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A Novel Hybrid Intelligent Method for Fault Diagnosis of the Complex System

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Abstract

In allusion to the low correctness and efficiency of fault diagnosis for the complex industrial system, rough set theory, particle swarm optimization and back propagation (BP) neural network are introduced to propose a hybrid intelligent fault diagnosis(RPBPNN) method in this paper. In the proposed RPBPNN method, rough set theory as a new mathematical tool is used to process inexact and uncertain knowledge in order to obtain the minimum fault characteristic set for simplifying the structure and improving learning efficiency of BPNN. The particle swarm optimization (PSO) algorithm with the global optimization ability is directly used to train the weights of BP neural network in order to establish the optimized BP neural network model. Then the minimum fault characteristic set is used to train the optimized BP neural network model in order to obtain the optimal BP neural network model for realizing the fault diagnosis. Finally, the proposed RPBPNN method is applied to an actual application case for verifying the effectiveness. The experimental results show that PSO algorithm can search for the optimal values of BPNN parameters and the proposed RPBPNN method can accurately eliminate false and improve the diagnostic accuracy. So the proposed RPBPNN method takes on better generalization performance and prediction accuracy in the real industrial application system.

***Keywords**: fault diagnosis, particle swarm optimization algorithm, rough set, BP neural network, rule extraction, complex industrial system*

1. Introduction

The complex development trend of modern industrial equipment leads to increase the failure probability and repairing difficulty. The stopping equipment will cause great economic loss to the enterprise. So it is great significance to study the fault diagnosis technology. Fault diagnosis technology is a kind of recognition technology by using the current state information and historical data of equipment and evaluating the state of the equipment with some analysis methods (such as signal processing and analysis method) [1]. The traditional fault diagnosis technology is poor in analyzing the deep fault of complex structure, and requires higher ability of the operator. In order to get rid of the fault diagnosis with relying on the professional technology and the expert and the embarrassing situation between a large quantity of machinery fault diagnosis and quite rare diagnosis experts, the efficient and reliable intelligent fault diagnosis methods are achieved. In recent years, with the development of artificial intelligence technology, the fault diagnosis technology is developed from the traditional fault diagnosis technology to intelligent fault diagnosis [2].

Intelligent fault diagnosis technology is an new fault diagnosis method based on knowledge processing technology on knowledge level. It implements the integration of the dialectical logic and mathematical logic, the unification of the symbolic processing and numerical processing, and the reasoning process and the algorithm. It realizes intelligent diagnosis method of the equipment fault diagnosis by the concept and process

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approach of knowledge [3]. The intelligent fault diagnosis method provides a powerful tool for solving the complex system fault problem. In recent years, there proposed a lot of intelligent optimization methods in the field of fault diagnosis. such as artificial neural network, genetic algorithm, rough set theory, particle swarm optimization, ant colony optimization algorithm, and other new algorithms. Le, *et al.*, [4] used multilayer perceptron (MLP) type neural networks to detect leakages in an electrohy draulic cylinder drive. The performance of MLPs is examined relating to the level of leakage flowrate and it was found that MLPs perform well for line leakages but for across-cylinder seal leakages they could only detect leakage over 1.01/min. Saravanan, *et al.*, [5] deals with the effectiveness of wavelet-based features for fault diagnosis of a gear box using artificial neural network (ANN) and proximal support vector machines (PSVM). Su [6] proposed a novel learning (AFSA-RBF neural networks) algorithm based on RBF with artificial fish-swarm algorithm (AFSA). Jaouher, *et al.*, [7] proposed a automatic bearing fault diagnosis method based on empirical mode decomposition and artificial neural network. The chosen features based on empirical mode decomposition (EMD) energy entropy are used to train an artificial neural network (ANN) to classify bearings defects. Lo, *et al.*, [8] proposed a fault diagnosis method based on genetic algorithms (GA's) and qualitative bond graphs (QBG's) for an in-house designed and built floating disc experimental setup. Huang, *et al.*, [9] proposed an integrated intelligent system that builds a fault diagnosis inference model based on the advantage of rough set theory and genetic algorithms (GAs). This integrated system successfully integrated the rough set theory for handling uncertainty with a robust search engine, GA. Fei and Zhang [10] proposed support vector machine with genetic algorithm (SVMG) to apply to fault diagnosis of a power transformer, in which genetic algorithm (GA) is used to select appropriate free parameters of SVM. Sun, *et al.*, [11] proposed an improving accuracy of fault diagnosis method based on rough sets, genetic algorithm (GA) and Tabu search (TS) in Smart Grid. Lu, *et al.*, [12] developed a novel dominant feature selection method using a genetic algorithm with a dynamic searching strategy. It is applied in the search for the most representative features in rotary mechanical fault diagnosis, and is shown to improve the classification performance with fewer features. Xiao and Feng [13] proposed a KLDA method based on maximal class separability for extracting the optimal features of analog fault data sets, where the proposed KLDA method is compared with principal component analysis (PCA), linear discriminant analysis (LDA) and KPCA methods. Kundu, *et al.*, [14] proposed a framework to analyze multiple faults based on multiple fault simulation in a particle swarm optimization environment. Experimentation shows that up to ten faults can be diagnosed in a reasonable time. Zhang, *et al.*, [15] proposed a fault diagnosis method based on SVM with parameter optimization by ant colony algorithm to attain a desirable fault diagnosis result, which is performed on the locomotive roller bearings to validate its feasibility and efficiency. Geng and Zhu [16] proposed a hybrid mechanism based on rough set integrating artificial neural network (Rough-ANN) for feature selection in pattern recognition. Meng, *et al.*, [17] proposed a hybrid fault diagnosis approach based on morphological filter-translation invariant wavelet and improved ensemble empirical mode decomposition.

2. Basic Methods

2.1. Rough Set Theory

Rough set theory was introduced by Pawlak 1982 [18] as a new mathematical framework for dealing with information with the uncertainty, incompletion and vagueness in decision process. It is a branch of computer science, called soft computing, and has been widely used in data mining, knowledge discovery, decision analysis, pattern recognition, machine learning, and other fields in the past decades. There are some basic concepts, notations and results of rough set theory, which are briefly introduced.

Decision Table: Suppose an information system $S = \{U, A, V, F\}$, where U is a non-empty finite set of objects, called the universe, $A = C \cup D$ is a non-empty finite set of attributes, C is a set of condition attributes, and D is a set of decision attributes, $C \cap D = \phi$. Each attribute $a \in A$ is associated with a set V_α, which designates each object x attribute value in U, called the domain of a.

Upper and Lower Approximations: Suppose an information system $S = \{U, A, V, F\}$, $B \subseteq A$ and $X \subseteq U$, then the B-lower and B-upper approximations of X are defined, respectively, as follows:

$$\underline{R}(X) = \{x \mid x \in U : [x]_R = X\} \quad (1)$$

$$\overline{R}(X) = \{x \mid x \in U and\ [x]_R \cap X \neq \phi\} \quad (2)$$

where $R(X)$ consists of all objects in U that certainly belongs to X. $\overline{R}(X)$ consists of all objects in U that possibly belongs to X under the equivalent relation R.

Indiscermibility Relation: Suppose an information system $S = \{U, A, V, F\}$, $B \subseteq A$ is a subset of attributes. The indiscernibility relation, denoted by $IND(B)$ is an equivalent relation on the set U defined as:

$$IND(B) = \{(x, y) \in U \times U \mid \forall A \in B, a(x) = f(y)\} \quad (3)$$

Where $a(x)$ is the value of attribute a of object x.

Object Set: Suppose an information system $S = \{U, A, V, F\}$, $A = C \cup D$ and $B \subseteq C$. Define the B positive region of D: $PosB(D) = \cup\{B(X) : X \in IND(D)\}$. $PosB(D)$ is an object set, which consists of the determinate $IND(D)$ classes by using classified $IND(B)$ for expressing the knowledge.

Attribute Set: Suppose an information system $S = \{U, A, V, F\}$, $A = C \cup D$ and the dependability between D and C is defined:

$$K = r_C(D) = | POS_C(D) | / | U | \quad (0 \le k \le 1) \quad (4)$$

For the attribute $c \in C$,if $r_C(D) = r_{C-c}(D)$, attribute c is redundant attribute to decision attribute D. Otherwise, attribute c is indispensable attribute. The importance is computed by following expression:

$$SSGF(c, C, D) = r_C(D) - r_{C-c}(D) \quad (5)$$

Attribute Reduction: Suppose an information system $S = \{U, A, V, F\}$, $A = C \cup D$ and $B \subseteq C$. If B is independent of D, and $r_C(D) = r_B(D)$, B in C is called relative reduction of D, and called $Rred(C)$. In general, all sets of indispensable relations in C are called the core of C, which is described as $Ccore(C)$. So $Ccore(C) = \bigcap Rred(C)$, $Rred(C)$ is the family of all relations of C.

2.2. Particle Swarm Optimization (PSO) Algorithm

The PSO algorithm is a population-based search algorithm based on the simulation of the social behavior of birds within a flock [19]. In PSO algorithm, individuals, referred to as particles, are "flown" through hyper dimensional search space. The particles' positions within the search space are changed based on the social-psychological tendency of individuals in order to delete the success of other individuals. The changing of one particle within the swarm is influenced by the experience, or knowledge. The consequence of modeling for this social behavior is that the search is processed in order to return toward previously successful regions in the search space. Namely, the velocity(v) and position(x) of each particle will be changed by the particle best value (pB) and global best value (gB). The velocity and position updating of the particle is shown by the followed expression:

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 \left(pB_{ij}(t) - x_{ij}(t)\right) + c_2 r_2 \left(gB_{ij}(t) - x_{ij}(t)\right) \tag{6}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{7}$$

where $v_{ij}(t+1)$, velocities of particle i at iterations j, $x_{ij}(t+1)$, positions of particle i^{th} at iterations j^{th}. w is inertia weight to be employed to control the impact of the previous history of velocities.

2.3. BP Neural Network

Artificial neural network (ANN) [20] is distributed system with massive interconnection between large numbers of simple processing neurons. Those neurons store experiences, learned so far, and make it available for the later. The ANN is judged on its ability to successfully produce a correct output given a certain set of inputs. The potential of ANN provides a lot of significant advances in the application of modeling engineering problems rests on their ability to model complex physical phenomena, even in the presence of noisy data, and on their ability to tackle nonlinear problems. There are different type of neural networks in the literatures differs in topologies used to interconnect the neurons or the training algorithms used to train the network.

In this work, the back propagation (BP) with momentum is used to train the samples, shown in Figure 1. It is the most commonly adopted ANN training algorithm.

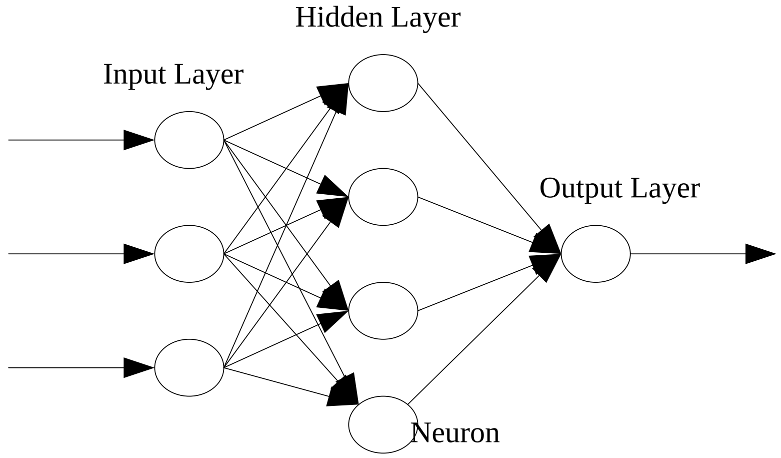

Figure 1. Structure of BP Neural Network

Where a BP with a hidden layer is applied in which the neural neurons take tan-sigmoid function for transform, and

$$O = \sum_{i=1}^{n} w_i y_i \tag{8}$$

A linear function is used in output layer for transform to get values with a broad range. And there is the S function of transform function values from 0 to 1, that is to say,

$$f(x) = \frac{1}{1+e^{-x}} \tag{9}$$

The BP neural network based on Levenberg-Marquardt algorithm is used to train learning algorithm of neural network and the particle swarm optimization algorithm with the global optimization ability is used to optimize the weights of BP neural network in order to establish the optimized BP neural network in this paper.

3. A Hybrid Intelligent Fault Diagnosis (RPBPNN) Method

3.1. The Idea of RPBPNN Method

Fault diagnosis plays an important role in the operation and maintenance of the complex industrial system. It can not only reduce or eliminate the accident, but also bring the potential of complex industrial system into full play and reduce expenditure. In the past decades, a lot of various techniques or methods have been proposed for reducing or eliminating fault diagnosis. These techniques and methods include artificial neural networks (ANN), rough set theory(RST), expert system(ES), fuzzy theory (FT), genetic algorithm(GA), particle swarm optimization(PSO) algorithm, petri net and other new algorithms. They take on stronger diagnosis ability for small-scale and precise-model system. But the complex industrial system, each method can't effectively obtain the fault diagnosis result with the high correctness and efficiency. The RST as a new mathematical tool can effectively illustrate the significance in knowledge expression system and reduction. It is one of the effective methods for finding a subset, which can preserve the meaning of the attributes. And it can discover data dependencies and reduce the number of attributes contained in a dataset by purely structural methods. But it is often helpless when it is used to deal with incomplete data. The PSO algorithm has the advantages with simple structure, easy implementation, fast convergence speed and global searching ability. It takes on the good robustness and efficiency in solving optimization problems. So the RST is used to mine the diagnosis rules, which are regarded as a diagnosis knowledge base to directly offer fault diagnosis service. The PSO algorithm is used to optimize the parameters of BP neural network in order to improve the performance of BP neural network. The optimization process of BP neural network is divided 2 steps. That is say to determine weight w_{ji} between the i^{th} node of input layer and the j^{th} node of hidden layer, weight w_{kj} between the j^{th} node of hidden layer and the k^{th} node of output layer. Before the BP neural network is trained, the numerical value of input vector must be ascertained in order to solve the parameters of weight w_{ji}, weight w_{kj}, threshold b_1 and threshold b_2. If the node number of hidden layer equals to the number of input vector, then threshold $b_2 = 0$. The first, the neurons number of hidden layer is 1, then the hidden neurons number of the network is automatically increased in course of training network until mean square error meets the precision or the number of neurons to reach the threshold. The optimal parameters of BP neural network are obtained in the process. So a hybrid intelligent fault diagnosis (RPBPNN) method based on combining rough set theory, particle swarm optimization and redial back propagation (BP) neural network is proposed to diagnose the fault. Clearly, the synthesized intelligent fault diagnosis method has better characteristics than single BP neural network or PSO or RST.

3.2. The Flow of RPBPNN Method

The course of fault diagnosis in the complex industrial system is to start from the equipment testing to fault symptoms information for obtaining the fault reason and processing. The flow of hybrid intelligent fault diagnosis(RPBPNN) method based on combining rough set theory, particle swarm optimization and redial back propagation (BP) neural network is shown in Figure 2.

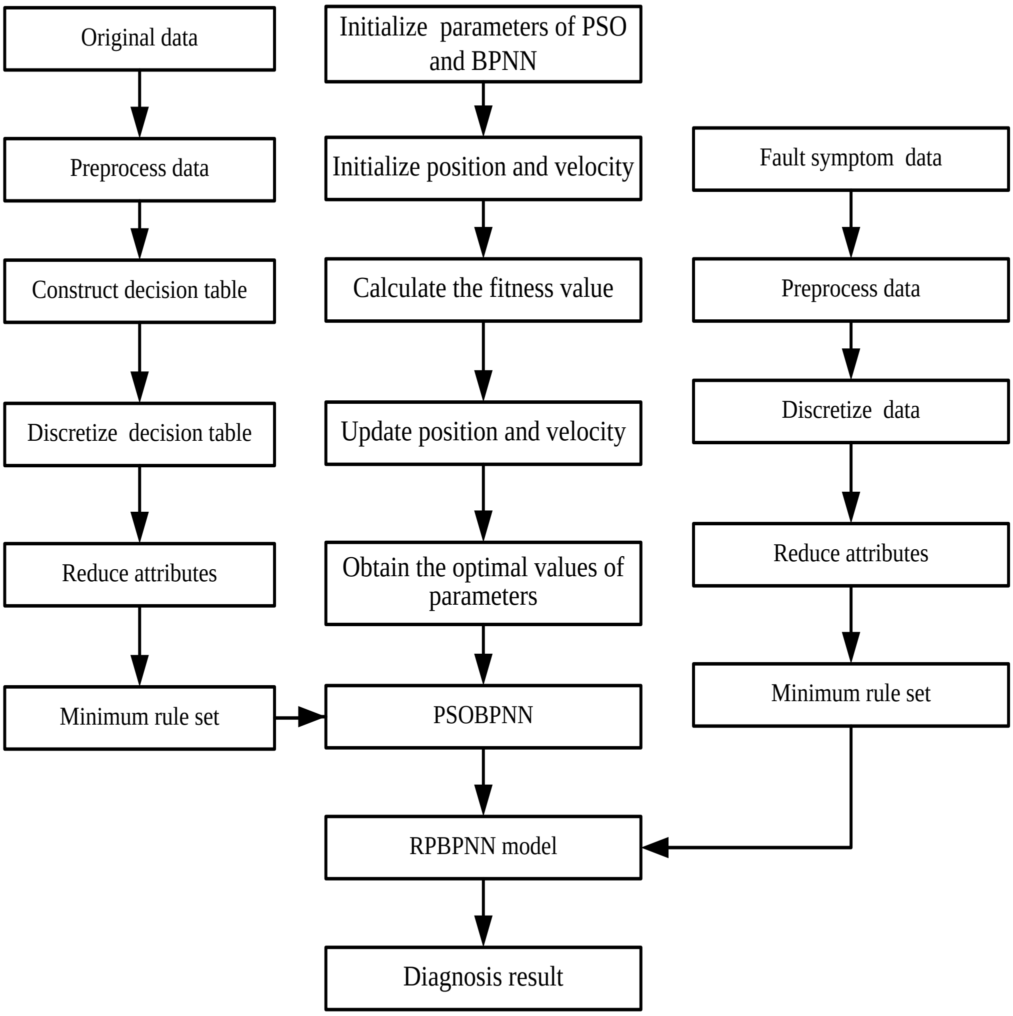

Figure 2. The Flow of Hybrid Intelligent Fault Diagnosis (RPBPNN) Method

4. Analyze Actual Application Case

In this Section, the motor bearing in a complex control system is regarded as the research object, in bearing seat of the motor drive, the sensors are used to gather vibration signal. Because the production site is very difficult to collect all kinds of data, the electrical process technology is used to deal with minor pitting in the normal bearing surface. Some parts of the data are select for validating the effectiveness of the RPBPNN method. The selected fault diagnosis data has normalized processing, as shown in Table 1.

Table 1. Fault Diagnosis Samples

U	z_1	z_2	z_3	z_4	z_5	H
a_1	0.229	0.946	0.332	0.051	0.019	1
a_2	0.182	0.805	0.291	0.027	0.016	1
a_3	0.055	0.791	0.218	0.045	0.017	1
a_4	0.035	0.039	0.962	0.276	0.057	2
a_5	0.015	0.061	0.394	0.193	0.267	2
a_6	0.042	0.021	0.864	0.302	0.066	2
a_7	0.015	0.035	0.438	0.491	0.169	3
a_8	0.039	0.042	0.391	0.540	0.236	3

In Table 1, $z_1 \sim z_5$ are the condition attributes, $a_1 \sim a_8$ are fault cases, U is the universe, f is the vibration frequency. z_1 indicates frequency energy amplitude of domain signature spectrum of the vibration signal $F < 0.35f$, z_2 indicates frequency energy amplitude of domain signature spectrum of the vibration signal $0.35 \le F \le 0.6f$, z_3 indicates frequency energy amplitude of domain signature spectrum of the vibration signal $F = 1f$, z_4 indicates frequency energy amplitude of domain signature spectrum of the vibration signal $F = 2f$, z_5 indicates frequency energy amplitude of domain signature spectrum of the vibration signal $F \ge 4.5f$. H is the decision attribute, which indicates the different motor faults. In this table, $H = 1$ indicates the oil-film whipping fault, $H = 2$ indicates the imbalance fault, $H = 3$ indicates the misalignment fault.

When the RST is used to process the decision Table, attribute value in decision table must be discrete. In order to discretize the continuous data, The hybrid hierarchical k-means clustering algorithm is used to discretize continuous attributes [21]. This algorithm combines the hierarchical clustering method with k-means clustering to exploit respective advantages. The first, the hierarchical clustering is carried in order to get some initial information, which are refined by using the k-means clustering method to et the high-quality clustering result. The discrete result of normalized processing data is shown in Table 2.

Table 2. The Discrete Result of Normalized Processing Data

U	z_1	z_2	z_3	z_4	z_5	H
a_1	1	3	1	1	1	1
a_2	1	3	1	1	1	1
a_3	2	3	1	1	1	1
a_4	1	2	3	2	1	2
a_5	1	2	2	2	2	2
a_6	2	1	3	2	1	2

a_7	1	1	2	3	2	3
a_8	1	1	2	3	2	3

For Table 2, a kind of attribute significance reduction algorithm based on RST is used to reduce decision Tables [22]. The results of computation are obtained and analyzed in detail. Attribute set { z_1, z_3, z_4, z_5 } is important to original decision table, and the set { z_1, z_3, z_4, z_5 } is proved that it is the minimal reduction attribute set of original decision table. Then the minimal reduction attribute set is regarded as the input of the PSO-BPNN model for training the model in order to obtain the optimal PSO-BPNN (RPBPNN) model. Finally, the diagnostic information {(0.025, 0.556, 0.721, 0.142, 0.032) is input the optimized RPBPNN model to forecast the fault diagnosis. The result of fault diagnosis is $H = 2$, which indicates the imbalance fault.

5. Conclusion

In this paper, particle swarm optimization algorithm, BP neural network integrated and rough set theory are used to propose a hybrid intelligent fault diagnosis (RPBPNN) method. The proposed RPBPNN method incorporates the excellences of rough set theory, BP neural network and particle swarm optimization algorithm and overcomes the disadvantages of the three. In the RPBPNN method, the hybrid hierarchical k-means clustering algorithm can discretize, rough set theory can reduce and delete redundant data in sample data. It can reduce the number of input node of BP neural network. The particle swarm optimization algorithm is used to optimize the weights of BP neural network in order to establish the optimized BP neural network model. Then the minimum fault characteristic set is used to train the optimized BP neural network model in order to obtain the optimal BP neural network model for realizing the fault diagnosis. Finally, an actual application case is used to verify the effectiveness of the RPBPNN method. The experimental results show the proposed RPBPNN method can effectively eliminate false and omit alarm of fault diagnosis, and offer a new kind of thought and method for fault diagnosis.

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