Application of Probabilistic Causal-effect Model based Artificial Fish-Swarm Algorithm for Fault Diagnosis in Mine Hoist

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Abstract—**This paper presents an intelligent methodology for diagnosing incipient faults in mine hoist. As Probabilistic Causal-effect Model-Based diagnosis is an active branch of Artificial Intelligent, in this paper, the feasibility of using probabilistic causal-effect model is studied and it is applied in artificial fish-swarm algorithm (AFSA) to classify the faults of mine hoist. In probabilistic causal-effect model, we employed probability function to nonlinearly map the data into a feature space, and with it, fault diagnosis is simplified into optimization problem from the original complex feature set. And an improved distance evaluation technique is proposed to identify different abnormal cases. The proposed approach is applied to fault diagnosis of friction hoist with many steel ropes, and testing results show that the proposed approach can reliably recognise different fault categories. Moreover, the effectiveness of the method of mapping hitting sets problem to 0/1 integer programming problem is also demonstrated by the testing results. It can get 95% to 100% minimal diagnosis with cardinal number of fault symptom sets greater than 20.**

Index Terms—**Mine hoist, artificial fish-swarm algorithm, Fault diagnosis, Probabilistic causal-effect model**

I. Introduction

The problem of detecting faults in complex real plants is strategically important for its various implications.Mine hoiest is a large-scale complicated system, and it has a strong influence on the economic efficiency at the mine. The reasons for the faults of mine hoist are complex and changeable, also the relationships between current faults and the symptoms that can be observed are often not obvious, and there is large number of uncertain factors in the course of the fault diagnosis, therefore, the classification process is needed for condition monitoring and faults diagnosis. For doing good classification process, the preparation of data inputs for classifier needs special treatment to guarantee the good performance in classifier. Many methods have been developed to create the best preparation for data inputs.

The problem with the mathematical model-based techniques is that under real conditions, no accurate models of the system of interest can be obtained. The major weakness of this approach is that binary logical decisions with Boolean operators do not reflect the gradual nature of many real world problems. The model-based diagnostic technology firstly proposed by Reiter [1] is a very effective method for fault diagnosis. How to get the minimum diagnosis rapidly based on this method is a problem on which people pay great interest. Usually all the fault sets should be obtained first, and then get the corresponding minimum diagnosis sets. However, this is usually a NP-Hard problem. An approach of establishing HS-tree to get minimal diagnosis was proposed in [1]. Jiang YF presented a BHS-tree method for diagnosis by improving HS-tree[2].

Due to the broad scope of the process fault diagnosis problem and the difficulties in its real-time solution,many analytical-based techniques have been proposed during the past several years for the fault detection of technical plants.Regarding the intelligent fault diagnosis of mine hoist, the existing research mainly concentrates in the knowledge-based expert system methods and artificial neural network, and so on. Because of the difficulty to establish an effective model and the no-comprehensive consideration of the link between the symptoms and the faults, the diagnosis was not a result of high precision by the method of the traditional expert system. Based on neural network diagnostic methods, the reserch have made some very successful applications [3-5]. But in the application of it the training requirements of large number of samples and the influencing factors to be considered in the network make architecture more complex, also there are some issues such as a long training time and easily leading to local minimum. The method based on SVM [6-7]gives a good application in the small samples of the fault diagnosis field, but it did not fully consider the multi-to-multi mapping relations between the current faults and the symptoms can be observed.

People continually abstract inspirations from biology system. Because may process the separate, non-linear

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data, these Bionic algorithms show their powerful abilities in information processing and problem resolving in many fields, especially in pattern recognition, intelligent optimization, machine learning, data mining, robotics, diagnostics and cybernetics etc.The mathematic framework of AFSA was raised in 2000s [8]. In 2003, Some researchers proposed some new theories from different view of points in model, algorithms and applications. (AFSA) [9, 10] introduce the idea of artificial intelligence into optimization solutions with autonomy model of animal.It is a random search optimization algorithm based on the simulation of fish-swarm acts. The tests in [10] show that the algorithm is effective to get the global extreme value by overcoming local extreme. It was described from the point of system design and applied in forecasting method successfully In [11-17]. To the best of our knowledge, the promotion of ASFA for fault diagnosis has virtually not been reported in the open literature.

In this paper, we combine probabilistic causal-effect model, the improved distance evaluation technique and ASFA, and then propose a new approach to intelligent fault diagnosis of mine hoist. First, this paper introduc conservation covering theory in view of the characteristics of hoist fault diagnosis to give a detailed re-description of the fault diagnosis model, then established a causal-effect network. And we has constructed a dynamic optimal model for fault diagnosis based on the above mathematic framework. Then, the feature set is evaluated by applying the improved distance evaluation technique proposed. Finally, the minimum diagnosis is mapped into 0/1 integer programming problem [18] based on ASFA to come up with the diagnosis results. The proposed approach is applied to fault diagnosis of mine hoist. The signals are collected from the friction hoist with many steel ropes under various operating loads and different conditions. The results demonstrate the effectiveness of the proposed approach.

II. BASIC DEFINITIONS

The basic idea of model-based fault diagnosis is to predict system behavior by comparing the differences between the observed behaviour and the expected behaviour, then to derive the candidate diagnosis using model already established. The reasoning method is obtained from the shallow knowledge related to causes and effects in solving the diagnosis question.

In this section, the basic definitions and notation of fault diagnosis based on the probabilistic causal-effect model to be used in the paper will be presented.

Definition 1. Let the dimensionality of original sample feature space be *m* and the number of sample classes be *N*. By the nonlinear mapping, the measured inputs are extended into the hyper-dimensional feature space as sets of fault symptoms $\mathbf{E} = \{e_1, e_2, \ldots, e_m\}$, which denote all potential manifestations (symptoms), all the observed fault symptoms are simply noted as $\mathbf{E_I} \subseteq \mathbf{E}$.

Definition 2.Sets of candidate-fault $\mathbf{F} = \{f_1, f_2, \ldots, f_n\}$ denote all possible faults, the *j*th mapped fault are given by $\mathbf{F_I} \subseteq \mathbf{F}$.

Definition 3. The probability of the candidate fault f_i is noted as P_{fi} ($P_{f_i} = \{P(f_i = yes \mid \mathbf{E_I})\}$) when symptom $\mathbf{E_I}$ is observed, where Priori-probability is $P_{f_i} \in (0, 1)$, $f_i \in \mathbf{F}_I$.

Definition 4.Probability sets of candidate fault P_{E_I} are given by $\mathbf{P}_{\mathbf{E_I}} = \{P(f_1 = yes \mid \mathbf{E_I}), P(f_2 = yes \mid \mathbf{E_I}), \ldots, P(f_n = yes \mid \mathbf{E_I})\}$ when $\mathbf{E_I}$ is observed.

Definition 5.The causal-effect relationship between the symptoms and Faults are noted as a relationship $\mathbf{C} \in \mathbf{F} \times \mathbf{E}$. $(f_i, e_j) \in \mathbf{C}$ denotes fault f_i can cause symptom e_j .the mapping relationship $C_{ij} \in (0, 1)$ denotes probability of symptom e_j caused by the existent known fault f_i. It is an associated "intensity of presence", denoting its absence (zero intensity), full presence (intensity of presence equal to one), or partial degree of presence (between zero and one).

Definition 6.The diagnosis question may be represented as $\mathbf{D} = (\mathbf{F}, \mathbf{E}, \mathbf{C}, \mathbf{E_I})$, and $\mathbf{F} \cup \mathbf{E} \cup \{f_i \mid e_j \in \mathbf{E_I}\} \cup \{\neg f_i \mid e_j \in \mathbf{E} - \mathbf{E_I}\}$ is coordinated.

We assume that the entire fault $f_i \in \mathbf{F_I}$ will happen, and the entire fault $f_i \notin \mathbf{F_I}$ will not happen when the fault set $F_I \subseteq \mathbf{F}$ is considered as the question to be solved. So $\mathbf{F_I}$ is the coverage of the given $\mathbf{E_I}$. Assumption that fault set $\mathbf{F_I}$ is a potential reason for the diagnosis set $\mathbf{E_I}$, there are no subsets of $\mathbf{E_I}$ caused by $\mathbf{F_I}$ can cover $\mathbf{E_I}$.

The process of getting the minimum diagnosis set from the known fault symptom is the process of searching $\mathbf{F_I}$ and making $\mathbf{F_I}$ minimum. This combinatorial optimization problem is a NP-Complete problem.

III. AFSA

The idea of AFSA is based on the simulation of the simplified natural social behaviour of fish schooling and the swarming theory. It has been successfully applied to neural network training, parameter tuning of robust PID controller, identification on line of time-variant system, and has been proved to have many advantages, such as good global astringency, strong robustness, insensitive to initial values and parameters, simplicity of implementation and so on.

AFSA is a kind of optimization algorithm based on the simulation of fish-swarm behavior. The algorithm imitate the fish's acts such as prey, swarm and follow by constructing a single fish's behavior, to achieve global optimum value from all the local optimization. The algorithm has auto-adapted ability in search space, because it can obtain the global extreme value by overcoming the local extremum. Starting from the potential solution set, ASFA generates the initial population which is encoded by a certain number of individual, and each individual is an actually entity with characteristics. ASFA changes the parameters by simulating the changes of the individual. The Ref. [5] constructed the Object-oriented model of individual by packaging the fish's own status and behaviour patterns using the binary code. The implementation of the algorithm is also the simulation of adaptive behavior of individual. And it is iterative every the individual moves.

AFSA has the unique advantages to solve the non-linear and large-scale problem. Its main feature is the strategy of group searching and the exchanging of information between the individuals, with the ability of parallel processing and faster Optimization, the optimum value is gained by tracking the state of the individual. So the bulletin board is used to record the best individual state. In order to be more effective, fitness evaluation is used to evaluate the fitness of an individual when taken as the standard individual in a population. So it is especially suitable for dealing with the complex and nonlinear problems which difficult to be solved by using the traditional method.

It is precisely for these above characteristics; AFSA has widely used in many fields, Such as forecasting of power grids, optimization of production planning, etc. Mine Hoist is characterized by that the fault causation is complex and changeable, and there are often no obvious correlation between the fault at present and the symptoms can be observed. Also the large number of uncertain factors makes mine hoist fault diagnosis more difficult. For these highly nonlinear systems, the mathematical model based on traditional methods often can not be effective. Using a bottom-up design, AFSA does not have the special request for the optimization space. And this method is, in principle, a search method based on comparison the values of objective function. So it does not use derivative information, and has a better ability to get global optimization with faster convergence speed. Some problems such as the slow pace of reasoning, the difficulties to get prior knowledge in mine hoist fault diagnosis can be better solved by ASFA. Thus AFSA used in mine hoist fault diagnosis is very important and valuable in theory and application of research.

A. The Principle of AFSA

In a water area, the fish can find the area which is more nutritional by individual search or dangling after other fish. Therefore, the water area where the number of the fish is the most is generally the most nutritional. Information about good solutions spreads through the swarm, and thus each artificial fish (AF) tend to move to good areas in the search space. AFSA emulates the prey, swarm, following behaviors of the fish swarm. The Artificial Fish (AF) acts these behaviors guided by some strategies and usually stays at the place with plenty food. Three behaviors are described as follows:

1. *Prey Behaviour*

In general, the fish stroll at random. When the fish discover a water area with more food, they will go quickly toward the area. So they move according to the following equation:

$$X_j = X_i + Rand() * V \tag{1}$$

where *Rand()*is a random function in the range [0,1] , and V represents the visual distance of AF.

Suppose that an AF move from urrent state X_i to the new state X_j in its visual field. If *f (Xi)< f (Xj)*,then AF’s state at the next iteration is calculated by following equation:

$$X_i^{i+1} = X_i^i + Rand() * Step * \frac{(X_j - X_i^i)}{(\|X_j - X_i^i\|)} \tag{2}$$

where X_i^{i+1} , X_i^i represent the AF’s next and current state ; We can compute the Euclidean relative distance between *Xi* and *Xj* by $\|X_j - X_i^i\|$,and *Step* represents the distance that AF can move for each step.

if still did not find to satisfy the onward condition, then random move one step .

2. Swarming behavior

While swarming, the fish move approximately toward other companions’ moving direction and the center of near companions’ moving direction avoiding congestion with other companions. then the AF’s state at the next iteration is calculated as follows:

$$X_i^{i+1} = X_i^i + Rand() * Step * \frac{(X_c - X_i^i)}{(\|X_c - X_i^i\|)} \tag{3}$$

Where X_c represents the center of near companions’ moving direction.

3. *Follow Behaviour*

When one fish of the fish-swarm discovers more food, the other fish will quickly find the food by dangling after it. then the AF’s state at the next iteration is calculated as follows:

$$X_i^{i+1} = X_i^i + Rand() * Step * \frac{(X_{\min} - X_i^i)}{(\|X_{\min} - X_i^i\|)} \tag{4}$$

Where $X_{\min}$ is minimum among all ones in its current neighbourhood.

B. Fitness Evaluation

In order to reflect the requirements of fault diagnosis in most cases, and highlight the main factors, we give the following assumption to solve diagnostic problem.

Assumption 1. Fault f_i is independent to each other.

Assumption 2. All symptoms are caused by fault.

The issue is still a NP-Complete problem, though the assumptions are gived. This is because that sometimes symptoms are not caused by a single fault, which makes it difficult to get the minimum diagnosis sets. However, the above assumptions are useful for the design of a fast algorithm, and are usually consistent with the practical diagnosis process.

The definition of fitness evaluation has obvious effects on the recognition ability of compound feature. as for fault diagnosis, an optimal compound feature needs to satisfy the following criteria: maximizing the" distance " between classes and minimizing the with in-class distance in the space. Here, each kind of class corresponds with a kind of fault. We turn it into a minimizing question; therefore, the fitness function can be calculated by the ratio of average with in-class distance to minimum the distance between classes:

$$Fit(e_i) = \frac{\frac{1}{n}\sum_{i=1}^{n}\sqrt{\sum_{j=1}^{m}(f(e_{ij})^2 - f(e_{kj})^2)}}{\min(\sum_{j=1}^{n}(f(e_{ij})^2 - f(e_{lj})^2))} \qquad (5)$$

where denominator denotes the "distance "between pairs of classes, numerator denominator denotes the with in-class" distance" .

$$f(\mathrm{e_{ij}}) = \frac{\prod_{e_j\in\mathbf{E_I}}\prod_{f_i\in\mathbf{F_I}} c_{ij} \square \prod_{f_i\in\mathbf{F_I}} \frac{p_{f_i}}{1-p_{fi}}}{\prod_{e_j\in(\mathbf{E}-\mathbf{E_I})}\prod_{f_i\in\mathbf{F_I}} c_{ij}} \qquad (6)$$

Where $\prod_{e_j\in\mathbf{E_I}} c_{ij}$ indications the weights of the symptoms caused by the fault, $\prod_{e_j\in(\mathbf{E}-\mathbf{E_I})}\prod_{f_i\in\mathbf{F_I}} c_{ij}$ indications the weights of the symptoms not exist, and C_{ij} is changeable with **E**, that is, it is always not to be the same of probability C_{ij} to cause e_j when $\mathrm{f_i}$ happens, $\prod_{f_i\in\mathbf{F_I}} \frac{p_{f_i}}{1-p_{fi}}$ indications the weights of the priori probability of $\mathbf{F_I}$.

For a given $\mathbf{E_I}$,we can calculate the value of $\mathrm{Fit(e_i)}$ according to this function, which reflected the probability of $\mathbf{E_I}$ caused by $\mathbf{F_I}$. So it is reasonable to make it optimization.

IV. FAULT DIAGNOSIS

Because that the fault is independent of each other, cardinal number of fault sets will be very big when there are many faults, which make it difficult to calculate the probability. Then fault diagnosis can be defined as a probability of causation network accroding to the above definition, that is, the network is composed together by $\mathbf{D} = (\mathbf{F}, \mathbf{E}, \mathbf{C}, \mathbf{E_I})$ and the input $\mathbf{E_I}$ .The solution is fault Set $\mathbf{F_I}$ which is most likely to occur when known symptoms Set $\mathbf{E_I}$ is observed.

Information fault diagnosis utilizing probabilistic causal-effect model based AFSA(PCAFSA) is a process of obtaining the optimal compound feature and detecting different faults with higher reliability and robustness.

A. *Encoding of Algorithm*

First gives coding of AFSA and the corresponding operating based on the probability causes and effects model.

1) Encoding

Theory of mapping the diagnostic problem to numeric values {0, 1} respectively is proposed to improve the solving efficiency for getting the fault set from symptoms.

Definition 7. $A = (a_{ij})_{1\le i\le m, 1\le j\le n}$ Denotes an n × m 0 / 1 matrix associated with the system.

In this definition, each line of A corresponds to an individual; each column corresponds to a fault. Supposes that the vector $A_i\,(i=1,...,m)$ represents each line of matrix A, $a_{ij}=1$ denotes fault j is included in subset A_i .Otherwise; fault j is not included in subset A_i. If the set is represented with m vectors, then the codes for diagnosis sets of artificial fish individual is $(x_1, x_2, ..., x_m)$, where x_i ranged from 0 or 1.

That is to say, the compound feature expression is a dimensionless expression. The terminal library is composed of dimensionless variables, which can reduce the influence of different working conditions and technical parameters on the diagnosis result, at the same time, can ensure that compound feature is sensitive enough to mechanical faults and defects.

Assumption that n typical fault was selected, then the length of each individual string defined as n×m, and m individuals randomly generated to compose a group.

2) Individual Selecting Operator

We should select a proportion of fitness when generating the group.Assume that the fitness evaluation for ith individual is Fit(i) , then the probability of individual choice is

$$P_i = \frac{\mathrm{Fit(i)}}{\sum_{k=1}^{N}\mathrm{Fit(k)}} \qquad (7)$$

Where P_i reflects the proportion of the individual's fitness occupies in the total value of the group.

The steps of algorithm are as follows

STEP1. Supposes the size of group is N, then generates k random number in [0, 1], and calculates the value of control variables x_k

$$x_k = Random(x_{k_{\max}} - x_{k\,\min}) + x_{k_{\min}} \qquad (8)$$

Where x_k is control variable, $Random(x_{k_{\max}} - x_{k\,\min})$ generat random number in $\left[x_{k_{\max}}, x_{k\,\min}\right]$, $x_{k_{\max}}, x_{k\,\min}$ is the upper limit and the lower limit of the controlled variable

STEP2. According to the value of each controlled variable, chooses the most 1/6 superior individual from k individual. The individual is selected in accordance with P_i.

STEP3.if N individuals have been generated, then jump To Step 3, else jump To Step 1

B. *Algorithm Model*

Below gives solution process of AFSA based on the probability causes and effects diagnostic model.

STEP1. Inputs the primary data, obtains the number of variables and their range. Set the groups -scale of artificial fish, the largest number of iterative, the domain, the maximum length of the moving of artificial fish and overcrowding parameter ECT

STEP2 The current iteration number Gen = 0, randomly generated N individual fish in the domain of the control variables Using random number generator to get the initial group. The choice of the individual is in accordance with the individual selecting operator.

STEP3 Calculating each individual's food density of current location in the initial swarm by fitness, And compare the value, then the minimum value is marked and the status of corresponding individual also is marked in bulletin board.

STEP4 Each artificial fish simulates the steps separately①following acts②Cluster acts. Default behavior is foraging behavior

STEP5 Each individual fish test their own state and the bulletin board status, moves every time one from now on. If the state is better than bulletin board, substitutes for it by its own condition.

STEP6 Terminate condition. The genetic operations of prey, swarm and follow are repeated until the individual meeting the terminate condition. The terminate condition can be the maximum generation, or the fitness variety of the optimal individual, or both of them.

V. EXPERIMENT

A. *The relationship between fault and symptoms*

According to the relationship between fault and symptoms, mine hoist failures can be classed in three categories

1.Symptom and fault is one against one correspondences, which usually corresponds to the independent object

2. Multi-symptoms against single–fault. For example, when some dynamic fault occur, armature current、magnetic field current 、 speed and transformer temperature may be abnormal.

3. Sole symptom against multi-faults.

So during the process of fault diagnosis, does not all the symptoms are necessarily need to be acquired in order to reduce testing costs? But require symptom sets cover the entire failure source in order to carry out accurate and reliable fault diagnosis. Namely, the fault symptoms are the unique performance of the fault.

B. *Data Sampl ing and Var iables Setting*

If the generated data are directly fed to the model as training patterns, higher valued input variables may tend to suppress the influence of smaller ones. Also, if the raw data is directly applied to the model, there is a risk of the simulated system reaching the saturated conditions,which affects the network training to a great extent. So the data are normalized before being presented to the model . Data normalization compresses the range of training data between 0 and 1 depending on the type of transfer function.

From the above analysis, we must first determine the symptoms set, fault set and causal strength between them .All the fault signals generated by the system. And transmits through RS232 serial communication protocol to diagnostic model, then test the signal transmitted into the diagnostic model by the knowledge library.

First, prior to executing discriminant analysis and building a classification tree, a preprocessing by applying equation (9) and (10) correction to the data was performed. The main purpose of this preprocessing is to improve the separability of different classes of faults by removing unwanted variation of data that does not contribute to separation.

In order to obtain enough input sampled data on the basis of standard fault symptom pattern, we can separately carries on the variable according to (9) to satisfy the requirements of getting the number of fault samples. Assume that there are n t symptoms for each fault pattern.

$$e_j = e_S + K\delta \cdot Random(1,n) \tag{9}$$

Where e_S denotes the sample data of symptoms, K denotes the amplitude of controlled variable, δ is the standard deviation, $Random(1,n)$ get the random number between [0, 1]. Then carry on standardized processing for the Matrix E by (10).

$$\mathbf{E'_{mn}} = (\mathbf{E_{mn}} - \alpha_m) / \delta_m \tag{10}$$

Where $\mathbf{E'_{mn}}$ is data matrix, α_m is mean value of each column of data in E, δ_m is standard deviation of each column of data in E.

After the treatment, we get standardized data matrix E ', each column of data is with zero mean and unit standard deviation. After obtained the standardized vector of covariance matrix of matrix X ',then get the standard sample set{F_n,E_m} of each fault mode.

C. *Terminals Selection*

According to the testing environment, we take E_m as the terminal library and achieve the compound feature in testing environment.

For the standard sample data with single – fault of being trained, we set $p_{f_i}(f_i \in \mathbf{F_1})$ =0.9, c_{ij} is obtained by (11)

$$c_{ij} = (e_{ij} - \alpha_j) / \alpha_j \tag{11}$$

α_j is mean value of each column of data in E.

For the test data, we set p_{f_i} =0.5, c_{ij} is obtained by (12)

$$c_{ij} = (e_{ij} - e_s) / e_s \tag{12}$$

Where e_S denotes the sample data after being trained.

In addition, the ASFA parameters are set as follows: scale of group is 50; maximum generation is 50; maximum trynumber is 100; Visual domain is 6; Overcrowding factor is 0.8; Encoding length of each individual is m×n. Assume that there are m faults and n fault symptoms for each fault.

D. Selection of input and output variables

For the application machine learning approaches, it is important to properly select the input variables, as AFSA are supposed to learn the relationships between input and output variables on the basis of input–output

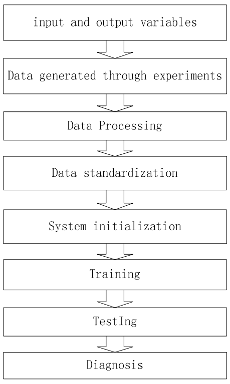

Fig1. Schematic of the AFSA model for fault detection.

pairs provided during training. In AFSA-based fault detection model, the input variables represent the operating state of the mine hoist, and the output will be the condition of normal or abnormal, which may in turn cause the faults. Normal and abnormal conditions are taken as the output of the AFSA model.

E. Optimization Result and Effect Analysis

We collect 210 samples with 30 for each fault. The full input dataset creates a matrix as the training dataset.

The number of failure symptoms needed in this application should be determined. Since orthogonal signal with each component removing structure from X that is orthogonal or unrelated to Y, the residual will model Y better though X actually contains no significant information about Y at all. In general, one symptom is recommended because it is enough to remove any unwanted variation. The result showed that better predictive power, i.e., discriminative classification performance in this case could be obtained in PCAFSA model by the orthogonal filter-based preprocessing with one component than by PCAFSA without a preprocessing.

The data set is collected under various operating loads, and different bearing conditions including different fault categories and severities.

The data set comprises 210 data samples covering three different braking operating conditions (normal condition, emergency brake in mine, emergency brake at mine mouth) and three different loads (0, 1, 2 hp). The 210 data samples are divided into 180 training and 30 testing instances.

ASFA is compared with GA in the same parameters to verify the recognition effect. The mean change of fitness of 60 training sample for brake shoe wear by *ASFA and GA* are show in Fig.1, scale of group is 10 for both and crossover probability is 0.85, mutation probability is 0.09 for GA. We can see that the difference is not obvious in Fig.1.then we set the scale of group as 50. Fig.2 shows that the convergence rate by ASFA can be improved, but the speed of evolution by GA is slowed down with the increase in the size of the group.

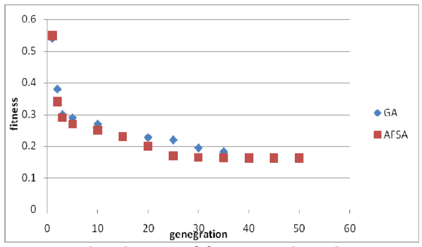

Fig2. The change of fitness with scale is 10

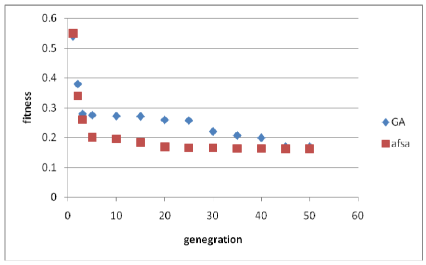

Fig3. The change of fitness with scale is 50

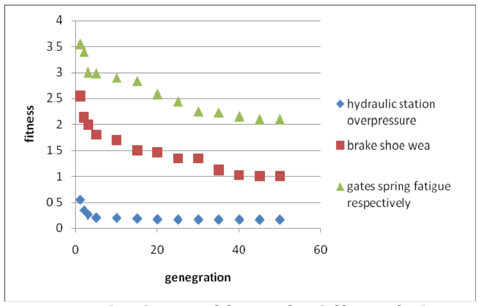

Fig4. The change of fitness for different fault

Table1

Standard sample data after being trained.

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}
F_1	2.3	-0.4	-0.4	2.3	-0.4	-0.4	2.3	-0.4	-0.4	0
F_2	0	0	0	0	0	0	-2.2	2.2	2.2	-2
F_3	-1.5	-1.5	0.38	0.38	0.38	-3.4	0.38	0.38	0.38	0.4
F_4	-1.9	0.48	-1.9	0.48	0.48	-1.9	-1.9	0.48	0.49	0.5
F_5	-2.9	0.32	0.32	-2.9	0.32	0.32	0.32	0.32	0.32	0.3
F_6	-3.1	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	0
F_7	-0.3	-0.3	2.9	2.9	-0.3	-0.3	-0.3	-0.3	-0.3	0
F_8	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	-2.9	-3
	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}	E_{18}	E_{19}	E_{20}
F_1	-0.4	-0	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4	-0.4
F_2	0	0	0	0	0	0	0	0	0	0
F_3	0.38	0.4	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38
F_4	0.49	0.5	0.48	0.49	0.49	0.49	0.49	0.48	0.49	0.48
F_5	0.32	0.3	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32
F_6	-0.3	1	1.	1.	-0.3	1.	1	1.	1	-0.3
F_7	-0.3	0	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3
F_8	0.32	0.3	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32

Fig. 3 shows the mean recognition result for the traing data with fault of hydraulic station overpressure, brake shoe wear and gates spring fatigue respectively. It shows that it can detect the samples effectively.

So table 1is standard sample data after being trained. According to hoist's movement characteristics, there are more than 100 common faults. in this example, select 20 common failure symptoms and eight failure source of the mine hoist.

$\mathbf{F_m}$={Transmission fault; hydraulic station overpressure; brake shoe wear; gates spring fatigue, gate-facing side; soon open fault; brake failure; High-voltage Switch Cabinet fault}.

$\mathbf{E_m}$={brake torque; brake shoe pressure; maximum working pressure for brake; second remaining pressure for brake; temperature of brake; pressure to arrester by brake; first pressure of hydraulic oil; second pressure of hydraulic oil; temperature of hydraulic oil station; second brake delay time; oil storage; temperature rise of reducer axletree; temperature rise of reducer oil pool; vibrancy frequency of reducer; altitude of lubricant oil; AC motor starting torque; AC motor starting current; AC motor speed; temperature of AC motor sliding bearing; temperature of AC motor rolling axletree}

F. *Examples of Diagnosis*

The generation of training data is an important step in the development of this model. To achieve a good performance, the training data should represent the complete range of operating conditions of the centrifugal mine hoist, which contains all possible fault occurrences.

The Following fault diagnosis examples are given. In the course of two test of a multi-rope friction mine hoist, with slippery and over-convoluted fault.

Judgeing from experience, the possible reasons of over-convoluted fault are：(1) Spring life is more than deadline, which lead to spring gates fatigue；(2) Brake shoe wear lead the gap between Gate brake disc and brake shoe do not meet the requirements；(3) There are Partial pendulum in gate, which make Connection between gateway disc and brake shoe bad；(4) Actual average dynamic pressure of gate Paper posted is no longer meet the requirements, if the value is too small may lead to its braking force is too small.

the possible reasons of slippery are：(1) By the known Euler formula from the principle of multi- friction transmission, friction drive is related with friction coefficientμ, cornersα and Static tension F1, changes of these three factors, may lead to slippery failure；(2) Brake speed is faster than the anti-skid limits

We analyzed signals in the course of two tests, and get the data two seconds before and after the faults were taken. According to structure parameters and operating parameters, these symptoms data need to be standardized in accordance with (5), the data after processing is as shown in table 2.

Then according to the alarm range to get the known symptoms set E_l , The results of two sets of data showed that the target value get the minimum in 15th, the value of Sample x_1 is 2.1341, the target value of Sample x_2 is 2.1671, and it fall into{F3} intervals . That is, the corresponding faults are brake shoe wear.

After training, the generalization performance is evaluated with the 30 test data that contain the combination of both normal as well as all types of fault categories. The trained system classified 28 data correctly, which shows an overall detection rate of 93.0%. During testing, the mean square error achieved by the system is 0.128, the system took 101.9520 s to reach the mean square error of 0.01.

The faults can be distinguished by comparing the compound feature value with the intervals. If it cannot fall into any intervals, the detection system thinks it an unknown fault or multi-fault and refuses to recognize it. According to theoretical analysis and records of the situation at the scene, it proved that the diagnosis implemented by the new method for mine hoist was consistent with the actual, which shows that the method is feasible.

Table 2
Standard sample data of being tested

test	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9	E_{10}
x_1	-1.36	-1.36	0.45	0.45	0.45	0.45	0.45	0.454	0.45	-3
x_2	-0.97	-0.97	0.52	0.52	0.52	-2.5	0.52	0.52	0.52	-2
test	E_{11}	E_{12}	E_{13}	E_{14}	E_{15}	E_{16}	E_{17}	E_{18}	E_{19}	E_{20}
x_1	0.45	-1	0.454	0.45	0.45	0.45	0.45	0.45	0.45	0.45
x_2	0.52	-1	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52

VI. Conclusion

AFSA is a novel method to search global optimal value by AF’s searching behavior, swarming behavior and chasing behavior.In this paper, we propose that feature selection and optimization of fault dagnosis architecture are done simultaneously by AFSA in each iterative process, and give out the method of encoding scheme and designing fitness function for the AF swarm to evolve toward the objective.

Generally speaking, the more the data detected, the more the diagnosis is reliable. But to get all the fault of all characterization often is less possible, and it will increase the cost of testing. However, to carry out accurate and reliable fault diagnosis, still need sufficient symptoms, at least to cover all the fault sources. Figure 4 reflects the accuracy of the algorithm in the conditiong that the fault set is certain and the number of symptoms is different. In the condition of the symptoms more than 20, the algorithm can get 95-100% minimum diagnosis.

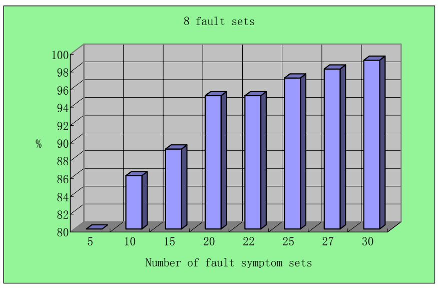

Fig.5 Accuracy of algorithms

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