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HCl emission characteristics and BP neural networks prediction in MSW/coal co-fired fluidized beds

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Abstract: The HCl emission characteristics of typical municipal solid waste(MSW) components and their mixtures have been investigated in a Φ150 mm fluidized bed. Some influencing factors of HCl emission in MSW fluidized bed incinerator was found in this study. The HCl emission is increasing with the growth of bed temperature, while it is decreasing with the increment of oxygen concentration at furnace exit. When the weight percentage of auxiliary coal is increased, the conversion rate of Cl to HCl is increasing. The HCl emission is decreased, if the sorbent(CaO) is added during the incineration process. Based on these experimental results, a $14 \times 6 \times 1$ three-layer BP neural networks prediction model of HCl emission in MSW/coal co-fired fluidized bed incinerator was built. The numbers of input nodes and hidden nodes were fixed on by canonical correlation analysis technique and dynamic construction method respectively. The prediction results of this model gave good agreement with the experimental results, which indicates that the model has relatively high accuracy and good generalization ability. It was found that BP neural network is an effectual method used to predict the HCl emission of MSW/coal co-fired fluidized bed incinerator.

Keywords: municipal solid waste(MSW); HCl emission; fluidized bed; BP neural networks; prediction model

Introduction

With the depletion of space for landfilling of municipal solid waste and the rising prices for raw materials, more and more fluidized bed incinerators have been used to treat MSW due to the primary advantages of hygienic control, volume reduction and energy recovery. Because the MSW has high moisture content and low heat value in China, in order to maintain stable combustion, the auxiliary fuel has to be added. China has the biggest coal production in the world, so it is a good choice to use coal as the auxiliary fuel for MSW incinerators.

However, a great amount of HCl is emitted when MSW is being incinerated because of relatively high chlorine content, which leads to not only serious environment pollution but also high temperature corrosion of superheater (Niu, 1999). Some reports about HCl emission in MSW combustion process can be found in previous studies(Manninen, 1997; Desroches-Ducamrne, 1998; Wang, 1999; Liu, 2000; Dong, 2002). However, MSW combustion is a process with multi influencing factors, so it is very difficult to build an accurate mathematical model of HCl emission characteristics. Preliminary study indicated that the total of HCl emissions of single-component wastes is greater than the HCl emission of equivalent raw wastes. Hence, HCl emission of MSW is absolutely not equal to the linear weighted sum of its components, and the interactions between the components have to be considered. The HCl emission characteristics have many influencing factors, and the relationship between HCl emission and each factor is nonlinear and very complex. BP neural network has good ability of self-adapting, self-organizing and fault tolerance, so it is suitable for pollution emission prediction of MSW incineration.

The aims of this study were to investigate the effects of several influencing factors, such as bed temperature, oxygen concentration, percentage of auxiliary coal, sorbent and fuel sulfur content etc., on the HCl emission characteristics in MSW/coal co-fired fluidized beds and to build a BP neural networks prediction model of HCl emission in MSW/coal co-fired fluidized bed incinerator.

1 Experimental

1.1 Apparatus and procedure

Experimental facility in Fig. 1 is composed of a riser of 150 mm i.d and 3000 mm height, a feed system, an airing system, a cyclone and a primary air electric preheater. The bed material consisted of 0.6 mm average diameter silica sand mixed with a minor quantity of the ash remaining in the bed after combustion. The recycle system included a cyclone that separates combustion gases and entrained solids, and then the collected solids were injected into the bed. The fuel was fed continuously by the band conveyer, and the delivery rate, about 0.2 kg/min, was regulated by the frequency control electric engine. The oxygen concentration at furnace exit was controlled by air preheater and flowmeters. The setup was

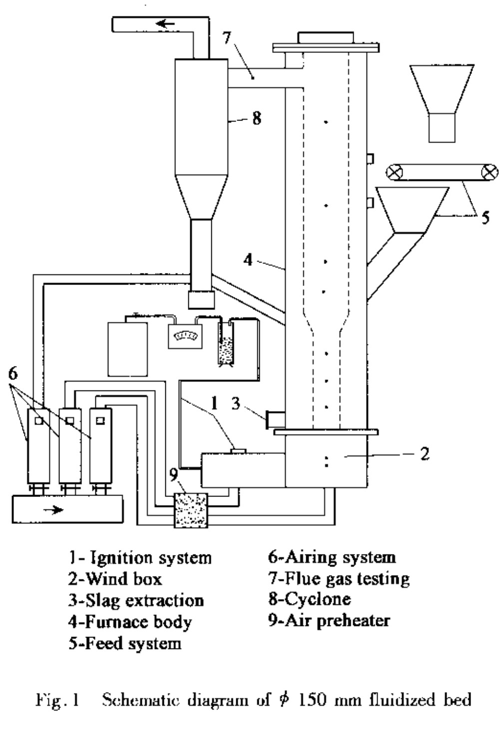

Fig. 1 Schematic diagram of ϕ 150 mm fluidized bed

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equipped for continuous measurement of temperature detected by HP 34970A data acquirer. Data were collected through computer every minute. The concentrations of CO, CO_2, O_2, NOx and SO_2 were measured by using Testo flue gas analyzer, and HCl concentration was measured by using DIKMA No.14 L HCl detector tube. The measuring point of flue gas was at the exit of furnace chamber.

1.2 Sample

The municipal refuse used in this work was collected by classification criteria of combustible municipal solid waste mainly classified in 6 categories (paper, plastic, rubber, kitchen residue, wood, fabric), and the coal was Leiyang anthracite. Each category was separately dried and broken into pieces that mean diameter less than 10 mm, with the properties listed in Table 1.

Table 1 Proximate and ultimate analysis of the fuels

Sample	Proximate analysis, W_{ad} %					Ultimate analysis, W_{ad} %				
	M	A	V	FC	C	H	N	S	Cl	O
Wood	16.18	0.82	68.08	14.92	45.88	5.54	0.97	0.50	0.06	30.05
Plastic	0.57	2.58	97.15	0.00	82.55	13.94	0.33	0.03	0.00	0.00
Paper	10.3	8.15	70.68	10.87	39.88	6.42	0.40	0.20	0.70	33.95
Fabric	5.20	0.58	83.52	10.70	51.72	5.04	2.32	0.12	0.09	34.93
Rubber	0.65	14.28	68.64	19.23	75.56	7.51	1.08	0.92	0.04	0.00
Kitchen residue	8.3	12.47	63.86	15.37	42.18	6.16	3.02	0.14	0.14	27.59
PVC	0.01	0.04	99.49	0.27	35.13	4.12	0.05	0.01	46.57	14.07
Anthracite	1.00	21.20	5.50	72.30	72.64	2.16	1.02	0.68	0.12	1.18

Notes: M, A, V and FC represent the weight percentages of moisture, ash, volatile and fixed carbon respectively in proximate analysis; and C, H, N, S, Cl and O represent the weight percentages of carbon, hydrogen, nitrogen, sulphur, chlorine and oxygen respectively in ultimate analysis

2 Results and discussion

HCl originates from both the combustion of organic chloride, such as PVC, rubber, fabric, wood, paper and coal, and the reaction between inorganic chloride, such as NaCl and KCl, and other substance. The formation and inhibiting reactions of HCl are mainly:

$$NaCl + H_2O \longrightarrow NaOH + HCl, \tag{1}$$

$$2NaCl + SO_2 + 0.5O_2 + H_2O \longrightarrow Na_2SO_4 + 2HCl, \tag{2}$$

$$2NaCl + H_2O + SiO_2 \longrightarrow Na_2SiO_3 + 2HCl, \tag{3}$$

$$RCl + O_2 \longrightarrow CO_2 + H_2O + HCl, \tag{4}$$

$$CaCl_2 + SO_2 + H_2O \rightarrow CaSO_4 + 2HCl, \tag{5}$$

$$2HCl + 0.5O_2 \rightleftharpoons Cl_2 + H_2O. \tag{6}$$

Only a part of fuel Cl transforms to HCl in the combustion process. In order to estimate the ability of releasing HCl of the fuel, conversion rate of fuel Cl η was employed in this paper.

$$\eta = \frac{HCl}{HCl_{\text{theory}}} \times 100\%. \tag{7}$$

HCl is the real emission concentration of HCl, and HCl_{theory} is the theory emission concentration of HCl when all of fuel Cl transforms to HCl.

2.1 Bed temperature

As shown in Fig.2, the conversion rate of Cl to HCl is increasing with the growth of bed temperature. The reasonable explanation is that the growth of temperature leads to the increment of vapor partial pressure of NaCl or RCl, and then the reactions (1)—(5) move to right, accordingly more HCl is produced (Ma, 1997). However, for different fuels, the conversion rates of Cl to HCl are different, in which those of anthracite, fabric, rubber, PVC and 2%PVC + anthracite are higher, and the others are lower. A probable explanation is that there are relatively more alkali oxides and alkali mental salts in the incineration ashes of paper, wood and kitchen residue, which have high dechlorinating ability. These substances are very apt to react with Cl in fluidized bed incinerator, and the resultants are kept as KCl or $CaCl_2$. $CaCl_2$ is able to decompose largely at high temperature because of its low melting point, accordingly, the Reaction (5) moves to right with temperature growing (Wawrzinek, 2001). Nevertheless, the incineration ashes of PVC and rubber almost do not contain alkali oxides and alkali mental salts, so their conversion rates of Cl to HCl are relatively high. NaCl has a lattice energy (786 kJ/mol) higher than the molecular bond energy of PVC, consequently, the chlorine in PVC are more readily available for being released than that in NaCl (Wang, 1999). That is, the conversion rate of Cl to HCl of NaCl is lower than that of PVC.

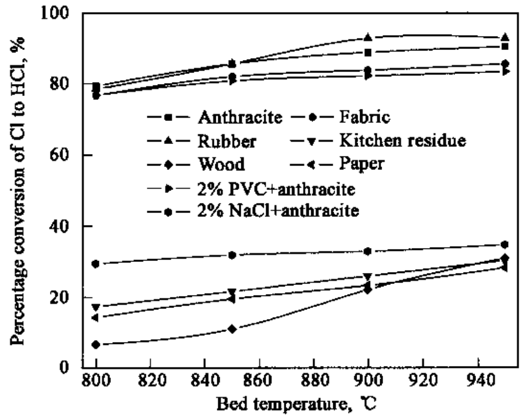

Fig.2 Cl→HCl variation with bed temperature (EA = 2.0)

2.2 Oxygen concentration at furnace exit

As shown in Fig.3, the conversion rate of Cl to HCl is decreasing with the growth of oxygen concentration at furnace exit, but the decrease degrees are different. A probable explanation is that all of the reactions (1)—(4) and (6) move to right with oxygen concentration increasing, but the effect of Reaction (6) is stronger than the total of the effects of reactions (1)—(4). In general, the effect of oxygen concentration at furnace exit on the conversion rate of Cl to HCl is not obvious.

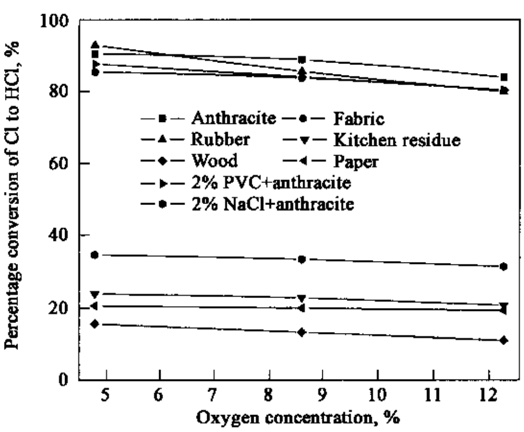

Fig.3 Cl→HCl variation with oxygen concentration (bed temperature = 850℃)

2.3 Percentage of auxiliary coal

As shown in Fig.4, the conversion rate of Cl to HCl is increasing with the growth of weight percentage of coal in the mixture. The conversion rate of Cl to HCl is about 40% when MSW firing separately, but that is greater than 80% when coal firing separately. The reasonable explanation is that the biomass wastes, such as wood, paper and kitchen residue, contain relatively more active ingredients(K, Ca, Na etc), which have strong chlorine retention ability.

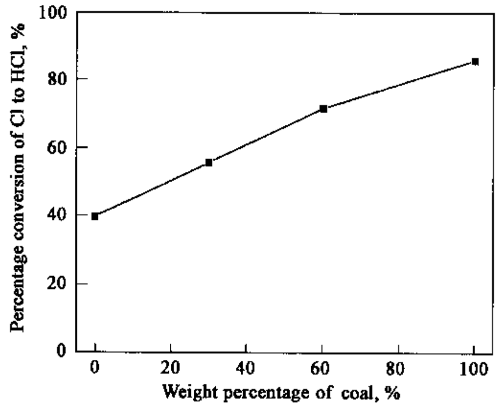

Fig.4 Cl→HCl variation with weight percentage of coal

2.4 Sorbent: CaO

Although MSW has strong chlorine retention ability, the chlorine retention efficiency is improved largely when CaO is added, as shown in Fig.5. On the other hand, the chlorine retention efficiency is declining with the growth of temperature. At high temperature, $CaCl_2$ is ready to sintering because of the low melting point (772℃), thereby the gaseous diffusion resistance is increased. Consequently, HCl can react with CaO only on its surface, and the most of CaO are not availably utilized. This indicates that the chlorine retention efficiency of CaO in MSW fluidized bed incinerator can be improved by means of decreasing its grain size and increasing its specific surface area.

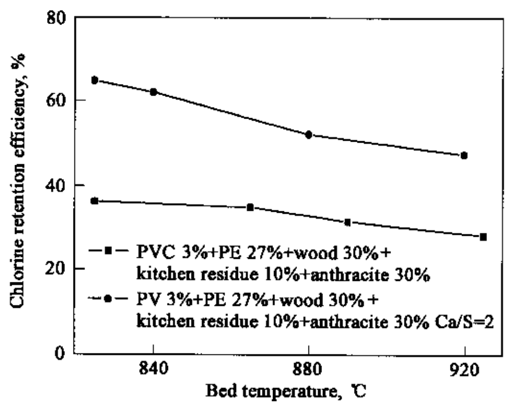

Fig.5 Effect of CaO on chlorine retention efficiency

2.5 Fuel sulfur content

When the fuel sulfur content is relatively high, adding Ca-based sorbent(CaO) can availably inhibit SO_2 emission, but it is more difficult to dechlorinate than before. The reason may be that CaO tends to react with SO_2 but not HCl, which can be explained by the following reactions:

$$CaO + 2HCl = CaCl_2 + H_2O, \tag{8}$$

$$CaCl_2 + SO_2 + O_2 = CaSO_4 + Cl_2, \tag{9}$$

$$CaCl_2 + SO_2 + H_2O = CaSO_4 + 2HCl. \tag{10}$$

3 BP neural networks prediction model

3.1 Model building

HCl emission is affected by many factors, such as MSW composition, bed temperature, oxygen concentration, weight percentage of coal, Ca/S mole ratio, secondary air percentage, bed material, turbulivity, residence time, furnace type, fluidization air velocity and bed height etc. Accordingly, it is very difficult to describe the influencing factors of HCl emission quantitatively, but it can be solved by canonical correlation analysis technique. Canonical correlation analysis technique is a statistical method that is used to investigate the correlation between two sets of variables. The modeling process is as the follows.

Given that original input and output data are X_0 and Y_0 respectively. In order to eliminate the effects of different dimensions and different orders of magnitude between data, X_0 and Y_0 are transformed to X and Y by using zero standard error of mean method. Let it be supposed that X and Y are as follow respectively, when $p_1 \leqslant p_2$ and $p_1 + p_2 = p$.

$$X = (x_1, x_2, \Lambda, x_{p_1}) = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p_1} \\ x_{21} & x_{22} & \cdots & x_{2p_1} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{np_1} \end{bmatrix}, \tag{11}$$

$$Y = (y_1, y_2, \Lambda, y_{p_2}) = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1p_2} \\ y_{21} & y_{22} & \cdots & y_{2p_2} \\ \cdots & \cdots & \cdots & \cdots \\ y_{n1} & y_{n2} & \cdots & y_{np_2} \end{bmatrix}. \tag{12}$$

$$\text{Consequently}, (X, Y) = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p_1} & \vdots & y_{1p_2} \\ x_{21} & x_{22} & \cdots & x_{2p_1} & \vdots & y_{2p_2} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{np_1} & \vdots & y_{np_2} \end{bmatrix}. \tag{13}$$

$$\text{The sample correlation matrix is } R = \begin{bmatrix} R_{XX} & R_{XY} \\ R_{YX} & R_{YY} \end{bmatrix}, \tag{14}$$

where R_{XX} is the sample correlation matrix of X, and R_{YY} is that of Y, but R_{XY} and R_{YX} are those of X and Y.

After the sample correlation matrix determines, we need to search vectors $\alpha_i = (\alpha_{i1}, \alpha_{i2}, \cdots, \alpha_{ip_1})$ and $\beta_i = (\beta_{i1}, \beta_{i2}, \cdots, \beta_{ip_2})$, and then make a linear transformation.

$$\left.\begin{aligned} \mu_i &= X\alpha_i \\ \upsilon_i &= Y\beta_i \end{aligned}\right\}, \tag{15}$$

where μ_i and υ_i are the ith couple of canonical correlation variables($i = 1, 2, \cdots, k$).

Then the ith canonical correlation coefficient λ_i, the corresponding generalized eigenvalue λ_i^2 and generalized eigenvector α_i will be solved according to $R_{XY}R_{YY}^{-1}R_{YX}\alpha_i - \lambda_i^2 R_{XX}\alpha_i = 0$. Finally we will analyze the correlation coefficient between two variables X and Y. If two variables are incorrelative, then the correlation coefficient between X and Y is 0; if two variables are entirely correlative, then the correlation coefficient between X and Y is 1.

The data sample sets used in this paper originated from experiments and literatures (Estelle, 1998; Dong, 2002; Xie, 1999), whose total number is 260. The results of canonical correlation analysis are listed in Table 2. As shown in this table, the loads of PVC and NaCl are the biggest two in all of these loads, which indicates that PVC and NaCl are the main source of HCl emission in MSW fluidized bed incinerator. The bed temperature has plus load for HCl emission, while the oxygen concentration has minus load for HCl emission. The load of fuel sulfur content is a very little minus, which indicates that the fuel sulfur content has tiny effect on HCl emission. The loads of kitchen residue, inorganic materials, paper, fabric, wood, plastic, rubber and coal are minus, and their values are close to each other. However, the loads of bed material and furnace type are close to zero, accordingly, it is proved that there is no direct relationship between HCl emission and bed material, furnace type, and they do not need to be considered in the modeling process.

Table 2 Canonical correlation coefficient of influencing factors for neural network prediction model

Kitchen residue	Inorganic materials	Paper	Fabric	Wood	Plastic	Rubber	Coal
-0.1523	-0.0582	-0.0872	-0.128	-0.218	-0.2134	-0.1768	-0.1892
Bed temperature	Oxygen concentration	PVC	NaCl	Ca/S mole ratio	Fuel sulfur content	Bed material	Furnace type
0.0178	-0.0682	0.5621	0.6733	-0.121	-0.0217	0.0001	-0.0012

In a word, the following fourteen parameters was chosen as the input nodes of the neural networks prediction model: kitchen residue, inorganic materials, paper, fabric, wood, rubber, plastic, coal, bed temperature, oxygen concentration at furnace exit, PVC, NaCl, Ca/S mole ratio and fuel sulfur content.

After the input and output nodes were fixed on, the hidden nodes need to be fixed on by dynamic construction method. That is, adequate nodes were employed in the beginning, and then the void nodes will be removed until the number of hidden nodes can not be minified. At last, six was adopted as the optimal number of hidden nodes. Consequently, the structure of neural networks prediction model of HCl emission is $14 \times 6 \times 1$, as shown in Fig.6.

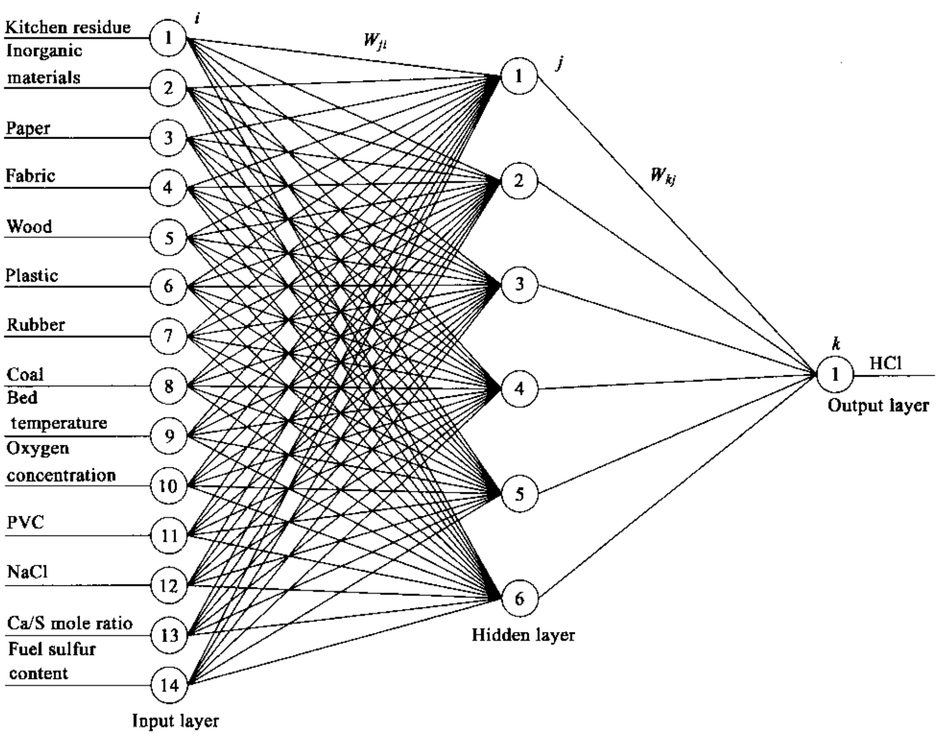

Fig.6 BP neural networks prediction model of HCl emission

3.2 Prediction examples

By using the BP neural networks prediction model mentioned above, several prediction results were obtained, as shown in Fig. 7. The prediction results indicate: the HCl emission is increasing with the growth of bed temperature, while it is decreasing with the increment of excess air coefficient; when Ca/S mole ratio is increasing, the HCl emission is decreasing; if the weight percent of auxiliary coal is raised, the HCl emission will increase; PVC and NaCl are the two important influencing factors of HCl emission in MSW fluidized bed incineration process. These results give good agreement with the experimental results.

3.3 Model assessment

The selected method of training samples and testing sample has rarely been reported before. Relatively more training samples not only expand the prediction scope but also decrease the error owing to lack of typical samples, but too many training samples prolong the training time. However, too few training samples affect the generalization ability badly. The principle advanced in literature (Qi, 1999) is that there should be 5—10 training samples at least per weight. In order to ensure the set of testing samples is included in the set of training samples and avoid the extrapolation phenomenon in testing process, the maximal and minimal samples should be selected as the training samples in actual application. There are 260 data samples in this paper, in which 178 for training and 82 for testing.

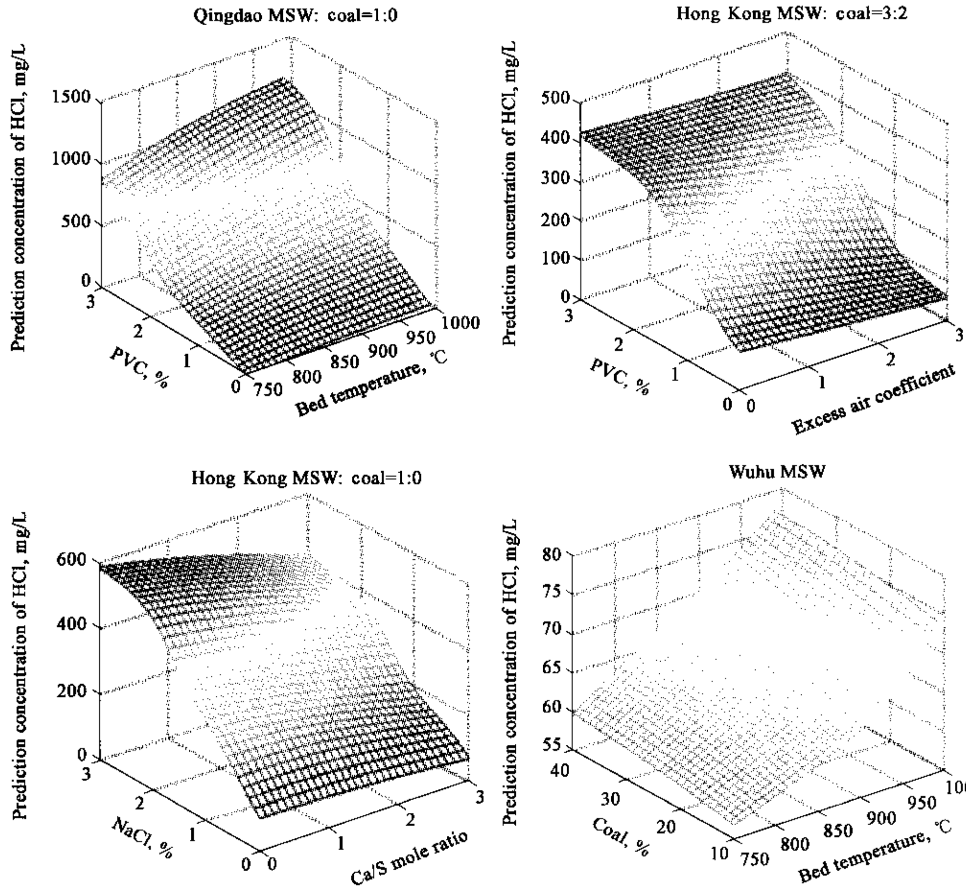

Fig.7 Several prediction examples

Fig.8 shows the absolute and relative errors of the HCl neural networks prediction model for training and testing samples. It indicates: the absolute errors of training samples are mostly within ± 20 mg/Nm^3, and those of testing are mostly within ± 25 mg/Nm^3; the relative errors of training samples are mostly within ± 15%, and those of testing are mostly within ± 20%. This proves that this model has good prediction effect and generalization ability. However, the errors of a few samples are relatively big, even very big. The probable reasons are as that: a few testing samples are situated in the blind area of the set of training samples; some wrong information was involved in the neural networks during training process; the self-errors of a few testing samples are relatively big; the neural networks have errors at some degree, because it adopts nonlinear approach. In general, this model established the nonlinear mapping from these influencing factors to the HCl emission with comparatively high accuracy.

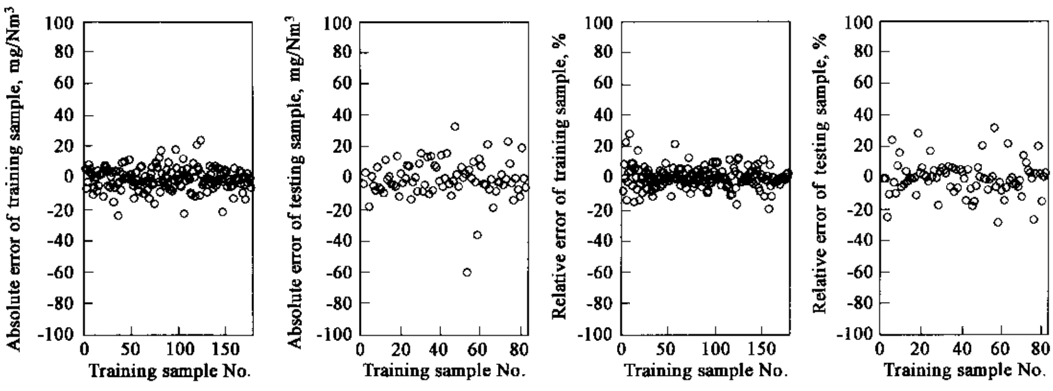

Fig.8 The errors of HCl neural networks prediction model with absolute error and relative error

4 Conclusions

Experimental studies have been carried out on the HCl emission during fluidized bed co-combustion of MSW and coal. The following are concluded:

(1) the conversion rate of Cl to HCl is increasing with the growth of bed temperature; the conversion rate of Cl to HCl is decreasing with increasing oxygen concentration at furnace exit;

(2) the conversion rate of Cl to HCl is increasing with

the growth of weight percentage of coal in the mixture;

(3) the HCl emission is decreased largely when CaO is added;

(4) when the fuel sulfur content is relatively high, adding Ca-based sorbent(CaO) can availably inhibit the SO_2 emission, but it is more difficult to dechlorinate than before;

(5) the HCl emission is directly affected by the characteristics of MSW components.

To simulate and predict the HCl emission of combustion process, a model based on BP neural networks are proposed and developed. Using this model, the HCl emission concentration during fluidized bed co-combustion of MSW and coal can be outputted by inputting 14 influencing factors mentioned above. The prediction results of this BP neural networks model give good agreement with the experimental results. Consequently, BP neural network is an effectual method used to predict the HCl emission of MSW/coal co-fired fluidized bed incinerator.

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