



Application research on rough set -neural network in the fault diagnosis system of ball mill

Xijuan Wang^{1*}, Tao Zhou¹, Jingxiao Feng² and Yupeng Pei²

¹School of Physical and Electrical Information, Luoyang Normal University, Luoyang-China

²Luoyang Mining Machinery Research Institute, Luoyang-China

ABSTRACT

The fault parameters of ball mill was unnoticed among large amount of data, According to the phenomenon, it put forward a fault diagnosis method of rough set to optimize neural network, and by using width algorithm, so that the fault sample set of ball mill had been processed with the discrete way. Firstly, it builded a diagnosis model of rough set-neural network, the diagnosis model had practicability and superiority compared with single network model.

Keywords: Rough Set, Fault Diagnosis, Ball Mill, Neural Network

INTRODUCTION

For a long time, due to the restrictions of diagnostic equipment and technology, the technician can't predict accurately and quickly the occurrence of ball mill fault, so it directly leads to shutdown, a major economic loss, and causes casualties if it broke down in the process of equipment operation; In theory, some fault can be avoided through regular repair and maintenance of the equipment, but because of blindness is very big, it easily lead to "Over Maintenance" or "owe maintenance", and it was a waste of resources and unnecessary economic losses. It need many monitoring parameters in the process of ball mill work. In addition, the correlation between the different parameters made the modeling more difficult. Due to the sudden, randomness, disorder of fault, maintenance and repair is very difficult. Therefore, how to effectively use the recorded history data to diagnose the cause of the fault in line with the known data, it was a problem to be solved that predict the future running status of ball mill.

EXPERIMENTAL SECTION

Design of the rough set -neural network diagnosis model

The operation parameters variation showed whether there were faults of the ball mill or not but the change of these parameters may not be perceived among a large amount of data, so the paper used the fault diagnosis method of rough set theory combination of BP neural network, in other words, rough set had been as the front system, using the rough set optimized neural network. Firstly, it selected the fault sample set of ball mill, and set up information system tables. Secondly, it had data preprocessing, and had reduced the information system by using rough set, eliminated the redundant attributes and repeat information, acquired the simplest decision table by the composition of minimum condition attribute sets and nuclear properties, and as the basis of neural network training sample, the training input and output sample of neural network had been determined from the simplest decision table. Finally, according to training samples, the node number of neural network input layer, hidden layer and output layer had been determined, based on these samples, it trained and tested the neural network. The flow chart of ball mill fault diagnosis as shown in Fig.1.

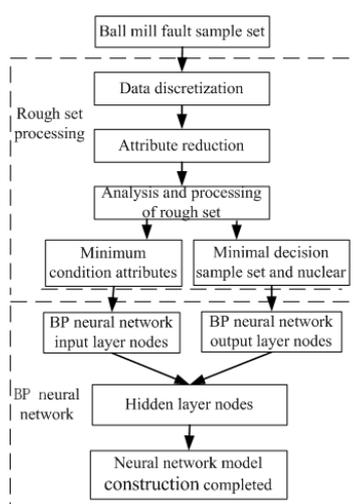


Fig. 1. The flow chart of ball mill fault diagnosis

Fault diagnosis process of ball mill

Ball Mill Fault Sample Set

The ball mill had very huge job data, so in some selection fault attribute were regarded as the condition attribute of rough set, it need to apply the observation data of field sensors, instrumentation, etc, now it selected part of the fault data as fault sample sets, and had application research of the algorithm. Specific as follows:

Selection of ball mill fault: high pressure pipeline of feed end leakage, high pressure pipeline of discharge end leakage, low voltage tube leakage, pinion-gear lubrication piping leakage, high pressure pump failure, low pressure pump failure, pinion-gear pump failure, lubricating oil dirty, cooling system failure, as the decision attribute of rough set, these were denoted by (1, 2, 3, 4, 5, 6, 7,8,9), respectively.

Selection of real-time parameters when the fault happened: main bearing temperature of feed end, main bearing temperature of discharge end, pinion-gear bearing temperature, high oil pressure of feed end, high oil pressure of discharge end, low oil pressure, pinion-gear oil flow, hyperbaric pressure differential transmitter, low voltage pressure differential transmitter, pinion-gear pressure differential transmitter, as the condition attribute of rough set, these were denoted by(a, b, c, d, e, f, g, h, i, j), respectively. And it created the attributes decision table of ball mill parts fault sample sets, as shown in Tab. 1.

Table 1. The ball mill parts fault samples information table

Fault samples	Condition attributes										Decision attribute
	a	b	c	d	e	f	g	h	i	j	
U1	63	35	32	1.2	3.5	0.3	100	0	0	0	1
U2	36	61	32	3.9	1.0	0.3	100	0	0	0	2
U3	36	35	32	3.9	3.5	0.06	100	0	0	0	3
U4	36	35	63	3.9	3.5	0.3	50	0	0	0	4
U5	65	65	32	0.8	0.9	0.3	100	0	0	0	5
U6	40	41	38	3.9	3.5	0.07	100	0	0	0	6
U7	36	35	65	3.9	3.5	0.3	30	0	0	0	7
U8	65	66	67	1.6	1.3	0.15	60	1	1	1	8
U9	64	65	66	3.9	3.5	0.2	100	0	0	0	9

Preprocessing of data

(1) Discretization of data

The saved data of mill failure data acquisition system were continuous analogue, so the data need discretization before adopting the algorithm of rough set. The discretization can reduce the number of given continuous attribute values, the expression of discrete attributes were closer than the continuous attributes in knowledge. Discrete attribute were easier to understand, use and interpretation to users and experts. The paper used the method of data discretization were width algorithm: there used interval number were 6, the range of numerical attributes $[X_{\min}, X_{\max}]$ had been divided 6 interval, and each interval had the same width, which were equal to $(X_{\max} - X_{\min}) / 6$. Through analysis of fault sample data of mill, there had discretization to fault sample information table with same width, after arrangement, as shown in Tab.2.

Table 2. The ball mill parts fault samples information table after discretization

Fault samples	Condition attributes										Decision attribute
	a	b	c	d	e	f	g	h	i	j	
U1	5	0	0	0	5	5	5	0	0	0	1
U2	0	4	0	5	1	5	5	0	0	0	2
U3	0	0	0	5	5	0	5	0	0	0	3
U4	0	0	5	5	5	5	1	0	0	0	4
U5	5	5	0	0	0	5	5	0	0	0	5
U6	0	1	1	5	5	0	5	0	0	0	6
U7	0	0	5	5	5	5	0	0	0	0	7
U8	5	5	5	1	0	1	2	1	1	1	8
U9	5	5	5	5	5	3	5	0	0	0	9

(2) Attribute reduction of rough set

Not all knowledge in the knowledge base were indispensable, at the same time, some knowledge was useless for knowledge decision, even it was redundant, it had counterproductive to the fault diagnosis of knowledge reasoning. There used reduction algorithm based on identifiability matrix.

If $S=(U,R)$ was a information decision system, where U was domain, and $U=\{x_1, x_2, \dots, x_n\}$; R was attributes combination, and $R=A \cup D$, $A=\{a_1, a_2, \dots, a_n\}$ was condition attributes; D was decision attribute. $a_i(x_j)$ was the values of attribute a_i in the sample x_j . The definition of c_{ij} was the element of line i column j in the identifiability matrix. C defined as follows:

$$c_{ij} = \begin{cases} \{a \in A : a(x_i) \neq a(x_j)\} & D(x_i) \neq D(x_j) \\ 0 & D(x_i) = D(x_j) \\ -1 & a(x_i) \neq a(x_j) \text{ and } D(x_i) \neq D(x_j) \end{cases}$$

where $i, j \in [1, n]$

In order to introduce conveniently the reduction method, if T was the original decision table, M was the identifiability matrix of T , A was the set of all condition attributes in the T , S was the set of all condition attributes B . The item of the condition attribute combinations was 1 in the matrix shown: In addition to the attributes, other attributes without the distinguishing ability between the two records, that is to say, the attribute was nuclear attribute.

The construction of rough set and neural network diagnosis model

The model used 3 layers BP neural network structure (that is: input layer, hidden layer and output layer), the goal was diagnosis for the ball mill failure. It builded BP neural network model with the fault samples of before and after rough set attribute reduction. Neural network training function was trained, its learning rate was variable in the process of training; learning function was the function based on gradient descent method: learned; the transfer function was log-sigmoid; the performance function was mean-variance function mse; the training number was 2000; the training error was 0.001; the learning rate was 0.08; the input layer were 15; the output layer were 3; the hidden layer had been selected 31 through the training. The training results of BP neural network before attribute reduction was shown in Fig.2. The fault samples (such as {b, d, f, g, i}) after rough set attribute reduction built BP neural network model, the training results had been shown in Fig.3.

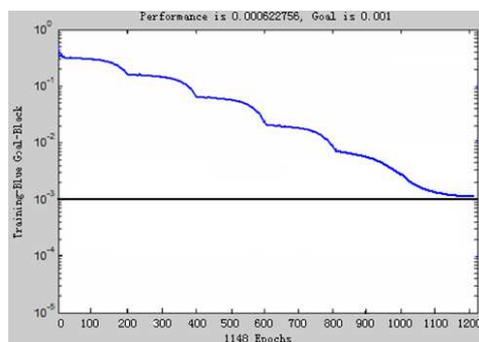


Fig.2. The BP neural network before the attribute reduction

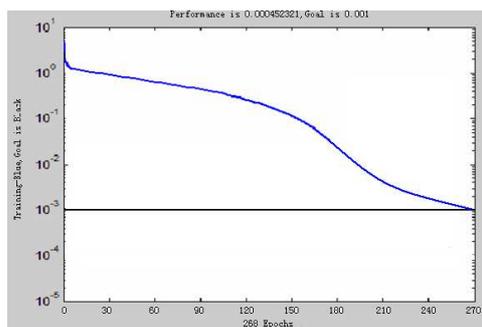


Fig.3. The BP neural network after the attribute reduction

As the training results of two pictures indicated, the results of classification were basic consistent, but according to the rough set algorithm reduction, the neural network of failure sample set training had change training parameters, that was: the training time decreased from 9.062s before the attribute reduction to 3.542s after the attribute reduction, the training number decreased from 1148 before the attribute reduction to 268 after the attribute reduction, the mean-square error reduced from 0.000622756 before the attribute reduction to 0.000452321 after the attribute reduction, on the whole, according to the rough set algorithm reduction, the neural network of failure sample set training had shorter training time, less training steps and higher training accuracy.

RESULTS AND DISCUSSION

The network training interface and fault diagnosis results of ball mill

The weight and thresholds of the input layer, hidden layer and output layer with BP neural network before and after attribute reduction had been saved, it had the BP neural network knowledge base of fault diagnosis. Fig4 was the network training interface and fault diagnosis tables of ball mill, the failure data were input to the diagnostic table, set the fault threshold was 0.7, if the fault threshold greater than 0.7, the fault had been considered. From Fig4, it had fault that BP neural network fault diagnosis results before and after attribute reduction, and the fault were both pinion-gear lubrication piping leakage, but the fault diagnosis result of rough set combined with BP neural network were more accurate than the fault diagnosis result of single BP neural network.

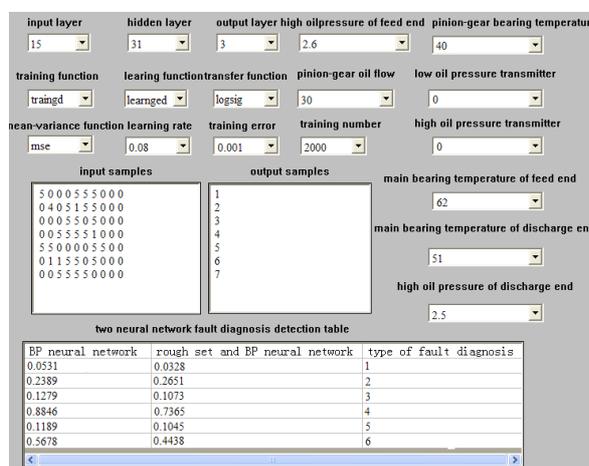


Fig.4. The network training interface and fault diagnosis table of ball mill

CONCLUSION

Through the above analysis, by comparing the fault diagnosis result of rough set combined with BP neural network with the fault diagnosis result of single BP neural network, it had reduction to information system using rough set, eliminated the redundant attributes and repeat information, and obtained the simplest decision table about consisting of minimum condition attribute set and nucleus attribute, as the basis for the neural network training samples, the neural network had shorter training time, less training steps and higher training accuracy, the fault diagnosis result were more accurate.

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