP neural network model and the SVM model are used to describe the complex relationship between the characteristics mentioned above.

An NOx emission concentration prediction model was constructed using the BP neural network and SVM methods for an ultra-super-critical boiler of 660 MW. The prediction results of NOx emission concentration demonstrated maximum relative errors of 6.3% and 4.2%, and average relative errors of 4.57% and 2.15% for the BP neural network and SVM models, respectively. Both proposed models can accurately describe the relationships between various furnace parameters, indicating that both models are reasonable. However, the SVM model is greatly superior to the BP neural network model in terms of simulation and generalizability.

Compared to other methods of mathematical modelling, artificial neural networks can best determine underlying information to avoid or reduce the workload of common data analysis and modelling with the use of training samples. The artificial neural network demonstrates strong nonlinearity, adaptability and robustness, and thus is beneficial for the determination of association, generalization, analogy and promotion. With additional training samples, its accuracy would be further improved with a larger training network.

As compared to the BP neural network, the SVM model is superior in terms of simulation and generalizability. Every

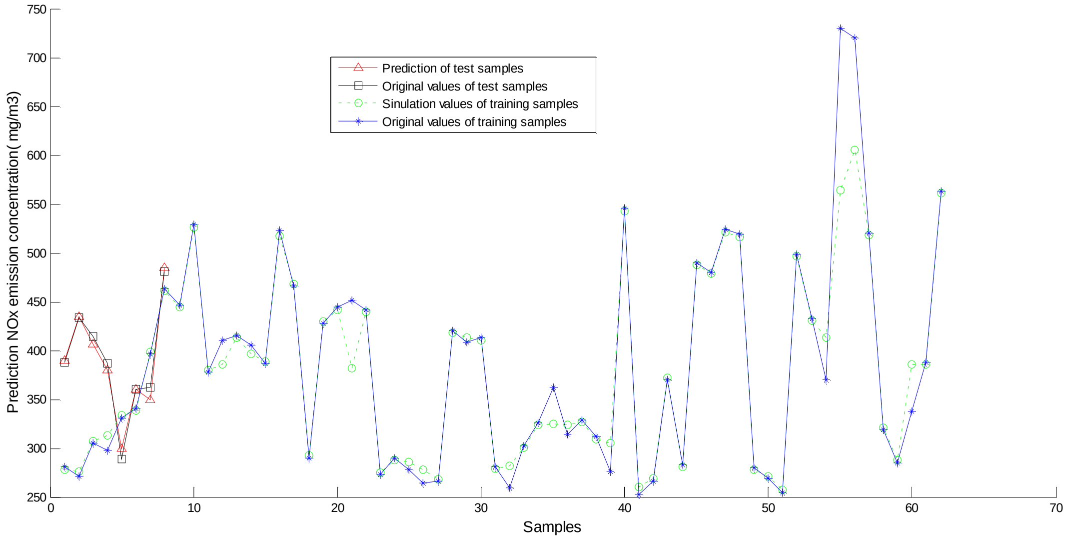

Fig. 6: Support vector machine (SVM) model prediction results.

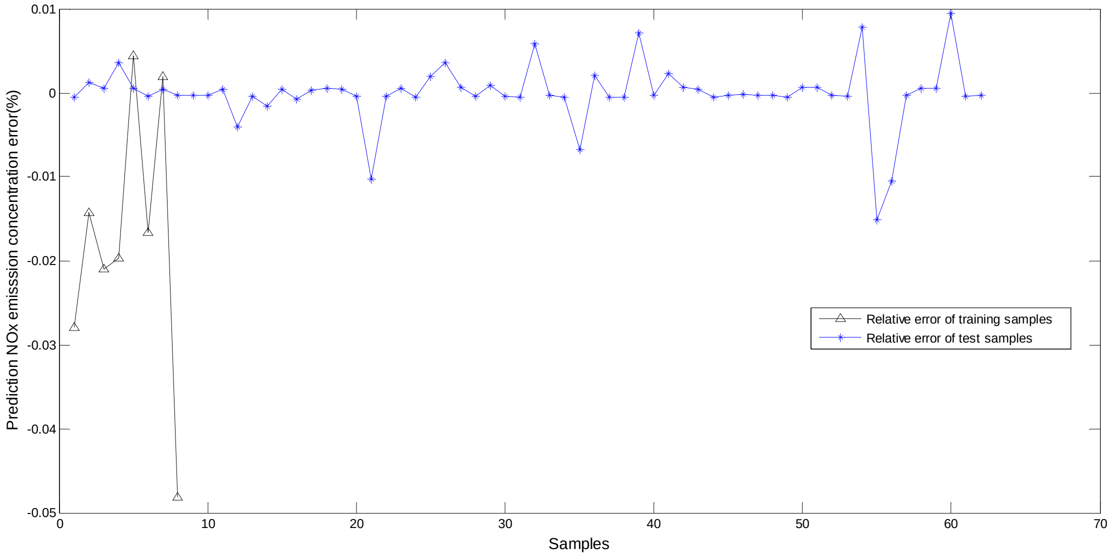

Fig. 7: Predicted relative error of the support vector machine (SVM) model.

calculated regression equation of SVM model is unique, but when an unstable training simulation occurs in the BP neural network model, calculations return "black box" functions. Alternatively, SVM model training samples demonstrate short training times, fast convergence speeds and high accuracy.

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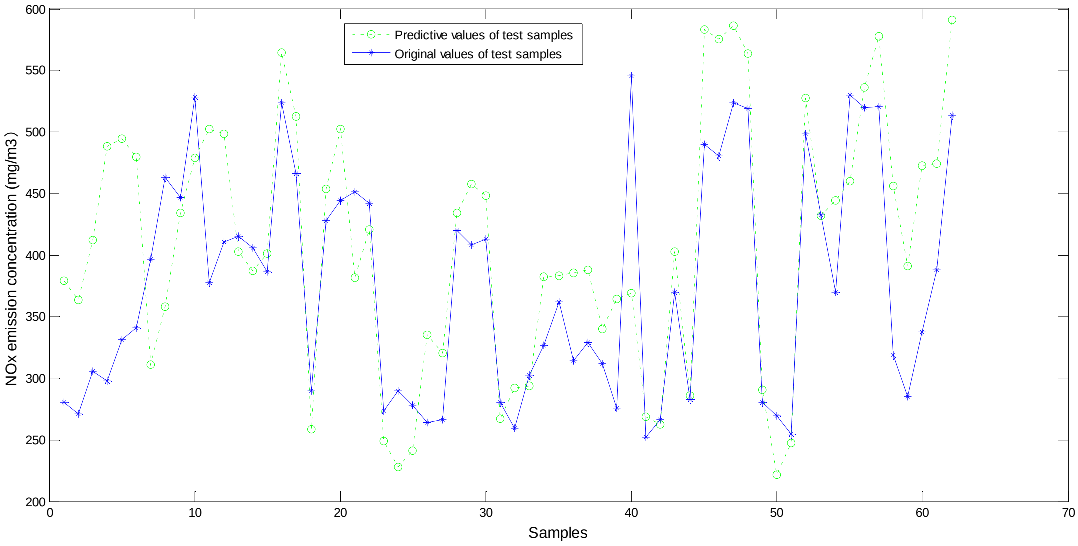

Fig. 8. Simulation results of the BP neural network model.

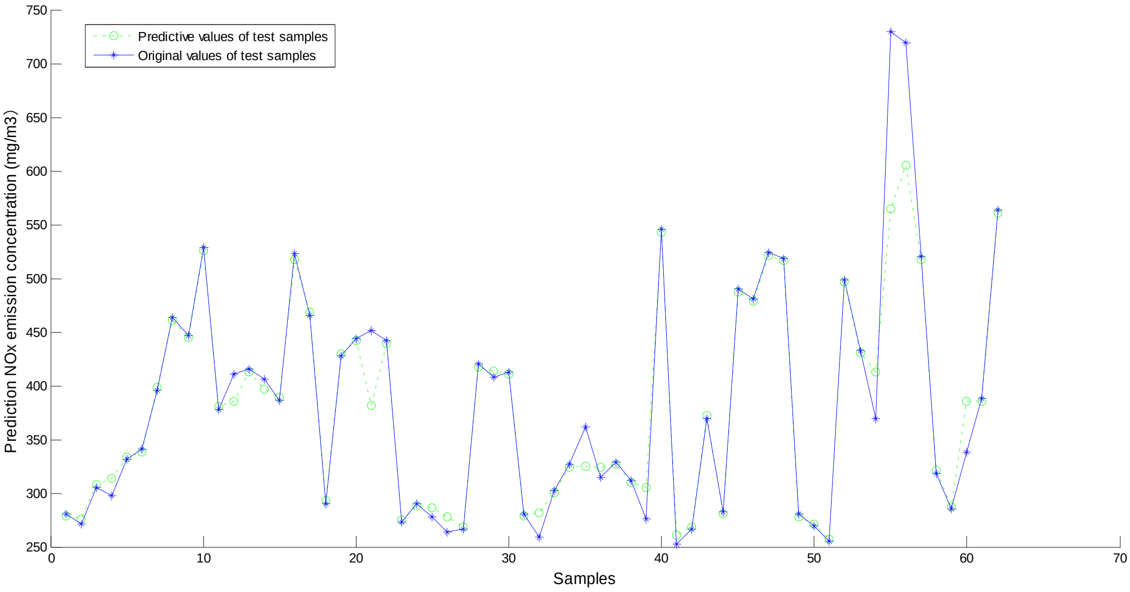

Fig. 9. Simulation results of the support vector machine (SVM) model.

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