SA-PSO Hybrid Algorithm for Gas Path Diagnostics of Gas Turbine

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Abstract

With an ever-increasing power demand in the world and also growing share of power generation by gas turbines, continuous and risk-free operation of these devices is of high significance. All types of gas turbines are susceptible to performance deterioration because of the working conditions and polluting environment etc. As a result, health monitoring and performance diagnosis are two of the most important priorities of gas turbine manufacturers and users. Non-linear model based diagnostic method, with higher accuracy, is suitable for GPA(Gas Path Analysis) diagnostics. One way of non-linear model based diagnostic method is to transfer the Fault Diagnosis into an optimization problem. Genetic algorithms have been applied to solve this high-dimensional optimization problem. Although it has overcome the shortcomings of other traditional methods for easily being fallen into the local minimal, it is criticized for the slow convergence speed and sensitive to algorithm parameters. In addition, it may eventually result in diagnostic delay and wrongly diagnosis. In this paper, a new diagnostic method is used for the gas path fault diagnosis of gas turbine. The method used particle generator which was designed by means of fast SA (Simulated Annealing) to produce an optimized initial swarm of particles for PSO (Particle Swarm Optimization). Combining the global search ability of SA and the high efficiency of PSO, the new method has a good performance in diagnosis speed and accuracy..

Keywords

Gas turbine —Gas Path Analysis — SA-PSO—Computational intelligence

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INTRODUCTION

The national energy structure adjustment has accelerated the application of gas turbines. Now it is playing a gradually important role in many areas due to its low toxic emissions, great reliability and broad fuel adaptability, on the other hand, Gas turbine experience degradations over time that cause great concern to gas turbine users on engine reliability, availability and operating costs[1]. In order to improve reliability and reduce maintenance costs, a further improvement named CBM (Condition Based Maintenance), based on current conditions of the gas turbine rather than historical operating data has drawn more and more attention [1,2]. This will call for the development of reliable diagnostic techniques.

There are many approaches for gas turbine fault diagnostics, such as gas path analysis, oil analysis, visual inspections, X-ray checks, vibration monitoring, noise monitoring, turbine exit spread monitoring, and so on [3,4]. Gas Path Analysis (GPA) is one of the most powerful tool among them [4], it can quickly isolate failures of engine components. and provide supports for engine maintenance.

In decades, a variety of techniques have been proposed to develop the GPA. A linear model based method was introduced to solve this problem firstly in 1967 by Urban [5]. And then in order to take into account the non-linearity of gas turbine behavior, a non-linear model based method with conventional optimization was firstly introduced in 1990 by Stamatis et al[6]. Unfortunately, conventional optimization may stop at a local minimum leading to a wrong diagnosis result. Especially when the number of components within turbine is large, the smearing effect may so strong that degraded components may not be recognized. In recent years, different methods have been used to overcome this disadvantage. Genetic Algorithm (GA) was used by Zedda and Singh in 1990 to estimate the engine performance through optimizing an objective function by a real coded GA [3,7], and the result showed a high level of accuracy. Particle Swarm Optimization (PSO) algorithm was used in a gas turbine health status estimation by Ying in 2015 [8]. The method was tested for a three-shaft marine engine and the case studies showed that the approach can accurately search and isolate the degraded components and quantify the degradation for major gas path components.

The accuracy of fault diagnosis is significantly improved by using these new intelligent optimization methods. However, the solving speed and diagnostic accuracy of these methods have an inverse trend. Faster and more reliable method is essential to diagnostic. In this paper, a Simulated Annealing (SA)-PSO hybrid algorithm is applied in gas turbine fault diagnosis. This proposed approach has been tested in six cases. The result shows that it has an excellent performance in diagnosis speed as well as the accuracy. The impact of different PSO models is investigated. Analysis and conclusions are made accordingly, compared with the typical GPA methods, such as GA, PSO, and traditional method.

1. Gas Turbine Fault Diagnosis Using Optimization method

When the gas turbine encountered a physical fault, it will result in the changes of characteristics. In the last step of the process, the changes of measurement parameters will be collected by sensors. The diagnosis process is to estimate the degradation extent of engine components based on sensor information, the process is shown in Fig. 1 [9].

During the steady state operation of the gas turbine, the relationship between measurement parameter z and the state parameter x can be represented by a nonlinear equation:

$$z = F(x) + v \qquad (1)$$

Where, ν is the measurement noise. The principle of diagnosis is shown in Fig. 2. The health parameters x of the gas turbine determines the state of the gas turbine, the change of different states are represented by the change of the measurement parameter z. Assuming an initial health parameter $\hat{x}$, the prediction of the measurement parameter $\hat{z}$ can be simulated by the gas turbine model. The optimization process is to minimize the objective function by adjusting the health parameters.

The objective function is the deviation between actual measurement parameters z and the predicting parameters $\hat{z}$. A minimization of the objective function is carried out iteratively until the best predicted engine health parameters $\hat{x}$ for real x are obtained.

$$objectionFun = \sum \phi(\| z_i - \hat{z}_i \|) \qquad (2)$$

The objective function is divided into different types, such as the absolute value type, square type, etc.

$$objectionFun = \sum | z_i - \hat{z}_i | \qquad (3)$$

$$objectionFun = \sum (z_i - \hat{z}_i)^2 \qquad (4)$$

Marco Zedda has compared the performance of classification in optimization process between these two types of objective functions [10], and the result showed that equation 3 was a better criterion.Thus equation 3 is adopted in this paper as the objective function.

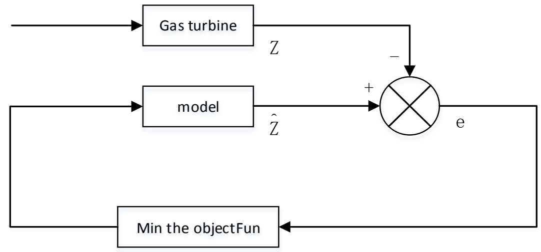

Figure 2. Model based gas turbine fault diagnostics

2. Proposed Algorithm

There are several adjustment variables in gas turbine diagnosis, so we need to search for the objective function in the high-dimensional space. Certainly, the search process should be quick and accurate for diagnostic requirements. The searching methods can be broadly divided into 2 categories: traditional optimization methods and intelligent optimization methods.

The basic idea of traditional nonlinear programming algorithms, such as the improved newton method, gauss-newton method, gold segmentation.etc. [11,12], is to obtain the gradient direction of the objective function, and searching along the rising or falling direction to get the minimum value of the objective function. These methods have obvious advantages, such as fast calculating speed, high efficiency, reliability, and stability. Although the traditional gradient based algorithms have many advantages, the objective function in practice is generally not “flat” with many local minimum points in the feasible region. Therefore, the gradient based method may obtain the local minimum point leading to the wrong diagnostic result ultimately [10].

The intelligent optimization algorithms, that differ from the traditional methods, have the global searching ability which can avoid being plunged into the local minimal effectivly. In addition, they usually have a better performance[3,8]. These intelligent optimization algorithms includes: the Simulated Annealing (SA) algorithm, GA, PSO algorithm, etc.

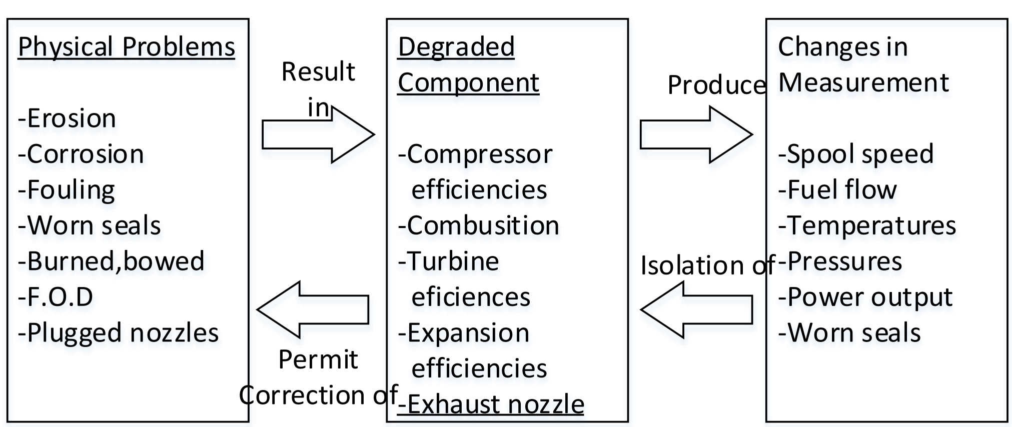

Figure 1. Gas turbine fault diagnostics approach

2.1 Simulated Annealing Algorithm

Simulated annealing (SA) algorithm was put forward by the Metropolis [13], based on iterative strategy for solving stochastic optimization problems. Its inspiration comes from the similarity between solids annealing process and optimization problems.

Firstly, the SA algorithm will randomly select an initial solution x and the initial temperature T in the solution space. At each step, it considers a neighbour state x' from the current state x, and probabilistically decides between moving the system to state x' or staying in state x. These probabilities ultimately lead the system to move to states that can fulfil the diagnostic rquirement or until a given computation budget has been exhausted. In fact, the probability can be determined according to Boltzmann-Gibbs:

$$P(\Delta f)=\begin{cases}1, & \text{if } f(x')<f(x)\\ \exp(-\Delta f/(KT)), & \text{otherwise}\end{cases} \tag{5}$$

Where T is the temperature in each cycle, K is the Boltzmann constant, $\Delta f = f(x) - f(x')$. In most situations, the temperature decreases according to the following formula:

$$T(t')=aT(t),\quad 0<a<1 \tag{6}$$

Where a is an exponential cooling coefficient; a new state is updated as follows [14]:

$$\Delta x=\pm T\times[(1+\frac{1}{T})^{|2\times rand-1|}-1] \tag{7}$$

2.2 Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) algorithm was proposed by Kennedy and Eberhart (1995) [15]. For details, a standard text can be referred Kennedyet al., 2001 and Poli et al 2007) [16,17]. In this section a brief introduction of PSO algorithm is presented. Each solution of the optimization problem is called a particle. Particles fly in the n-dimensional search space with a certain speed, using the fitness function to evaluate the merits of the particles, and the particles dynamically adjust their position and velocity according to the flight experience and the best particle position. Standard PSO algorithm is described as follows: Supposing the searching space is d-dimensional, the N particles are grouped as the swarm. The position and velocity of the i^{th} particle at the k^{th} generation is represented as a d-dimensional vector:

$$x_{i,k}=\left(x_{i,k}^{1},x_{i,k}^{2},..x_{i,k}^{d}\right) \tag{8}$$

$$v_{i,k}=\left(v_{i,k}^{1},v_{i,k}^{2},..v_{i,k}^{d}\right) \tag{9}$$

The i^{th} particle's velocity and position could be update by the equation (8) and (9)

$$\begin{aligned}v_{i,k+1}&=w\times v_{i,k}+c_1\times rand\times(Pbest_{i,k}-x_{i,k})\\&+c_2\times rand\times(Gbest_k-x_{i,k})\end{aligned} \tag{10}$$

$$x_{i,k+1}=v_{i,k+1}+x_{i,k} \tag{11}$$

Where $Pbest$ is the best current positions of all particles, $Gbest$ is the historical best position of the whole swarm (global or neighborhood), w is the inertia coefficient, c_1 and c_2 are the acceleration factor, the values of w, c_1, c_2 could be adjusted depending on the specific problems. In the original algorithm, w = 0.7, $c_1 = c_2 = 2$.

The original PSO algorithm has also some disadvantages. All individuals which learn from the same global best particle will make the algorithm converge faster. However it is inclined to access the local minimum point. Thus an improved algorithm called optimal particle disturbance strategy PSO (OPDS-PSO) is chosen [18]. Compared to the original PSO, OPDS-PSO adds a small disturbance on the global best particle based on an adjustable perturbing normal distribution. The other particles will be updated by the speed updating function:

$$Gbest_k'=N(Gbest_k,\sigma) \tag{12}$$

$$\begin{aligned}v_{i,k+1}&=w\times v_{i,k}+c_1\times rand\times(Pbest_{i,k}-x_{i,k})\\&+c_2\times rand\times(Gbest_k'-x_{i,k})\end{aligned} \tag{13}$$

$Gbest_k'$ is the global optimal particle after adding a disturbance, which is produced by the normal distribution. σ is the deviation of normal distribution function. Perturbation algorithm will let the particles move to the neighborhood of the global optimal position, so this algorithm has better searching ability to avoid premature.

Because the significant drawback of original PSO, in this paper OPDS-PSO is chosen as our test method, and $\sigma = 0.005$. As for the parameters w, c_1, c_2, we design w = 0.7, $c_1 = c_2 = 2$, as PSO Model I, Trelea [19] investigated massive dynamic processes, and recommended two sets of parameters: w = 0.729, c_1 = 1.494, c_2 = 1.494 and w = 0.6, c_1 = 1.7, c_2 = 1.7. In this paper, these two sets are named as PSO models II and III. In the referenced papers, better results were obtained by using a decreasing inertia weight w from 0.9 to 0.4 linearly during the whole process [8], so it will also be tested in this paper as PSO Model IV.

2.3 Diagnostic Procedure

SA-PSO hybrid algorithm is used as an effective optimization tool to predict health parameters based on a self-adaptive gas turbine model. The main process of this diagnostic method includes two parts: particles generator based on fast SA to produce an optimized initial swarm of particles for PSO, and PSO algorithm is responsible for the precise searching in diagnosis. The main process of diagnosis is shown in Figure 3.

(1) SA initialization of particle position

Firstly, a global search is implemented based on SA in feasible area, this will lock the approximate location of the global optimum. The result will be the initial point of particle swarm optimization.

(2) Objective function

The objective function should reflect the difference between simulation result and the measurement parameters.

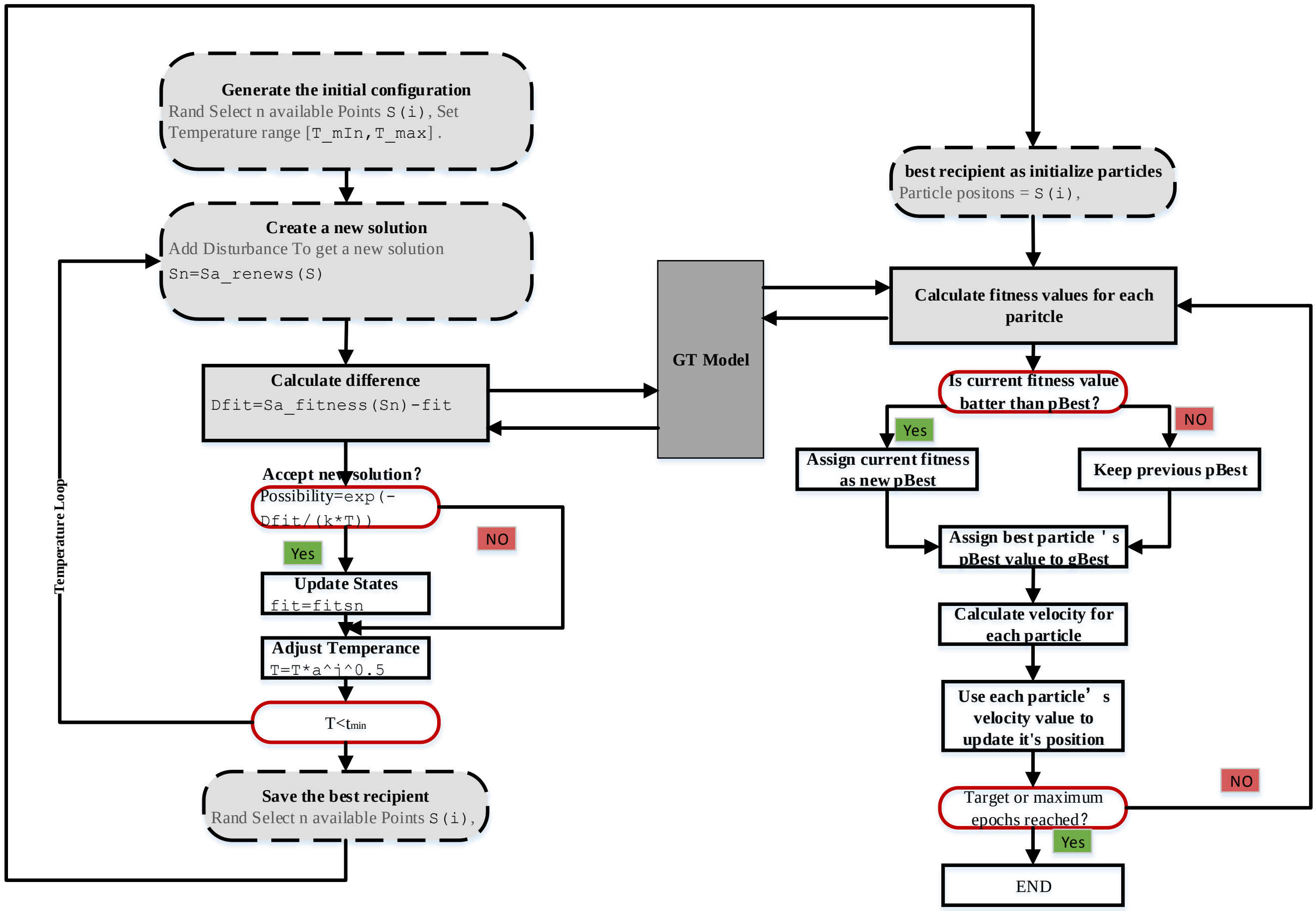

Figure 3. Fault diagnostic procedure of SA-PSO method

Table 1. Performance parameters and measurement parameters

Variable type	Notation	Description
Performance parameters	DGC	Compressor flow rate degradation
	DEC	Compressor efficiency degradation
	DGT	High pressure turbine flow rate degradation
	DET	High pressure turbine efficiency degradation
	DGP	Power turbine flow rate degradation
	DEP	Power turbine efficiency degradation
Measurement parameters	PL	Power load
	T1	Compressor inlet temperature
	P1	Compressor inlet pressure
	n1	Gas generator speed
	P4	Power-turbine exhaust pressure
	PRC	Compressor pressure ratio
	PRP	Power turbine expansion ratio
	T2	Compressor outlet temperature
	T34	high pressure turbine exhaust temperature
	T4	Power turbine exhaust temperature
	Qf	Fuel flow

Lots of work focusing on the effect of different function has been done [4.5]. Equation 3 is regarded as the preferred one because it provides a robust estimation.

(3) PSO searching process

In each cycle, the speed and position of the particles is updated in PSO algorithm in accordance with the above equation for different PSO model I-IV. So the algorithm can achieve an accurate and fast seaching in the particular region to get the global optimal solution.

(4) Termination criteria

Termination condition is the maximum number of iterations or minimum difference in every generation.

3. Application and Analysis

In this paper the test object is a GE LM2500 gas turbine which is a two-shaft gas turbine engine used for driving. The basic specifications of this engine are as follows:

total air flow rate : 32 kg/s,
total pressure ratio :21
power output: 29.8 MW
thermal efficiency: 38%.

The diagnostic process is tested by a PC with 3.3GHz i5 processor and 4GB RAM. The modelling of the gas turbine and optimization methods are carried out using Matlab. Six performance parameters to be estimated by using 11 measurement parameters in this paper is described in Table 1.

The optimization algorithm needs to search in the six-dimensional space in which the six parameter variations are from -0.2 to 0.1. -0.2 means that efficiency or flow rate is reduced by 20%. The other parameters for the method are shown in Table 2:

Table 2. Parameters for SA-PSO

SA	T_max	100
	T_min	0.1
	a	0.93
	K	0.8
PSO	population size	5
	Max number of iterations	200
	minimum global error	1e-6
	PSO model type	I-IV

3.1 Model Validation

Fault implanted here is a typical compressor fouling fault and turbine erosion. According to statistical analysis, more than 70% of engine performance degradation are related with compressor fouling [20]. It was assumed that compressor fouling fault causes a 3% of flow rate decrease and 1% efficiency degradation [20, 21], and the turbine erosion causes 2% of flow rate increase and 1% efficiency degradation. Six cases are shown in Table 3. Case1 to case 3 are three single component faults(compressor fouling fault, high pressure turbine erosion fault and power turbine erosion fault) and case 4 to case 6 is multiple component faults(combination of these three kinds of faults). SA-PSO Model I is chosen to test the diagnosis result, the first 80 cycles are seaching by SA algorithm and the last 120 cycles is taken charge by PSO Model I. The related SA-PSO seaching results are shown in Table 4. It can be seen that the degraded components are sucessfully isolated and the predicted result is accurate due to the fact that the principle of the new method is a global optimun seaching method. It also can be seen that the multiple component faults diagnosis(case 4~case 6) is much harder comparing to the single component fault diagnosis. The error level of case 1 to case 3 is 10e-3 comparing to case 4~case 6 with a 10e-2 error level.

3.2 Result analysis

3.2.1 Comparison between original PSO and SA-PSO

Case 6 is chosen as the test case. It can represent the searching process due to the complexity with multiple component faults. Two diagnosis processes, with the original PSO algorithm and proposed SA-PSO method, are shown in Figure4. It can be seen that these two are both global optimum searching methods. After a number of generations the two methods both get the accurate diagnostic result but with different speeds. For the SA-PSO method, 80 cycles is made by the SA algorithm for a global seaching, and about 120 cycle is made by the PSO algorithm for refining search. The original PSO method is much slower than the SA-PSO method. For original PSO algorithm, about 200 more cycles is needed to reach the same accuracy compared to SA-PSO method. It means that about half diagnostic time will be saved.

Table 3. Implanted degradation of different cases

Component	Symbols	Implanted degradation (%)					
		Case1	Case2	Case3	Case4	Case5	Case6
CP	DGC	-3	0	0	-3	0	-3
	DEC	-1	0	0	-1	0	-1
HT	DGT	0	2	0	2	2	0
	DET	0	-1	0	-1	-1	0
PT	DGP	0	0	2	0	2	2
	DEP	0	0	-1	0	-1	-1

Table 4. Diagnosis result of different cases

Component	Symbols	Diagnosis degradation(%)					
		Case1	Case2	Case3	Case4	Case5	Case6
CP	DGC	-2.995	7.2e-4	-1.0e-3	-3.021	6.7e-3	-3.009
	DEC	-0.997	-3.5e-4	2.3e-3	-0.995	-1.2e-3	-1.005
HT	DGT	-2.5e-3	1.9925	-2.9e-4	1.984	1.995	1.8e-2
	DET	6.2e-3	-0.9984	-2.2e-3	-1.008	-0.996	-2.1e-2
PT	DGP	3.5e-3	3.8e-3	2.018	-1.9e-2	2.039	2.039
	DEP	-2.9e-3	-3.5e-3	-0.995	3.4e-2	-0.953	-1.050

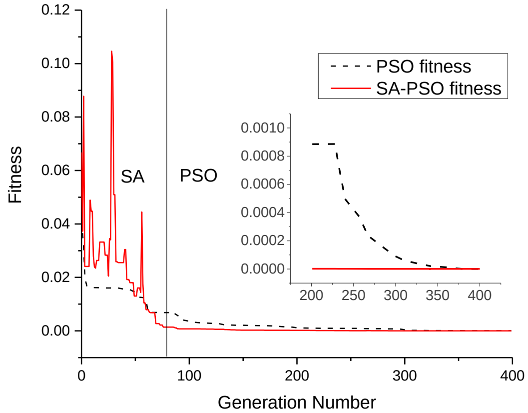

Figure 4. Fault diagnostic process comparison between original PSO and SA-PSO

3.2.2 Comparison between different PSO models

Figure 5 shows the diagnosis results with different PSO algorithm (model I-IV) of the same case (Case 6). Here, the same particle swarm simulated by annealing generator isused. It can be seen that different types of particle swarm algorithm can achieve the same accurate diagnosis results. However, the convergence processes have slightly differences. Model II has a fastest convergence speed, and model IV has the worst performance. For above models, most particles can get the area near the global optimization point after the annealing process. This will make the particle inertia be the most important factor to affcet the convergence process. Mode II is the fastest model for using the largest particle inertia and Model IV have a good speed at the begining but then it become much slower for the inertia value become smaller.

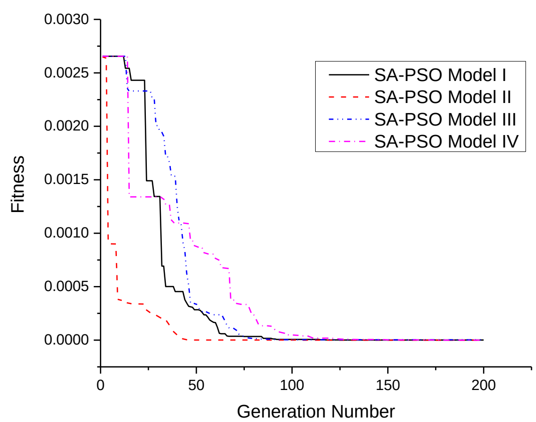

Figure 5. Fitness with different PSO Model

3.2.3 Comparison among different optimization methods

Traditional optimization method and GA method are commonly used in model based gas turbine falut diagnosis. GA algorithm is firstly used in the gas turbine fault diagnosis by Zedda and Singh for its global seaching ability. In order to get accurate results, several problems were found such as slow diagnosis speed and difficult selection with proper parameters. In this paper, a comparison between the SA-PSO, GA and traditional method is made to test the effectivencess of the proposed method for Case 6.

Considing that both GA and SA-PSO method have global searching abilities, so here the covergence speed is taken as the key goal to be compared . Figure 6 shows the coveragence process with these two methods. It can be seen that the GA method is much slower than the SA-PSO method. The time cost by the SA-PSO method is on the range of 2~3 seconds involving generation number of 200 by using a PC with 3.3GHz i5 processor and 4GB RAM. It is much shorter than the GA method which is 12~15 seconds.

Figure 7 and Figure 8 show the diagnosis process and result for the same case. It can be seen the traditional method is much faster than the SA-PSO method. The smearing effect, which usually occures with traditional method in the diagnosis process, can be effectively eliminated by SA-PSO algorithm.

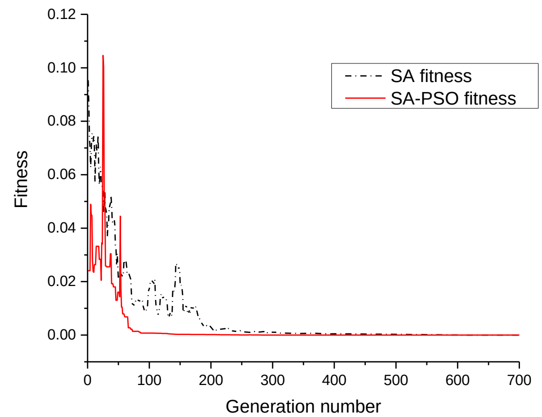

Figure 6. Fitness with GA and SA-PSO algorithm

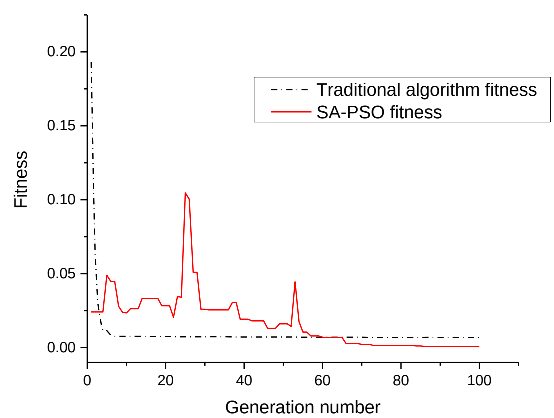

Figure 7. Fitness with traditional and SA-PSO algorithm

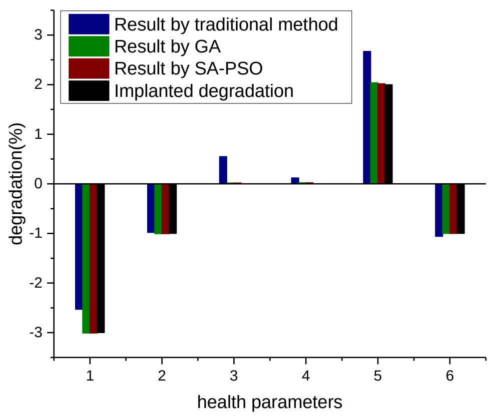

Figure 8. Diagnostic results for Test Case 6 by GA and traditional method

4. Conclusions

A new fault diagnosis method using Intelligent optimization algorithm is proposed in this paper and it is tested in a diagnostic platform for LM2500 gas turbine engine. The effectiveness of the method has been verified by six cases compared with the original PSO, the GA, and the traditional method. Different PSO models are also tested and it can be a reference for selecting parameters. Some conclusions have been obtained as follows:

(1) The method can be used successfully for single and multi component degradation diagnosis.
(2) The effect of algorithm parameters on diagnostic accuracy and speed are studied. A big particle inertia is advantageous for PSO model.
(3) The diagnostic result of this new algorithm is compared with other algorithms, such as GA, the original PSO, and traditional method. The result shows that the proposed method is much faster than the GA and original PSO. And the smearing effect which is observed by traditional method can be effectively eliminated.
(4) The numbers of iterations and population for diagnosis are substantially smaller than the GA-based method while guarantee the accuracy. Diagnostic time, on a PC with i5 processor of 3.3GHz and 4GB RAM, is on the range of 2-3s, which is much shorter than GA based method (12-15s). The result shows that the method is suitable to be used in gas path diagnostics.

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APPENDIX

Nomenclature

CBM	condition based maintenance
GPA	gas path analysis
GA	genetic algorithm
PSO	particle swarm optimization
SA	simulated annealing
OPDS	optimal particle disturbance strategy
ν	measurement noise
z	measurement parameter
x	state parameter
$\hat{z}$	prediction of measurement parameter
$\hat{x}$	prediction of state parameter
CP	compressor
HT	high pressure turbine
PT	power turbine
DGC	compressor flow rate degradation
DEC	compressor efficiency degradation
DGT	high pressure turbine flow rate degradation
DET	high pressure turbine flow rate degradation
DGP	power turbine flow rate degradation
DEP	power turbine efficiency degradation
PL	power load
T1	compressor inlet temperature
P1	compressor inlet pressure
n1	gas generator speed
P4	power-turbine exhaust pressure
PRC	compressor pressure ratio
PRP	power turbine expansion ratio
T2	compressor outlet temperature
T34	high pressure turbine exhaust temperature
T4	power turbine exhaust temperature
Qf	fuel flow