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Adaptive Neuro-Fuzzy Inference System-Based Pulverizing Capability Model for Running Time Assessment of Ball Mill Pulverizing System

***Abstract**. Ball mill pulverizing system (BMPS) of thermal power plant has high energy consumption and the running time assessment of BMPS is of important theoretical significance and practical motivation for the energy saving. In the paper, an adaptive neuro-fuzzy inference system-based pulverizing capability model (ANFIS-PCM) for running time assessment of BMPS is proposed. The proposed model integrates of the artificial neural network and the Takagi-Sugeno type fuzzy rule to construct an input-output mapping based on both human knowledge and stipulated input-output data pair. For the proposed method, the subtractive clustering algorithm is used to obtain the initial rules, and the membership functions and the rules could be determined by the learning ability. The proposed model is performed on the field data under different work conditions. The experiments results verify that the proposed model has higher prediction precision. Moreover, the proposed model has been put into practice and the field operation curve verifies that the pulverizing capability could be predicted correctlly and the running time assessment of BMPS would be realized.*

***Streszczenie.** W artykule przedstawiono model szacowania czasu pracy urządzenia do proszkowania w młynie kulowym, opracowany w oparciu o system wnioskowania neuro-rozmytego. W systemie zintegrowano sztuczną sieć neuronową oraz model rozmyty Takagi-Sugeno. Proponowany model zbudowano na podstawie pomierzonych wartości w różnych warunkach pracy. Przeprowadzono zostały próby weryfikujące skuteczność działania, które potwierdziły wysoką sprawność algorytmu. (**Modelowanie proszkowania w szacowaniu czasu pracy urządzenia do proszkowania w młynie kulowym – zastosowanie adaptacyjnego wnioskowania neuro-rozmytego**).*

Keywords: BMPS; Pulverizing Capability; Running Time Assessment; ANFIS.
Słowa kluczowe: BMPS, skuteczność proszkowania, szacowanie czasu pracy, ANFIS.

Introduction

Ball mill pulverizing system (BMPS) is an important equipments in a thermal power plant and provides the coal powder for the boiler [1]. Since BMPS uses 15~25% of the whole energy consumption of the thermal power plant, BMPS is stopped for the coal powder level of bunker reaching a certain height. Currently, the coal powder level is still obtained by periodic manual measurement. Hence, the work intensity of operators is increased and the downtime of BMPS can not be evaluated accurately, which would not save the energy effectively and causes difficulties to the arrangement of equipment maintenance.

Pulverizing capability could mainly represent the efficiency of BMPS and determine the coal powder level of bunker. The running time assessment of BMPS would be realized by the pulverizing capability measurement. Some methods of measuring the concentration of pulverized coal are used for predicting the pulverizing capability. The γ-ray absorption is adopted for measuring the concentration of pulverized coal in one-time air pipe [2]. A wireless sensor network is used to measure the concentration of pulverized coal based on the pulverized coal plow [3]. Because BMPS is a multi-variable, nonlinear and strong coupling system, the single signal measurement is not suitable. The grey entropy and the chaos analysis are presented for establishing the soft sensor model of pulverizing capability [4]. The support vector regression algorithm is adopted for estimating the pulverizing capability of BMPS [5]. Although the approaches based on the multiple process variables could overcome the lack of single signal measurement in a certain extent, they are complex and could not be implemented in field easily. Adaptive neuro-fuzzy inference system (ANFIS) is an artificial neural network with Takagi-Sugeno (TS) fuzzy inference mechanism, and could construct an input-output mapping based on both human knowledge and stipulated input-output data pair [6]. Since ANFIS could make fuzzy system more systematic and less relying on expert knowledge, it has a lot of practical applications in many different domains [7-11].

This paper proposes an ANFIS-based pulverizing capability model (ANFIS-PCM) for running time assessment of BMPS. For the proposed method, the subtractive clustering algorithm is firstly used to obtain the initial rules, then ANFIS optimizes the membership functions and rules base of the pulverizing capability model by using the learning ability of the neural network. In order to demonstrate the usefulness of the proposed model, the effectiveness of the ANFIS-PCM is compared with those of the back-propagation neural networks-based pulverizing capability model (BPNN-PCM) and the support vector machine-based pulverizing capability model (SVM-PCM). Two datasets are used in the experiments and they are obtained from the field database of real thermal power plant under different work conditions. Furthermore, the proposed method has been put into practice in field successfully.

The organization of the paper is as follows. Section 2 provides the problem statement. The proposed model is presented in detail in section 3. In section 4, the experimental results are explained to demonstrate the effectiveness of the proposed model. Finally, section 5 concludes the paper.

Problem statement

The schematic diagram of a ball mill pulverizing system is shown in Fig. 1. When the raw coal is fed into ball mill, the hot air and recycle air are blown to dry and deliver the coal powder. Then the accepted powder is stored in the bunker, and the unqualified powder is sent back into ball mill for further pulverizing.

There are many process variables in BMPS and they may affect the pulverizing capability in a certain extent. However, not every variable can be used for establishing the pulverizing capability model. For example, although the coal hardness affects the pulverizing capability greatly, it could not be adopted for the on-line prediction model in field because the coal hardness only can be calibrated by the periodical chemistry experiment. Hence, the variables for building the prediction model are always determined by the expert knowledge or an automated method. In the paper, for decreasing the model complexity and ensuring the prediction accuracy, we use the ball mill load, the inlet negative pressure, the outlet temperature, the different inlet-outlet pressure and the ventilation rate for establishing the pulverizing capability model. These variables are related to the pulverizing capability and will be discussed in the following.

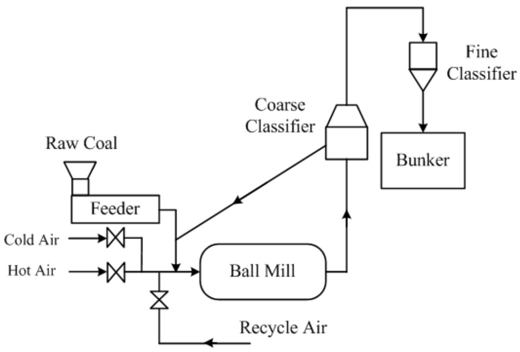

Fig.1. Ball mill pulverizing system

The ball mill load is the ratio between the volume of coal powder in the mill and the interstitial volume of the static ball charge [12]. The pulverizing capability would increase with the ball mill load increasing but the larger ball mill load may lead the ball mill to be clogged.

The inlet negative pressure is used for letting the BMPS system work under the negative pressure state. If it is not enough, the coal powder would not be transferred efficiently. If it gradually increases until converts to positive pressure, the coal powder would spray outside, which would cause the bodily injury and the environmental pollution [13].

The outlet temperature affects the drying of coal powder. The abnormal outlet temperature would either decrease the pulverizing capability or make a risk that the coal powder may be ignited.

The different inlet-outlet pressure is affected by the effective flow area decrease and the flow resistance of the ball mill, so it usually used to represent the clog situation of coal powder in ball mill.

The ventilation rate could represent the air draft capability of BMPS in a certain extent. It is generally affected by the opening degree of inlet baffle of mill exhauster. Furthermore, the measuring point of the ventilation rate is in the vertical pipe of the outlet of ball mill.

The proposed model

According to the characteristics analysis of pulverizing capability, ANFIS-PCM is presented in the paper. Let BML, INP, OT, DP, VR and PC represent the ball mill load, the inlet negative pressure, the outlet temperature, the different inlet-outlet pressure, the ventilation rate and the pulverizing capability, respectively. The first-order TS model fuzzy inference is used in the proposed model, and a typical rule for our prediction model can be written as:

IF BML is L_1 **AND** INP is L_2 **AND** OT is L_3 **AND** DP is L_4 **AND** VR is L_5 ,

THEN PC= a_1 BML+ a_2 INP+ a_3 OT+ a_4 DP+ a_5 VR+ b

where { L_1 , L_2 , L_3 , L_4 , L_5 } is the fuzzy cluster set defined in the antecedent space, a_1, a_2, a_3, a_4, a_5 and b are the consequent parameters.

The subtractive clustering algorithm is firstly adopted to determine the centers of clusters, which are always used to generate the initial membership functions and a set of rules. So, the input variables use the same linguistic terms and the set of fuzzy linguistic terms could be represented by { A_1 , A_2 , $\cdots$, A_m }, where m is the number of obtained clusters, namely m is the number of rules of ANFIS-PCM.

If each data is considered as a potential cluster center, the potential value of a datum x_i is P_i and can be calculated by the following equation [14]:

$$P_i = \sum_{j=1}^{n} \exp(-\frac{4}{r_a^2}\left\|x_i - x_j\right\|^2) \tag{1}$$

where n is the number of data, r_a is the neighborhood radius and $r_a > 0$.

Then, the datum with highest potential value is determined to the first cluster center and the potential values of other data will be updated by the following equation:

$$P_i = P_i - P' \exp(-\frac{4}{r_b^2}\left\|x_i - x'\right\|^2) \tag{2}$$

where x' is the first cluster center and P' is the potential value of x' . r_b represents the neighborhood radius and usually equals $1.25 r_a$.

The datum with the highest potential value among the remaining data is selected as the second cluster center. The process mentioned above is repeated untill the potential value of the h th cluster center is less than $\varepsilon \cdot P'$, where h is a integer and ε is a small fraction. For ε , $\overline{\varepsilon}$ and $\underline{\varepsilon}$ are always used as the accept threshold and the reject threshold, respectively.

After the membership functions and fuzzy rules are initialized, the pulverizing capability model is established by ANFIS. The architecture of ANFIS-PCM is shown in Fig. 2. There has fixed five layers and the node functions in the same layer are of the same function. Let $O_{k,i}$ represent the output of the i-th node of k-th layer, and every layers would be discussed in detail as follows.

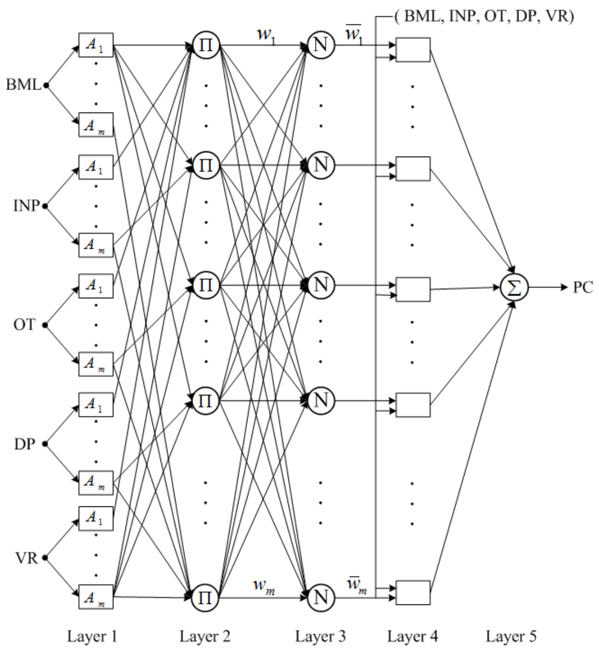

Fig.2. ANFIS-based pulverizing capability model

Layer 1: The membership values of the each input variable are generated, and the node function is

(3) $$O_{1,i} = \mu_{A_j}(x)$$

where $i \in \{1,2,\cdots,5m\}$, $j \in \{1,2,\cdots,m\}$, x represents the input variable, namely, $x \in \{\mathrm{BML,INP,OT,DP,VR}\}$, and $\mu_{A_j}(x)$ is the membership value respect to linguistic term A_j .

The Gaussian function is used as the membership functions and can be represented by

(4) $$\mu_{A_j}(x) = \exp\left(-(x-c^x_{A_j})^2 \Big/ 2(\sigma^x_{A_j})^2\right)$$

where $c^x_{A_j}$ and $\sigma^x_{A_j}$ are the centres of the function and the widths of the function, respectively.

Layer 2: Each node in the layer is a simple multiplier, and the number of obtained clusters is m , namely, the total number of rules is m . Therefore, there are m nodes in the layer. Each node output represents the activation level of a rule:

(5) $$O_{2,i} = w_i = \prod\nolimits_{k=1}^{5} \mu_{A_j}(x_k)$$

where $i \in \{1,2,\cdots,m\}$, x_k represents the input variables.

Layer 3: Each node of the layer calculates the ratio of the activation level of the i-th rule to the total of all activation level. The total number of nodes is m and the output of each node is

(6) $$O_{3,i} = \bar{w}_i = w_i \Big/ \sum\nolimits_{s=1}^{m} w_s$$

where $i \in \{1,2,\cdots,m\}$.

Layer 4: There are m nodes in the layer and each node calculates the product of the normalized firing strength and the function of consequent, which is a first order polynomial and is

(7) $$O_{4,i} = \bar{w}_i \cdot f_i(x_k) = \bar{w}_i \cdot \left(\sum\nolimits_{k=1}^{5} a^i_k x_k + b_i\right)$$

where a^i_k and b_i are the consequent parameters.

Layer 5: The layer has a single fixed node and the output is PC, which is given by:

(8) $$\begin{aligned} O_{5,i} &= \sum\nolimits_{i=1}^{m} \bar{w}_i \cdot f_i(x_k) \\ &= \sum\nolimits_{i=1}^{m} \bar{w}_i \cdot \left(\sum\nolimits_{k=1}^{5} a^i_k x_k + b_i\right) \end{aligned}$$

For the proposed model, a hybrid-learning algorithm is adopted in the training process. For the backward path, the error signals propagate backward. The antecedent parameters are updated by descent method through minimizing the error between the network outputs and real values. For the forward path, the least square method identifies the consequent parameters. Therefore, the pulverizing capability could be predicted correctly and the running time assessment of BMPS would be realized. In the next section, the experiments results will show the effectiveness of the proposed model.

Experiments results

In the section, some experiments are performed to evaluate the effectiveness of the proposed model. The experiments focus on comparing ANFIS-PCM with BPNN-PCM and SVM-PCM for predicting the pulverizing capability of BMPS. Two datasets are used in the experiments and they are obtained from the field database of Thermal Power Plant under different work conditions, which are the work condition I and the work condition II. Each field dataset includes 370 samples and some data are listed in Table 1 and Table 2 respectively, where PC are measured based on the field experiments in the steady state.

Table 1. The field data under the work condition I

BML [%]	INP [Pa]	OT [□]	DP [Pa]	VR [Km3/h]	PC [ton/h]
52.67	-775.05	84.9	2726.58	155.7	42.94
52.7	-783.8	84.9	2732.61	155.82	42.98
52.76	-794.97	84.9	2728.17	156.14	43.03
52.61	-805.03	84.8	2703.11	156.55	43.08
52.62	-809.21	84.8	2678.68	156.37	43.14
52.82	-790.75	84.8	2709.22	156.17	43.19
52.45	-779.48	84.8	2717.59	155.83	43.23
52.5	-801.24	84.7	2688.88	155.47	43.28
52.59	-812.36	84.7	2729.23	156.01	43.34
52.92	-803.24	84.6	2744.43	156.72	43.4
52.53	-790.26	84.6	2757.42	156.48	43.47
52.5	-792.82	84.6	2756.46	154.23	43.54

Table 2. The field data under the work condition II

BML [%]	INP [Pa]	OT [℃]	DP [Pa]	VR [Km3/h]	PC [ton/h]
63.82	-678.66	95.9	2904.18	146.24	55.96
63.93	-684.69	95.6	2889.35	146.79	55.97
63.35	-672.18	95.2	2921.01	146.13	55.98
63.69	-675.82	95.5	2899.18	145.63	55.99
66.11	-667.28	94	2935.68	147.7	56.03
63.21	-668.77	95.1	2909.61	144.92	56.12
64.33	-669.24	95.1	2921.43	144.93	56.13
63.76	-670.72	95.1	2908.07	144.93	56.14
63.56	-665.61	94.6	2902.19	147.34	56.15
63.92	-668.91	94.5	2921.03	146.78	56.16
63.77	-675.45	94.5	2881.66	146.98	56.17
64.08	-667.06	94.4	2930.58	147.65	56.18

For the experiments, each dataset are divided into the training set and the validation set based on the Monte Carlo cross-validation at the ratio equaled 4:1. The training set is used for building the prediction model, and the validation set is used for evaluating the effectiveness of the model. For assessing the sampling bias, the division and the modelling process mentioned above would be implemented repeatedly 50 times. The root-mean-squares error of prediction (RMSEP) is used to assess and compare the predictive ability of the various models.

For BPNN-PCM, the classical three-layers structure is adopted. Since the number of the input variables and the output variable are 5 and 1, respectively. The number of nodes of the input layer, the hidden layer and the output layer are 5, 5 and 1, respectively. Moreover, for BPNN-PCM, the number of training epochs is 100, the learning rate is 0.01, the number of hidden neurons is 5 and the training error goal is zero. For SVM-PCM, the radial basis function is used as the kernel function, and the width parameter and the penalty factor are 3 and 10, respectively. For ANFIS-PCM, the training epoch number is 100, the training error goal is zero, the initial step size 0.01, the step size decrease rate is 0.7 and the step size increase rate 1.3. For the subtractive clustering algorithm in ANFIS-PCM, the radii value is 0.3 for the work condition I and is 0.5 for the work condition II. The accept threshold and the reject threshold is 0.5and 0.15, respectively. ANFIS-PCM, BPNN-PCM and SVM-PCM are implemented in MATLAB 7.11.0.

For work condition I and work condition II, the RMSEP values of 50 times experiments are shown in Table 3.

Table 3. Experiments results

No.	Work Condition I			Work Condition II		
	BPNN-PCM	SVM-PCM	ANFIS-PCM	BPNN-PCM	SVM-PCM	ANFIS-PCM
1	0.0339	0.1085	0.0308	0.0254	0.0668	0.0209
2	0.0339	0.1618	0.0183	0.0245	0.0748	0.0199
3	0.0390	0.1593	0.0199	0.0230	0.0787	0.0202
4	0.0544	0.1183	0.0561	0.0209	0.0715	0.0212
5	0.0405	0.1300	0.0652	0.0202	0.0691	0.0170
6	0.0429	0.1349	0.0297	0.0201	0.0727	0.0204
7	0.0528	0.1413	0.0499	0.0642	0.0675	0.0193
8	0.0502	0.1238	0.0356	0.0383	0.0713	0.0223
9	0.0504	0.1381	0.0650	0.0247	0.0716	0.0247
10	0.0588	0.1888	0.0368	0.0238	0.0778	0.0220
11	0.0352	0.1090	0.0263	0.0233	0.0744	0.0208
12	0.0406	0.1239	0.0307	0.0232	0.0762	0.0182
13	0.0260	0.0975	0.0368	0.0220	0.0781	0.0236
14	0.0640	0.1452	0.0367	0.0209	0.0774	0.0273
15	0.0663	0.1452	0.0265	0.0207	0.0778	0.0304
16	0.0442	0.1375	0.0358	0.0300	0.0751	0.0229
17	0.0430	0.1125	0.0751	0.0247	0.0773	0.0226
18	0.0863	0.1789	0.0419	0.0241	0.0704	0.0258
19	0.0424	0.1535	0.0337	0.0230	0.0716	0.0246
20	0.0547	0.1019	0.0201	0.0211	0.0668	0.0186
21	0.0486	0.1293	0.0496	0.0239	0.0669	0.0165
22	0.0505	0.1019	0.0359	0.0229	0.0694	0.0182
23	0.0606	0.1685	0.0604	0.0228	0.0730	0.0208
24	0.0371	0.1532	0.0311	0.0228	0.0760	0.0232
25	0.0390	0.1214	0.0222	0.0207	0.0669	0.0232
26	0.0465	0.1657	0.0312	0.0199	0.0698	0.0162
27	0.0530	0.1218	0.0300	0.0399	0.0707	0.0198
28	0.0735	0.1549	0.0373	0.0216	0.0730	0.0228
29	0.0344	0.1114	0.0271	0.0204	0.0745	0.0197
30	0.0886	0.1898	0.0486	0.0203	0.0830	0.0221
31	0.0620	0.1175	0.0447	0.0199	0.0652	0.0202
32	0.0542	0.1205	0.0390	0.0195	0.0765	0.0196
33	0.0492	0.1753	0.0298	0.0379	0.0811	0.0214
34	0.0392	0.1608	0.0258	0.0267	0.0702	0.0194
35	0.0624	0.1516	0.0236	0.0249	0.0675	0.0216
36	0.0321	0.1174	0.0215	0.0206	0.0669	0.0177
37	0.0523	0.1467	0.0187	0.0201	0.0723	0.0263
38	0.0465	0.1356	0.0272	0.0255	0.0721	0.0222
39	0.0796	0.1132	0.0675	0.0204	0.0654	0.0193
40	0.0465	0.1324	0.0401	0.0197	0.0773	0.0242
41	0.0896	0.1863	0.0230	0.0210	0.0702	0.0203
42	0.0337	0.1239	0.0358	0.0200	0.0634	0.0288
43	0.0430	0.1178	0.0254	0.0197	0.0682	0.0220
44	0.0351	0.1562	0.0499	0.0196	0.0741	0.0210
45	0.0446	0.1114	0.0347	0.0196	0.0773	0.0186
46	0.0505	0.1399	0.0233	0.0200	0.0808	0.0213
47	0.0329	0.1529	0.0318	0.0230	0.0764	0.0181
48	0.0767	0.1435	0.0359	0.0210	0.0841	0.0219
49	0.0215	0.1188	0.0228	0.0204	0.0674	0.0191
50	0.0427	0.1225	0.0257	0.0343	0.0715	0.0163

For work condition I, The average RMSEP values of BPNN-PCM, SVM-PCM and ANFIS-PCM are 0.0497, 0.1374 and 0.0358, respectively, which shows that ANFIS-PCM is most effective. For the average RMSEP value, the resulting rules with their associated parameters of ANFIS-PCM for 24-th experiment are described in the following and eight clusters are obtained, namely, there are eight rules.

Rule 1:
IF BML belongs to cluster1 **AND** INP belongs to cluster1 **AND** OT belongs to cluster1 **AND** DP belongs to cluster1 **AND** VR belongs to cluster1
THEN PC=-0.0128BML+0.00055INP-0.00073OT-0.0269DP +0.0443VR+39.157

Rule 2:
IF BML belongs to cluster2 **AND** INP belongs to cluster2 **AND** OT belongs to cluster2 **AND** DP belongs to cluster2 **AND** VR belongs to cluster2
THEN PC=0.0129BML-0.000538INP+0.00015OT+ 0.0033 DP +0.0018 VR +43.448

Rule 3:
IF BML belongs to cluster3 **AND** INP belongs to cluster3 **AND** OT belongs to cluster3 **AND** DP belongs to cluster3 **AND** VR belongs to cluster3
THEN PC=0.0253BML-0.00076INP-0.00039OT+ 0.04263 DP +0.00481 VR +38.261

Rule 4:
IF BML belongs to cluster4 **AND** INP belongs to cluster4 **AND** OT belongs to cluster4 **AND** DP belongs to cluster4 **AND** VR belongs to cluster4
THEN PC=0.00273BML-0.00035INP-0.00015OT-0.0983DP-0.0156VR+74.9

Rule 5:
IF BML belongs to cluster5 **AND** INP belongs to cluster5 **AND** OT belongs to cluster5 **AND** DP belongs to cluster5 **AND** VR belongs to cluster5
THEN PC=-0.0224BML+0.000553INP+0.00001OT-1.42DP-0.0266VR+168.75

Rule 6:
IF BML belongs to cluster6 **AND** INP belongs to cluster6 **AND** OT belongs to cluster6 **AND** DP belongs to cluster6 **AND** VR belongs to cluster6
THEN PC=0.0042BML-0.00034INP+0.000047OT+ 0.038DP+0.0233VR+37.64

Rule 7:
IF BML belongs to cluster7 **AND** INP belongs to cluster7 **AND** OT belongs to cluster7 **AND** DP belongs to cluster7 **AND** VR belongs to cluster7
THEN PC=-0.0116BML+0.0007INP+0.00096OT+ 0.035DP+0.0257VR+37.014

Rule 8:
IF BML belongs to cluster8 **AND** INP belongs to cluster8 **AND** OT belongs to cluster8 **AND** DP belongs to cluster8 **AND** VR belongs to cluster8
THEN PC=0.0667BML-0.0003INP-0.00014OT-0.278DP-0.0028VR+66.66

For work condition II, the effective of the three model become better, and the average RMSEP values of BPNN-PCM, SVM-PCM and ANFIS-PCM are 0.0241, 0.0728 and 0.0213, respectively, which shows that ANFIS-PCM is still most effective. For the average RMSEP value, the resulting rules with their associated parameters of ANFIS-PCM for 29-th experiment are described in the following and eight clusters are obtained, namely, there are eight rules.

Rule 1:
IF BML belongs to cluster1 **AND** INP belongs to cluster1 **AND** OT belongs to cluster1 **AND** DP belongs to cluster1 **AND** VR belongs to cluster1
THEN PC=-0.032BML+0.00065INP-0.001OT-0.117DP-0.0077VR+67.825

Rule 2:
IF BML belongs to cluster2 **AND** INP belongs to cluster2 **AND** OT belongs to cluster2 **AND** DP belongs to cluster2 **AND** VR belongs to cluster2
THEN PC=0.076BML+0.00036INP+0.0018OT-0.038DP-0.0039VR+55.578

Rule 3:
IF BML belongs to cluster3 **AND** INP belongs to cluster3 **AND** OT belongs to cluster3 **AND** DP belongs to cluster3 **AND** VR belongs to cluster3
THEN PC=0.0503BML+0.0007INP+0.0023OT+ 0.568DP+0.1014VR-14.254

Rule 4:
IF BML belongs to cluster4 **AND** INP belongs to cluster4 **AND** OT belongs to cluster4 **AND** DP belongs to cluster4 **AND** VR belongs to cluster4
THEN PC=-0.009BML+0.0001INP+0.0012OT+ 0.2246DP+0.018VR+33.945

Rule 5:
IF BML belongs to cluster5 **AND** INP belongs to cluster5 **AND** OT belongs to cluster5 **AND** DP belongs to cluster5 **AND** VR belongs to cluster5
THEN PC=-0.929BML+0.021INP-0.026OT+ 1.32DP-0.58VR-4.79

Rule 6:
IF BML belongs to cluster6 **AND** INP belongs to cluster6 **AND** OT belongs to cluster6 **AND** DP belongs to cluster6 **AND** VR belongs to cluster6
THEN PC=-0.017BML+0.00049INP-0.004OT-0.117DP+0.066VR+54.15

Rule 7:
IF BML belongs to cluster7 **AND** INP belongs to cluster7 **AND** OT belongs to cluster7 **AND** DP belongs to cluster7 **AND** VR belongs to cluster7
THEN PC=-1.11BML+0.019INP-0.05OT+ 0.83DP-0.18VR-12.24

Rule 8:
IF BML belongs to cluster8 **AND** INP belongs to cluster8 **AND** OT belongs to cluster8 **AND** DP belongs to cluster8 **AND** VR belongs to cluster8
THEN PC=0.061BML+0.0017INP-0.01OT-0.009DP+0.236VR+6.207

The experiments results show that the proposed model has higher effectiveness. Moreover, the proposed method has been put into practice in field. When BMPS works stably, it accords with the rule of indestructibility of matter, namely, the coal feed per unit of time equals the quantity of pulverized coal powder per unit of time. Therefore, for estimating the performance of the proposed model, BMPS should work in the steady state. We keep the coal feed per unit of time, the opening degree of hot air damper, the opening degree of recycle air damper, the opening degree of cold air damper and the opening degree of inlet baffle of mill exhauster being not changed for thirty minutes. The running curves of thirty minutes for the ball mill load, the inlet negative pressure, the outlet temperature, the different inlet-outlet pressure and the ventilation rate are shown in Fig. 3.

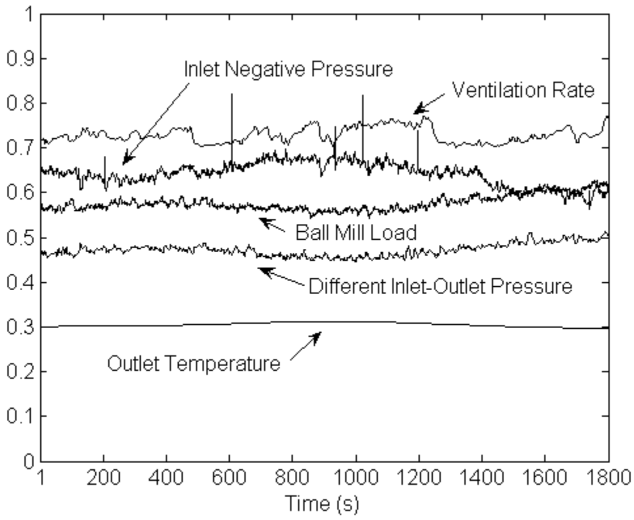

Fig.3. Running curves of process variables in field

To facilitate analysis, the measured values of all variables are normalized to [0, 1]. Because the five process variables are relatively stable, BMPS could be seemed to be in the steady state during 0~1800sec.. The running curve of the prediction value of pulverizing capability is shown in Fig. 4. The average value of coal feed per unit of time is 43.4 ton/h. It could be seen that the pulverizing capability could be predicted correctly and continually. Although there is error between the predicted value and the coal feed per unit of time, the proposed model could satisfy the filed requirement. Furthermore, since the size of the coal powder bunker could be supplied by the manufacturer, the operators could determine the running time of BMPS based on the predicted value, and the equipment maintenance program could be arranged in advance. The energy consumption would be reduced and the efficiency of enterprise would be improved.

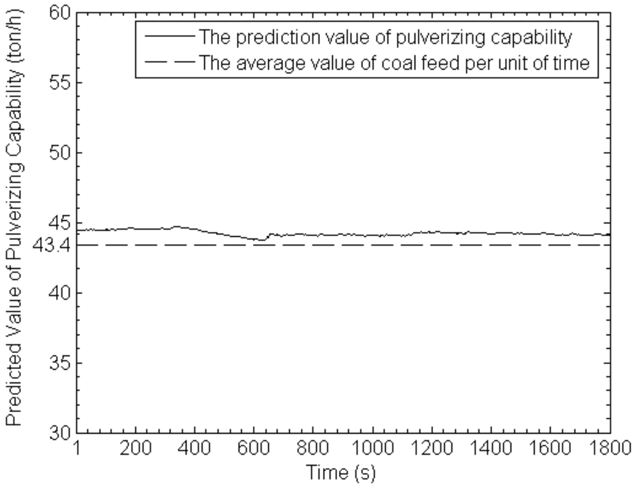

Fig.4. Running curves of pulverizing capability in field

Conclusions

The paper presents an adaptive neuro-fuzzy inference system-based pulverizing capability model for running time assessment of ball mill pulverizing system. The proposed model has some advantages as follows. First, it integrates the advantages of the artificial neural network and the fuzzy rule to predict the pulverizing capability correctly. Second, it uses the learning ability of the neural network to implement and refine Takagi-Sugeno type fuzzy rules to describe the behaviour of the pulverizing capability. Third, by the hybrid learning procedure, the best parameters of the membership functions of the fuzzy rules are obtained. The experiments results also verify the effectiveness of the proposed model. Moreover, the proposed model has been put into practice successfully. Since the performance of the proposed model may be affected by the training process, in the future research work, we will use some advanced implementation schemes to further improve the effectiveness of the proposed model.

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