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Research Article

Intelligent Control of the Complex Technology Process Based on Adaptive Pattern Clustering and Feature Map

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A kind of fuzzy neural networks (FNNs) based on adaptive pattern clustering and feature map (APCFM) is proposed to improve the property of the large delay and time varying of the sintering process. By using the density clustering and learning vector quantization (LVQ), the sintering process is divided automatically into subclasses which have similar clustering center and labeled fitting number. Then these labeled subclass samples are taken into fuzzy neural network (FNN) to be trained; this network is used to solve the prediction problem of the burning through point (BTP). Using the 707 groups of actual training process data and the FNN to train APCFM algorithm, experiments prove that the system has stronger robustness and wide generality in clustering analysis and feature extraction.

1. Introduction

Sintering is the most widely used agglomeration process for iron ores and is a very important chain of iron making. In general, the process of sintering includes three major phases. First, it involves blending all the ores thoroughly according to certain proportions and adding water to the ore mix to produce particles. Second, the actual sintering operation is initiated by the ignition of the cokes as the raw mix passes under gas ignition. Finally, after traveling the length of the strand, the finished sinter is broken up, cooled, and screened [1, 2]. In the recent twenty years, many methods of integrity and fusion have been explored by the metallurgy and automation experts.

1.1. Mathematical model

According to the chemical/physical characteristics for sintering, a model was formulated as a series of differential equations to describe the relation between the thick martial, the ignition temperature, and the bellows temperature at the tail of the machine. For the time varying and randomness of the sintering process, many mechanisms have still not been understood. Although the dynamic model is tenable at a certain boundary condition, it is difficult to cover the whole process.

1.2. Neural network-based model

For the fast approach of neural network, a model can be established rapidly from the given input and output data, and it can also solve the problem of this long-time delay system. In general, genetic algorithm is used to optimize the parameters of the network and improve the generalization of the system, but it has still not been reported to be used in real-time control.

1.3. Rule-based model

The rule base, acknowledge, database, and inference machine can be constructed by the technology and operation experts' experience [3]. Rule base and inference machine are mainly used in estimating the process, analyzing cause, and deciding guideline. Acknowledge includes operation data, fact, mathematical model, and elicitation and unit knowledge. Database stores real-time data from production and equipment. Unfortunately, most results of this model are still simulation results.

2. Fuzzy neural network

In general, the dynamic behavior of a fuzzy logical controller is characterized by a set of linguistic control rules based on the knowledge of an expert [4].

Consider the fuzzy controller with Gaussian MFs and multiplication implication; the topology structure of fuzzy neural network is shown in Figure 1.

The fuzzy rule is as follows:

$$R^{(l)} : \text{if} \quad x_i = F_i^l,\ x_n = F_n^l, \tag{2.1}$$

then

$$y = G_i^l. \tag{2.2}$$

The input and output relationship is shown as

$$f(x) = \frac{\sum_{l=1}^{M} \overline{y}^l \left(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\right)}{\sum_{l=1}^{M} \left(\prod_{i=1}^{n} \mu_{F_i^l}(x_i)\right)}, \tag{2.3}$$

where $x = (x_1, x_2, \ldots, x_n)^T$ is the system input, M the is rule number, n is the input number, $\mu_{F_i^l}(x_i)$ is the membership function in the input $x_i = F_i^l$, and $\overline{y}^l$ is the value when the membership function equals the maximum in l rule. The fuzzy neural network [4] has five-layer structure.

The first layer is input variable layer. In this layer, the ith inputs are represented as x_i; the system can have n inputs.

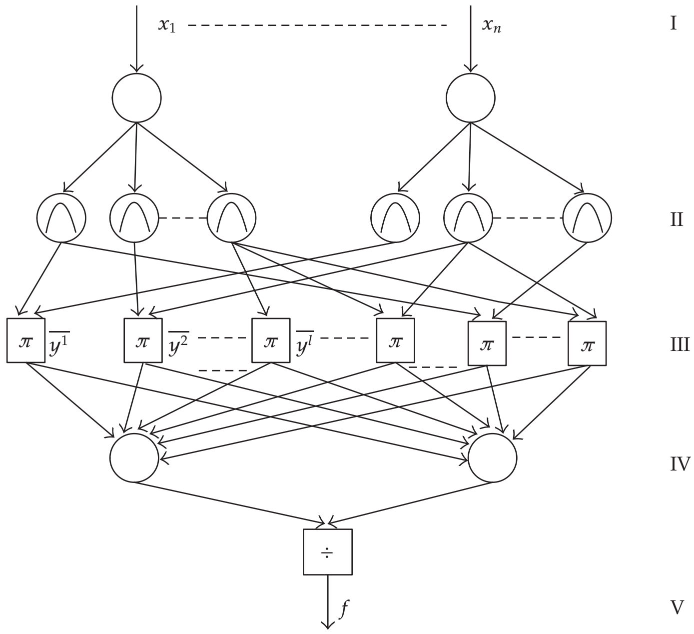

Figure 1: The topology structure of fuzzy neural network.

The second layer is membership layer. In this layer, each node performs the Gaussian function; the function is adopted as a membership function. The membership function of the input is defined as

$$\mu_{F_i^l}(x_i) = \exp\left[-\left(\frac{x_i - \overline{x}_i^l}{\sigma_i^l}\right)^2\right], \tag{2.4}$$

where $\overline{x}_i^l$ is the Gauss meaning of the rule input x_i, and σ_i^l is the square error.

The third layer is rule layer. The layer is used to implement the antecedent matching. The matching operation or the fuzzy and aggregation operation is chosen as the simple product operation. In this layer, summing is finished by neuron.

In addition to $\overline{y}^l$ between the third and the fouth layers, other layer weights equal 1.

The fifth layer is output of the fuzzy neural network.

Thus, the entire fuzzy neural network [5] needs to adjust $\overline{x}_i^l$, σ_i^l, $\overline{y}^l$ parameters to control the process. These parameters have specified signification; therefore, they are initialed by language information in order to improve learning convergence speed.

3. Adaptive pattern clustering and feature map network

3.1. Initial data space clustering

According to technology character and equipment requirement, density sintering speed and burning temperature are selected as input vectors; the temperature and pressure of 18 windboxes and the waste gas temperature are chosen as output vectors. The input space scatter diagram is obtained by using the input sample to do three-vector space map, and the

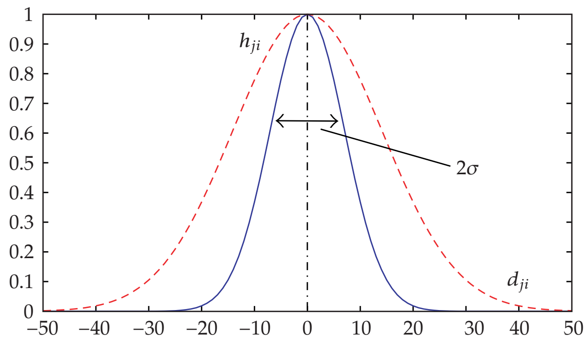

Figure 2: The trend of topology neighborhood coast line.

clustering center C_{ij} $(i = 1, 2, 3;\ j = 1, 2, \ldots, k_i)$ and subspace $[a_j, b_j]$ of every vector are found by utilizing feature extract based on density clustering. These rectangle areas are intersected with each other to form $k = k_1 \times k_2 \times k_3$ subregions.

3.2. Feature map

Feature map network developed by Kohonen is an unsupervised competitive learning cluster network in which only one neuron is on at any time. The map is an artificial system that emulates the brain in the visual system, and which includes three major phases [5–7].

Competitive phase: the inputs of the network can be written as vector by $X = [x_1, x_2, \ldots, x_m]^T$, and the synaptic weight vector of neuron j in the two-dimensional (2D) array is given by $w_j = [w_{j1}, w_{j2}, \ldots, w_{jm}]^T$, $j = 1, 2, \ldots, l$, where m is the local number of output neurons in the 2D array and l is the total number of the neurons of network. In order to find the best match of input vector x with the synaptic weight w_j, the multiplication $w_j^T x$ determined the center location of the exciting neuron's topology neighborhood and the maximum of $w_j^T x$ is equal to the Euclid norm in mathematics.

Cooperative phase: the winner neuron is located in the center of the cooperation neuron's topology neighborhood. We supposed that h_{ji} is the topology neighborhood whose center is the victory neuron i, and d_{ij} is the inclination distance between victory neuron i and excited neuron j. A classical selection of h_{ji} to satisfy these conditions is

$$h_{ji} = \exp\left(-\frac{d_{ji}^2}{2\sigma^2}\right), \tag{3.1}$$

where σ is the effective width of topology neighborhood. The trend of topology neighborhood is shown in Figure 2.

Self-adjusting phase: it includes self-ordering and converging stages; self-ordering formula is

$$\begin{gathered} w_j(n+1) = w_j(n) + \eta(t) h_{j,i(x)}(n)\left(x(n) - w_j(n)\right), \\ \eta(n) = \eta_0 \exp\left(-\frac{n}{\tau}\right). \end{gathered} \tag{3.2}$$

The equation is in converging stage; learning rate $\eta(n)$ is made smaller gradually.

3.3. Learning vector quantification

The learning vector quantification (LVQ) algorithm is used to adjust fine weight vector to improve quality in decision area by utilizing supervisor learning skill. The foundation method is first to find the average value of the attribute of every subclass on the basis of clustering, second to make a comparison between the average value of the subclass and the whole vector, and last to label the up-arrowhead tag with the larger values and the down-arrowhead with the smaller values. The set of every labeled subclasses may be expressed as the direction of its weight shifting. For this purpose, let the Lx_i stand for the tag of the input vector x_i, and let Lw_j stand for the tag of the weight w_j; the recursive function is defined as follows.

If $Lw_j = Lx_i$, then

$$w_j(n+1) = w_j(n) + \alpha_n(x_i - w_j(n)). \tag{3.3}$$

If $Lw_j \neq Lx_i$, then

$$w_j(n+1) = w_j(n) - \alpha_n(x_i - w_j(n)), \tag{3.4}$$

where $0 < \alpha_n < 1$.

Passing through a period of time iteratively, the subclasses with the same property may be converged together, and the other subclasses with different properties may be departed from each other.

In this paper, we use the actual data as the samples from sintering process. The input vectors are density, velocity, and ignition temperature, and the output vectors are the temperature and pressure of 18 windboxes and the temperature of waste gas.

4. Experiment

4.1. Analysis of the input in three-dimensional space

The distributing diagram of the two-year input samples in three-dimensional space is shown in Figure 3. We can obtain 12 subspaces by using the initialization clustering of the samples, which is based on the density of the samples, and maps the feature of 12 subspaces to form the topology structure, which is shown in Figure 4, and the center of every subspace is dotted in Figure 3.

4.2. Analysis of the input samples' classification

Computing the average value of every property for each subclass, respectively, such as density (D), velocity (V), and ignition temperature (T), and comparing the average value of the subclass property with the property of the whole samples, if the result of a subclass is bigger than the average value of the whole samples, we use up-arrowhead marking; otherwise we use down-arrowhead marking. The marking classification is listed in Table 1.

In this table, we can find 5 different large classes. Row 1 is a class, rows 2, 3, 5 are a class, rows 4, 7, 8, 10 are a class, rows 6, 9, 12 are a class, and row 11 is a class. Figure 5 shows the relations between the topology structure and the class table.

According to the characters of process and performance of equipments, we can get the property of each class in Figure 4.

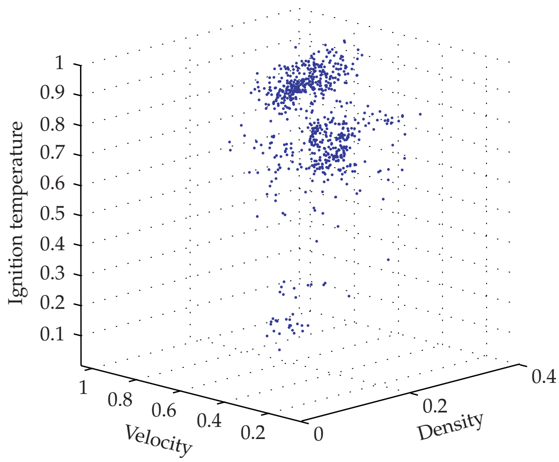

Figure 3: The distributing diagram of samples.

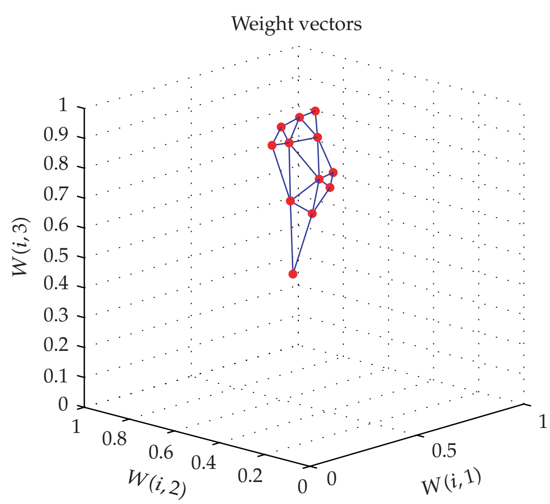

Figure 4: The topology structure of clustering.

Class 1 ($D\downarrow V\uparrow T\uparrow$). The samples of class denote the thick stuffing of sinter bed, high ignition temperature, and fast velocity, and it may cause raw ore.

Class 2 ($D\downarrow V\uparrow T\downarrow$). It denotes the thick stuffing of sinter bed, low ignition temperature, and fast velocity, and it causes easily raw ore, and the burning through point will be back to the strand tail.

Class 3 ($D\uparrow V\uparrow T\uparrow$). The class denotes loose stuffing on the sinter bed, high ignition temperature, and fast velocity, and it causes easily sintering for sintering process.

Class 4 ($D\downarrow V\downarrow T\downarrow$). The phenomenon shows the thick stuffing on the sinter bed, low ignition temperature, and slow velocity, and it is in accordance with the thick and slow sintering.

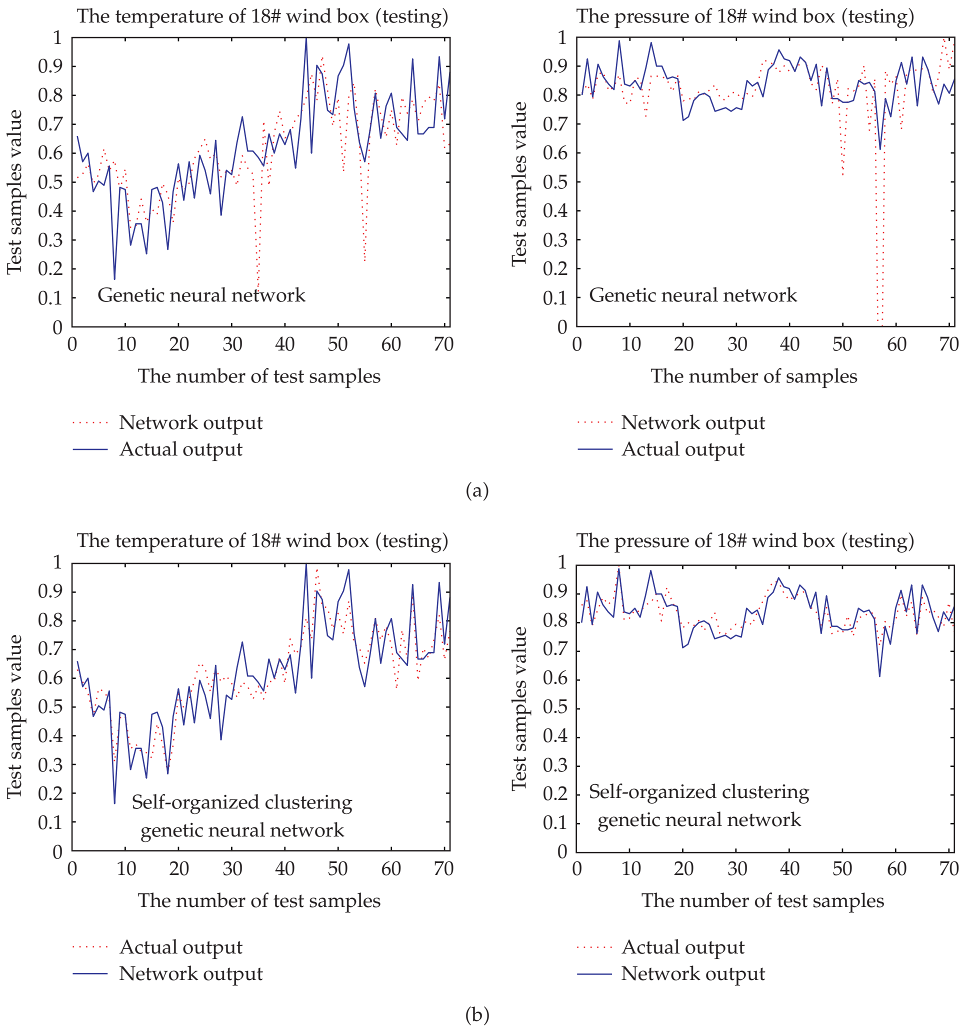

Figure 5: (a) The results of fuzzy neural network training (FNN). (b) The results of adaptive pattern clustering and feature map (APCFM).

Class 5 ($D \downarrow V \downarrow T \uparrow$). This state denotes the thick stuffing of sinter bed, high ignition temperature, and slow velocity, and we should direct our attention to the sinter bed earlier in order to avoid the oversintering.

4.3. Learning vector quantization

According to the analysis above, 12 subclasses have been readjusted into 5 classes. Now, retraining the whole input samples by using the LVQ network, the network is a characteristic studying of having teacher. The training network with the LVQ can improve the hitting accuracy of feature map that is proved by [6]. The network output can get the tag of the class when it enters the sample through the network. We show the step as follows. List the

Table 1: The setting of subclass property.

Subclass	Num	D	V	T	Compare results
1	65	0.6643	0.7986	0.8039	$D\downarrow V\uparrow T\uparrow$
2	29	0.6659	0.7893	0.6781	$D\downarrow V\uparrow T\downarrow$
3	40	0.6462	0.7208	0.3900	$D\downarrow V\uparrow T\downarrow$
4	92	0.7039	0.7779	0.8215	$D\uparrow V\uparrow T\uparrow$
5	17	0.6471	0.6775	0.6662	$D\downarrow V\uparrow T\downarrow$
6	32	0.6149	0.5921	0.5671	$D\downarrow V\downarrow T\downarrow$
7	95	0.7549	0.7505	0.8696	$D\uparrow V\uparrow T\uparrow$
8	27	0.6987	0.6771	0.8178	$D\uparrow V\uparrow T\uparrow$
9	96	0.6067	0.5184	0.7202	$D\downarrow V\downarrow T\downarrow$
10	75	0.7558	0.6892	0.8749	$D\uparrow V\uparrow T\uparrow$
11	34	0.6468	0.5361	0.7817	$D\downarrow V\downarrow T\uparrow$
12	105	0.5993	0.4557	0.7410	$D\downarrow V\downarrow T\downarrow$

input vectors P, the output vectors T, and the class of classificatory tag C:

$$\begin{aligned}
\mathrm{P} &= [0.75607, 0.81711, 0.78968, 0.6468, \ldots, 0.75626;\\
&\quad 0.67327, 0.66337, 0.64356, 0.5361, \ldots, 0.68317;\\
&\quad 0.96873, 0.92471, 0.95533, 0.7817, \ldots, 0.95406;],\\
\mathrm{T} &= \begin{bmatrix} 1 & 2 & 4 & 5 \cdots 3 \end{bmatrix},\\
\mathrm{C} &= \begin{bmatrix} 1 & 0 & 0 & 0 & \cdots & 0\\ 0 & 1 & 0 & 0 & \cdots & 0\\ 0 & 0 & 0 & 0 & \cdots & 1\\ 0 & 0 & 1 & 0 & \cdots & 0\\ 0 & 0 & 0 & 1 & \cdots & 0 \end{bmatrix}.
\end{aligned} \tag{4.1}$$

4.4. Training every subclass sample by using fuzzy neural network

The testing results are shown in Figures 5(a) and 5(b); Figure 5(a) is only genetic neural network testing results, and Figure 5(b) is the testing results by using the adaptive pattern clustering and feature map FNN. We compare the two figures and find out that FNN can obtain the trend of network output, but the precision is low. The adaptive pattern clustering and feature mapFNN can improve a high precision for network output and have a good generalization for the samples which belong to the same class.

5. Conclusion

In this paper, in order to predict the BTP, an APCFM reference and FNN system have been proposed to solve the challenging problem of the sinter production process, which is a typical nonlinear, time-varying, and multimode process, and is very difficult to solve using traditional methods. In our approach, a density clustering is used to determine the number of the initial input vectors consciously, and a feature map algorithm is used to extract data relevance property from different subclasses and improve the confidence of the vector. By using the teacher's instruction, LQV network can herd effectively feature categories together on this basis FNN algorithm. The constructed system has been trained with input sample consisting of 707 technology groups and measuring apparatus of two-year actual process and has obtained very good performance; especially, comparing APCFM+FNN with FNN [8, 9], the precision of training and testing has raised one time and three times, respectively, and the running time decreases more than one time, and it is satisfied with the demand of real time running and improving the robustness of the system.

Acknowledgment

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