Journal of Theoretical and Applied Information Technology
31 August 2012. Vol. 42 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A METHOD FOR DIAGNOSIS OF LARGE AIRCRAFT ENGINE FAULT BASED ON PARTICLE SWARM ROUGH SET REDUCTION

ZHUANG WU
Information College, Capital University of Economics and Business, Beijing 100070, China

ABSTRACT

The large aircraft engine fault diagnosis in the problem of accurate. General components with different, large aircraft engine structure and its complex, the work in higher frequency failure, failure appear in a relatively short time, and it is difficult to retrieval, leading to establish the connection between the fault occurs when the connection breaks. The traditional fault detection method is based on the relationship between the fault information fault mining, once the fault can't reiteration, will lead to mining failure, reduce the detection accuracy. Put forward the particle group of rough intensive Jane's fault diagnosis method, and applied to the plane engine, through fault knowledge acquisition, rules optimization, using the fault prediction method, set up the relevance of fracture. Complete fault recognition. The experimental results show that this method is good for improving fault diagnosis accuracy.

Keywords: *Particle Swarm, Rough Set, Fault Diagnosis*

1. INTRODUCTION

Fault diagnosis refers to detection on the diagnosed system according to certain diagnostic strategies. Through detection, the fault mode, signs of fault, characteristics of the faults of the diagnosed objects are obtained, and according to the predetermined principles of reasoning, to judge the subsystems or elements that lead to system faults, to identify the cause and nature of faults, and to predict the development trend of the status, which are extensively applied in some important equipment[1]. With the increasingly high safety requirements for the aircraft, especially the increasing investment in R & D of large aircrafts, studies on fault diagnosis of large aircraft engines become increasingly extensive. Accurate and timely identification of fault areas and accurate positioning of faults parts will not only involve in the safety of national assets, but also life safety. The existing dominant methods are to identify the in-depth fault information through the relations among the faults information based on the dynamic relevance between the fault characteristics. Therefore, such method is more dependent on the relevance among faults. Since this technology is extensively applied, it becomes hot issue for many researchers [2, 3].

Unlike from ordinary components, the engine of a large aircraft is extremely complicated in structure, when working, faults occur frequently in many parts, and especially, many parts in the engine do not work real time, once faults occur, it is very short and difficult to reoccur, which causes the fracture of the relevance among faults. Traditional fault detection methods are to identify faults based on the relevance among the fault information; and once a fault cannot reoccur, the identification of fault will fail; the minimum reduction of many factors such as large semaphore and sample attributes, cannot be determined within limited time, which reduces the accuracy of detection[4].

To solve this problem, a method for diagnosis of large aircraft engine fault based on particle swarm rough set was raised. In the course of aircraft engine fault diagnosis, through fault knowledge access, optimization of rules of relevant engine parts, we predict the potential fault information and establish the fractured relevance among fault signals by means of the fault prediction to complete the fault detection of large aircraft engines. The experimental results show that this method improves the accuracy of fault diagnosis.

2. SELECTION OF FAULTS FEATURES BASED ON ROUGH SET AND PARTICLE SWARM

At present, due to subjective and objective reasons in the practice of mechanical malfunction diagnosis, the judgment conditions of the diagnosis rules are redundant or incomplete with uncertainty of descriptions of the fault symptoms, which is not

Journal of Theoretical and Applied Information Technology
31 August 2012. Vol. 42 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

conducive to practical application. How to optimize the diagnostic rules and eliminate the unfavorable factors have become a new topic in the machinery industry practice and the rough set theory has laid a theoretical foundation to solve such problems. In the field of fault diagnosis, the application of rough set method can remove redundant information by extracting or optimizing the diagnostic rules from the diagnostic data or diagnostic cases and detect the key diagnostic conditions through finding the symptoms sensitive to the failure. Due to factors such as a large amount of data and multi-sample properties, the attribute reduction in rough set theory, often fail to find the smallest reduction in the limited time period. However, the swarm intelligence algorithm provides an effective way for the rough set attribute reduction. Particle swarm optimization is an important branch of the swarm intelligence algorithms and it mainly carry out a reduction iterative search by simulating the process of information exchange among biological populations to obtain the smallest reduction or a similar one. Therefore, the particle swarm algorithm applied to the rough set attribute reduction has a certain practical significance and the method of particle swarm and rough set theory is an important development direction of fault diagnosis.

2.1 STANDARD PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization(PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbors of the particle. This location is called lbest. when a particle takes all the population as its topological neighbors, the best value is a global best and is called gbest[5].

PSO algorithm of N-dimensional space optimization, which is used to solve the optimization problem of N variable, that is N-dimension $\overrightarrow{x_i}=(x_{i1},x_{i2},\cdots,x_{iN})$, at the same time, the speed is vector $\overrightarrow{v_i}=(v_{i1},v_{i2},\cdots,v_{iN})$, the particle i, get one best position according to the results of every search $\overrightarrow{pbest_i}=(pbest_{i1},pbest_{i2},\cdots,pbest_{iN})$, get one best position of all the particle swarm for the whole group according to the search results of each round, $\overrightarrow{gbest}=(gbest_1,gbest_2,\cdots,gbest_N)$, in which, $i=1,2,\cdots,m$.

The formula performed on particles is:

$$\overrightarrow{v_i}=w\overrightarrow{v_i}+c_1r_1(\overrightarrow{pbest_i}-\overrightarrow{x_i})+c_2r_2(\overrightarrow{gbest}-\overrightarrow{x_i}) \quad (1)$$

$$\overrightarrow{x_i}=\overrightarrow{x_i}+\overrightarrow{v_i} \quad (2)$$

The particles will adjust their position and speed according to the past optimal position that they have flew and the one others have flew in the adjacent area of the group in the flight of each particle. The other constants remain unchanged, while the number of variables in the corresponding dimension fitness function is the number of dimensions of problem space[6,7]. Flow chart of the particle swarm algorithm is as follows:

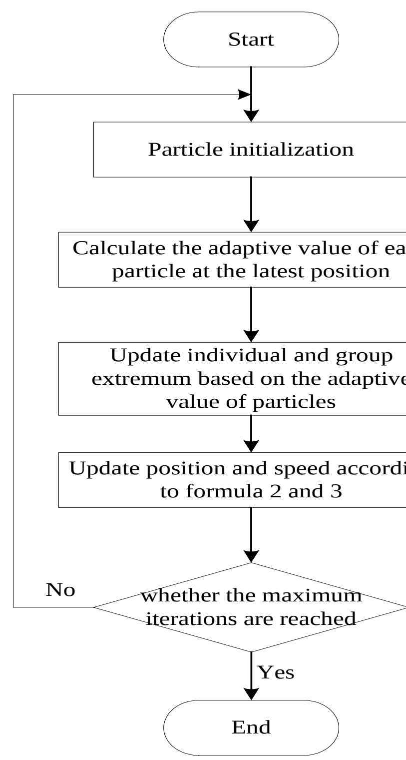

Figure 1: A flowchart of particle swarm optimization algorithm

Journal of Theoretical and Applied Information Technology
31 August 2012. Vol. 42 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.2 The Attribute Reduction of Rough Set

The rough set theory thinks that knowledge is an ability to classify the objects. Presumed that necessary information or knowledge of the elements in the whole domain is obtained initially, and then objects can be classified into different categories according to this knowledge. If two elements share the same information, they are indistinguishable. Indistinguishable relation is the most basic concept of the rough set theory, on which the membership and concepts of Upper and Lower Approximation will be introduced to characterize the imprecision and fuzziness.

1） Attribute dependence

Attribute dependence is a relationship between the properties. If an attribute is regarded as a kind of knowledge reflecting certain objects, this concept will become the capacity of deriving a kind of knowledge from another one. That is to say, the attribute dependence can be seen as a measurement of knowledge dependence.

2） Attribute importance

The concept is to describe the importance of knowledge classification. We measure the attribute importance according to the concept of quality with approximate classification. Strictly speaking, when facing different problems, the properties show different degree of importance. The importance presented by "weight" requires prior assumptions under the conditions of auxiliary information. In the decision-making system, the association between condition attributes and decision attributes reflects the degree of importance of the condition attributes. When the condition attribute a obtains an attribute value of V_a , the number of possible values of decision attribute is capable of reflecting the importance of the condition attribute to the decision attribute. If the value of condition attribute a is V_a but there is only one possible value of decision attribute, then the condition attributes a can be uniquely mapped to this decision attribute. Therefore, the object building rules of condition attribute a with a value of V_a , do not need to consider properties of other conditions.

3） Attribute reduction of decision table

The decision table is a special and important class of knowledge representation system and a majority of decision-making problems can be displayed in a decision table. Let $S=(U,A,V,F)$ be an information system, then in $A=C\bigcup D$, $C\bigcap D=\varphi$, C is the condition attributes and D is the decision attribute. An information system contains condition attributes and decision attributes is called a decision table. When the decision attribute in a decision table is unique, it is called a single decision-making; otherwise, it is known as multi-decision-making. In fact, a decision table with multiple decision attributes can transform into a single decision-making table, which is conducive to the simplification of and the solution to a problem[8,9].

2.3 Selection and Diagnosis of Faults Features Based on the Attribute Reduction of Rough Set of Particle Swarm

As the variables measured within the fault system cannot be recognized as fault-related feature variables, our objective is to find an optimal subset that contains all the related fault characteristic variables. Since the selection of fault characteristics is a combinatorial optimization problem, the particle in the optimization algorithm had better be a series of binary encoding that can express the variable information of the fault feature. Each system variable is indicated by 1 or 0. If 1 is selected, the corresponding variable is chosen as the characteristic variables; if 0 is taken, the corresponding characteristic variable is not selected.

Faults features are selected based on the attribute reduction algorithm of rough set of particle swarm and the diagram of particle encoding is shown in Figure 2:

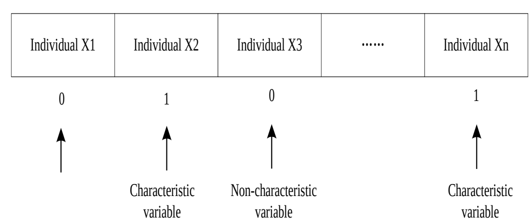

Figure 2: Coding diagram

In terms of the selection of training set and the test set in evaluation of particle adaptability, 200 sets are respectively chosen randomly from normal data and three kinds of fault data as the training set from the primary simulating original data while 300 sets are respectively chosen randomly as the test set. The obtained data shall be first preprocessed then dimensioned and normalized before corresponding fault feature extraction and selection[10].

The following indicators will be used to compare and measure the influence of this algorithm on the reduction performance:(1) the number of reduction attributes, (2) the excellent rate, (3) the running time.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table I
Results of Attribute Reduction in Each Data Set

Name of the data set	Number of the attributes	record Number of the records	Number of the reduction attributes	Number of the minimum reduction attributes	The excellent rate	The running time
Vote	17	435	9	8	90	6453.751
Wine	14	178	6	5	80	1082.538
Soybean_ large	36	307	9	9	100	4031.657
Zoo	17	101	6	5	80	463.136
Lymphography	19	148	6	6	100	737.375
Sponge	45	76	8	8	100	417.636

From the effect of the reduction, the algorithm can acquire a reduction on the relatively small number of attributes in all data sets, which is attributed to the larger search space of particle based on the optimization capability of the PSO algorithm.

3. PRINCIPLES FOR DETECTION OF AIRCRAFT ENGINE FAULT

3.1 Information Relevance-Based Fault Detection

The major methods of the aircraft engine sensor fault diagnosis is to monitor signals of the key parts through acquisition of sensors; but this method is mainly for the fault diagnosis of linear signals; for nonlinear signals, various kinds of classification algorithms that have a more strong nonlinear signal processing ability are usually adopted for the fault diagnosis. Through the infinite approximation ability of a continuous bounded nonlinear function, we established the fault diagnosis model for the large-scale aviation aircraft engines to carry out fault diagnosis. No matter for which way, the fault diagnosis of large aircraft engines should be based on the wireless sensor network; by establishing the dynamic relationship among the data and through such continuous dynamic relevance, we completed the identification of deep faults. The schematic diagram for the aircraft engine sensor fault diagnosis is shown in Figure 3.

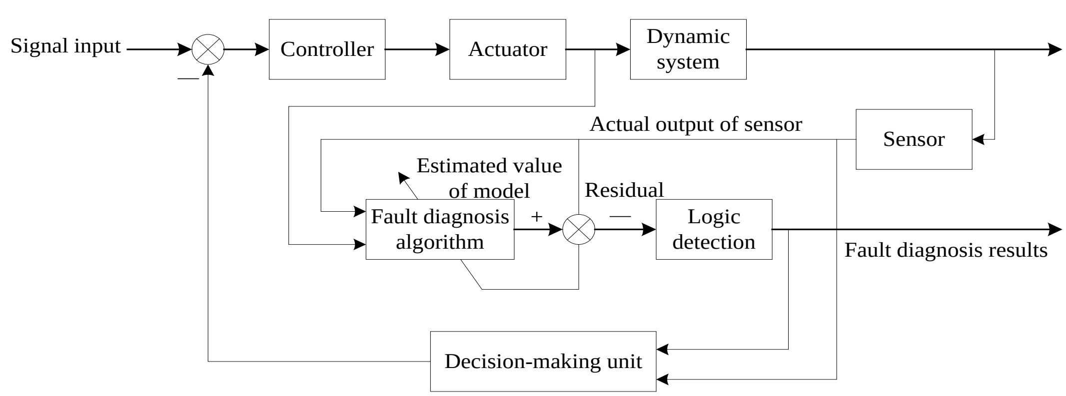

Figure 3: Schematic diagram of diagnosis of aircraft engine sensor fault

3.2 Drawbacks of Diagnosis for Large Scale Complex Aircraft Engine Fault

As shown from the above analysis, for traditional wireless sensor signal acquisition, the analysis and judgment of in-depth faults are carried through the dynamic relation among signals, however, such method has a great drawback. The aircraft engines, especially the engines of large aircrafts ,different from ordinary components, are extremely complicated. When in a complicated working environment for a long time, many

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

components in the engine are not working real time, once any fault occurs, it is very short and difficult to reoccur, which causes the fracture of the relevance among faults. The traditional fault detection methods are to identify the faults based on the relevance among the fault information; and once the fault cannot reoccur, the identification of fault will fail; the minimum reduction of many factors such as large semaphore and sample attributes, cannot be determined within limited time, which causes to fail in the engine deep fault detection for large-scale aircrafts.

4. FAULT DIAGNOSIS METHOD BASED ON PARTICLE SWARM ROUGH SET REDUCTION

4.1 Calculation of Relative Value for Fault Attributes

1) Dependence degree of attribute of aircraft engine fault signal

The dependence degree of attribute of aircraft engine fault signal represents a kind of relevance between faults attributes. If one category of attribute is regarded as the knowledge reflecting the relations among the aircraft engine signals, then this concept is an ability to derive another kind of knowledge from one kind of knowledge. It can be used for measuring the knowledge dependence.

Where all concepts from the fault signal set Q can be defined with some concepts used in the potential fault signal P, we can say that Q is dependent on P, recorded as $P \Rightarrow Q$ Where the prior fault knowledge Q is dependent on knowledge P, we can say that knowledge Q is derivable from the knowledge P.

Attribute dependence: It is assumed that $K=(U,R)$ is a knowledge base, and $P,Q \subseteq R$; where

$$k = r(P,Q) = r_p(Q) = |POS_P(Q)| / |U| \tag{3}$$

we can say that knowledge Q is dependent on P on k degree, recorded as $P \Rightarrow_k Q$. Wherein, $\|$ represents the number of elements of the set, $POS_P(Q) = \bigcup_{x \in U/Q} P\_(x)$ is the P positive domain of Q in the domain of discourse U. Therefore,

$$k = r(P,Q) = \sum_{x \in U/Q} \frac{|P\_(x)|}{|U|}.$$

In the above formula, if $k=0$, Q is totally independent of P; if $0<k<1$, Q is partially dependent on P; if $k=1$, Q is totally dependent on P.

2) Importance of aircraft engine fault signal attributes

This concept is to describe the importance of the aircraft fault signal knowledge classification. The measurement of the importance of aircraft engine fault signal attributes is carried out according to the concept of quality in the approximate classification. Strictly speaking, the aircraft engine fault signal attributes have different importance for different faults. If the "weight" is used to indicate the importance, it is necessary to make prior assumptions under the condition of auxiliary information. In the decision-making system, the relevance between the condition attributes and the decision attributes reflects the importance of the condition attributes. Where the condition attribute a obtains an attributive value V_a, the possible value of the decision attribute of the aircraft engine fault signal can reflect the importance of condition attribute against the decision attribute. Where the condition attribute a of aircraft engine fault signal is V_a, the value of decision attribute is unique, indicating that this condition attribute a can solely reflect this decision attribute, therefore, the rules for the object generation when the condition attribute a of aircraft engine fault signal is V_a need not consider other condition attributes. $M_a = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{l_i}$ is the importance of attribute a of aircraft engine fault signal in the decision–making system, and among of which, $a \in A$, n is the number of V_a $\{V_{a,1}, V_{a,2}, ..., V_{a,n}\}$, i.e. the number of samples for V_a, l_i is the number of classification of decision attribute when attribute a of aircraft engine fault signal obtains the i-th value $V_{a,i}$. As seen from above, in one decision-making system, the larger the M_a value, the stronger the decision–making ability of aircraft engine fault signal attribute a, and thus the attribute a is more important for the decision-making system.

4.2 Attribute Character-based Fault Prediction Mechanism

After the attribute character of the aircraft engine fault signal is obtained, a certain amount of fault prediction can be made according to these

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

characteristics, and such prediction can newly combine the fractured association character to ensure accuracy. The method is as follows: It is assumed that there exist n fault signals in the M-dimensional search domain of aircraft engine fault signal to form a group randomly. $X_i = (x_{i1}, x_{i2}, ..., x_{im})$ is the current location of Fault i, $V_i = (v_{i1}, v_{i2}, ..., v_{im})$ is the current deviation from Fault i, $P_i = (p_{i1}, p_{i2}, ..., p_{im})$ is the experienced position with best fitness value in the optimization process, and $P_g = (p_{g1}, p_{g2}, ..., p_{gm})$ is the optimal position that the a whole signal group has experienced.

Where i = 1,2, ..., n, and the fault signals are M-dimensional.

Then, the signal i at t generation would be iterated to the t+1 generation, and the j-dimensional prediction signal and its location are described as the following iterative equation:

$$v_{ij}(t+1) = \omega \cdot v_{ij}(t) + c_1 \cdot r_1 \cdot (p_{ij}(t) - x_{ij}(t)) + c_2 \cdot r_2 \cdot (p_{gj}(t) - x_{ij}(t)) \tag{4}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{5}$$

Wherein i = 1,2, ..., n, j = 1,2, ..., m, ω stands for inertia weight, c_1, c_2 stands for acceleration constant, r_1, r_2 are two independent random functions uniformly distributed in [0,1]. Fault prediction mainly contains the following parameters: inertia weight function ω, predictive weighting factor c_1, c_2, maximum frequency of iteration, $iter_{\max}$, maximum speed, $V_{\max}$, size of population N, signal length D and coordinate range and termination condition of signal. Inertia weight ω: usually the constant between[0.8, 1.2], but sometimes also need to set a variable ω to achieve better convergence effect of iteration prediction. The predicted weight function ω is determined by the following equation:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} \times iter \tag{6}$$

Wherein, the maximum and minimum ω are respectively expressed as $\omega_{\max}$, $\omega_{\min}$ ($\omega_{\max} \in [2,3]$, $\omega_{\min} \in [0.8,1.2]$) and the current frequency of iteration and maximum frequency of iteration are respectively expressed as $iter$, $iter_{\max}$.

4.3 Aircraft Engine Fault Signal Detection Process

The specific steps of the algorithm are as follows:

Input: aircraft engine fault detection system, $S = (U, A, V, f)$, U stands for universe of discourse, $A = C \cup D$ stands for a set of attributes, C and D are respectively conditional attribute and decision attribute. Output: a relative reduction aircraft engine fault detection system, $S = (U, A, V, f)$.

Step1: the set containing w aircraft engine fault signals were randomly generated. For each signal, initial constant v_0 and initial position x_0 are randomly given. x_0 real number is rounded;

Step2: The iterated signal-based x real number is rounded, and then transformed into a binary string corresponding to attribute reduction, 0 means to do not contain this attribute, vice versa 1 do. The number of bits of binary string is determined by the number of attributes of condition attribute of the information system S;

Step3: Find the predicted value that each signal corresponds to, if it exists, it is directly obtained; otherwise proceed to Step4 for calculating the appropriate value of the signal;

Step4: attribute dependency k_i is calculated by Formula (3), and the (m_0^i / m) of zero in each signal can be calculated, among of which, m_0 means the number of Signal Zero, m is the length of signal, signal fitness $f_i = k_i + m_0^i / m$;

Step5: New fitness value, current fitness value and the best history fitness value are compared to determine two extreme values $pBest_i$ and $gBest$;

Step6: The position x_i and velocity v_i of the signal are updated by Formula (4), (5), and check the range if the new position x_{i+1} and new velocity v_{i+1} to prevent the signal from leaving the maximum search range;

Step7: Judgment of the termination condition (i.e., the frequency of iteration). If the conditions are met, you should terminate iteration, otherwise return to Step 2 for continuing cyclic iteration;

Step8: The optimal integer solution is converted to a binary string, and then the relative reduction of attribute is obtained.

5. EXPERIMENTAL SIGNAL SIMULATION

5.1 Experimental Environment Erection

Unlike from ordinary components, the engine of a large aircraft is extremely complicated in structure, when working, faults occur frequently in

Journal of Theoretical and Applied Information Technology
31 August 2012. Vol. 42 No.2

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

many parts, and especially, many parts in the engine do not work real time, once faults occur, it is very short and difficult to reoccur, which causes the fracture of the relevance among faults. The traditional fault detection methods are to identify faults mostly based on the relevance among the fault information. Once the fault can not reoccur, it will lead to failed identification of fault, reducing the detection accuracy. In order to effective verify the method proposed in this paper, comparative simulation experiments were used. In the experiments, signals from a large aircraft aviation signal library were used. The signals contain random fault signals of engine. Massive signals have a interval of 15 seconds each other. The signals is divided into two sets: the first 1950 signals consist of a sample set while the 50 fault signals consist of a simulation testing set for the simulation in Matlab.

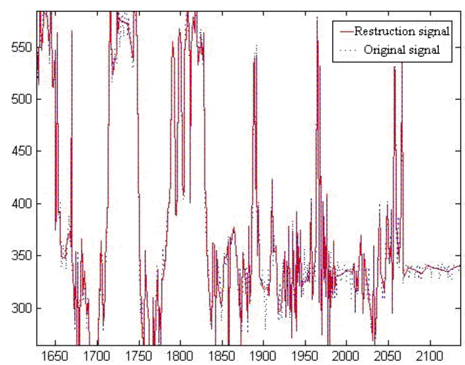

Figure 4: Actual output signal of an aircraft engine sensor

5.2 Engine Sensor Fault Residual Decision Making

Through the aircraft engine fault signal attribute dependence degree and aircraft engine fault signal attribute importance acquired for the aircraft engine sensor, as well as through the difference calculated between the actual output value and the estimated output value, the threshold was compared to set reasonable interval, and thus whether there exist unreasonable signal values can be determined. If residual results fall within a reasonable range, the device works normally; If residual results exceed the threshold standard, the device need to be repaired due to fault. Data of the large aircraft engine should be detected using this principle. The distribution methods used are the method proposed in this paper and traditional methods.

5.3 Simulation and Results

After the test set is tested by establishing the optimal fault diagnosis model of aircraft engine sensor, the obtained results are shown in Figure 5. According to the results of Figure 5, we find that the calculated results obtained by the method used in this paper is basically consistent with the actual output of the engine sensor, indicating the method used in this paper can be used to relatively accurately simulate this output relationship, having a very good robustness and fault accuracy, and is a more ideal diagnosis method for aircraft engine sensor fault.

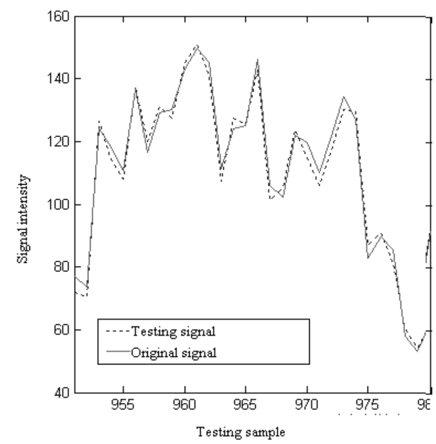

Figure 5: Fault estimates versus actual output value

Through such comparison, we can see that the output value calculated by the method used in this paper is minimally different from the actual output value, having a better output result and more method robustness and thus achieving good results.

6. CONCLUSIONS

This paper represents a method for diagnosis of large aircraft engine fault based on particle swarm rough set. In the course of aircraft engine fault diagnosis, through fault knowledge access, optimization of rules of relevant engine parts, we predict the potential fault information and establish the fractured relevance among fault signals by means of the fault prediction to complete the fault detection of large aircraft engines. The experimental results show that this method improves the accuracy of fault diagnosis, having certain application value and prospect.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Acknowledgements

This work was supported by the Funding Project for Academic Human Resources Development in Institutions of Higher Learning Under the Jurisdiction of Beijing Municipality (No.PHR201007117), the "11th Five-Year Plan" project of Beijing Philosophy and Social Science (No.10BaJG384), the Beijing Natural Science Foundation (No.9123025), the Beijing Philosophical Social Science Project (11JGB077), the Beijing Natural Science Foundation (No. 9122003), the Special Project of Beijing Municipal Education Commission (00791154430107), the National Natural Science Foundation (60703007) and the Planning Project of Capital University of Economics and Business.

REFRENCES:

[1] X. L. Tang, L. Zhuang, J. Cai, C. B. Li, "Multi-fault classification based on support vector machine trained by chaos particle swarm optimization", *Knowledge-Based Systems*, Vol. 23, No. 5, pp. 486-490, 2010.
[2] K. Salahshoor, M. S. Khoshro, M. Kordestani, "Fault detection and diagnosis of an industrial steam turbine using a distributed configuration of adaptive neuro-fuzzy inference systems", *Simulation Modelling Practice and Theory*, Vol. 19, No. 5, pp. 1280-1293, 2011.
[3] Q. Wu, R. Law, "Complex system fault diagnosis based on a fuzzy robust wavelet support vector classifier and an adaptive Gaussian particle swarm optimization", *Information Sciences*, Vol. 180, No. 23, pp. 4514-4528, 2010.
[4] N. R. Sakthivel, V. Sugumaran, B. B. Nair, "Comparison of decision tree-fuzzy and rough set-fuzzy methods for fault categorization of mono-block centrifugal pump", *Mechanical Systems and Signal Processing*, Vol. 24, No. 6, pp. 1887-1906, 2010.
[5] S. S. Fan, E. Zahara, "A hybrid simplex search and particle swarm optimization for unconstrained optimization", *European J of Operational Research*, Vol. 181, No. 2, pp. 527-548, 2007.
[6] Y. X. Shen, G. Y. Wang, C. H. Zeng, "Correlative particle swarm optimization model", *Journal of Software*, Vol. 22, No. 4, pp. 695-708, 2011.
[7] J. M. Xiao, J. J. Li, X. H. Wang, "Convergence analysis of particle swarm optimization and its improved algorithm based on gradient", *Control and Decision*, Vol. 24, No. 4, pp. 560-564, 2009.
[8] R. Bello, J. L. Verdegay, "Rough sets in the soft computing environment", *Information Sciences*, Vol. 212, No. 1, pp. 1-14, 2012.
[9] M. L. Othman, I. Arisa, M. R. Othman, H. Osman,"Rough-Set-based timing characteristic analyses of distance protective relay", *Applied Soft Computing*, Vol. 12, No. 8, pp. 2053-2062, 2012.
[10] S. K. Mandal, T. S. Chan, M. K. Tiwari, "Leak detection of pipeline: An integrated approach of rough set theory and artificial bee colony trained SVM", *Expert Systems with Applications*, Vol. 39, No. 3, pp. 3071-3080, 2012.