An Effective Fault Diagnosis Method for Aero Engines Based on GSA-SAE

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Abstract: The health status of aero engines is very important to the flight safety. However, it is difficult for aero engines to make an effective fault diagnosis due to its complex structure and poor working environment. Therefore, an effective fault diagnosis method for aero engines based on the gravitational search algorithm and the stack autoencoder (GSA-SAE) is proposed, and the fault diagnosis technology of a turbofan engine is studied. Firstly, the data of 17 parameters, including total inlet air temperature, high-pressure rotor speed, low-pressure rotor speed, turbine pressure ratio, total inlet air temperature of high-pressure compressor and outlet air pressure of high-pressure compressor and so on, are preprocessed, and the fault diagnosis model architecture of SAE is constructed. In order to solve the problem that the best diagnosis effect cannot be obtained due to manually setting the number of neurons in each hidden layer of SAE network, a GSA optimization algorithm for the SAE network is proposed to find and obtain the optimal number of neurons in each hidden layer of SAE network. Furthermore, an optimal fault diagnosis model based on GSA-SAE is established for aero engines. Finally, the effectiveness of the optimal GSA-SAE fault diagnosis model is demonstrated using the practical data of aero engines. The results illustrate that the proposed fault diagnosis method effectively solves the problem of the poor fault diagnosis result because of manually setting the number of neurons in each hidden layer of SAE network, and has good fault diagnosis efficiency. The fault diagnosis accuracy of the GSA-SAE model reaches 98.222%, which is significantly higher than that of SAE, the general regression neural network (GRNN) and the back propagation (BP) network fault diagnosis models.

Key words: aero engines; fault diagnosis; optimization algorithm of gravitational search algorithm (GSA); stack autoencoder (SAE) network

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0 Introduction

Aero engines are very important for aircraft. As the core system of air engines, the gas path system has been the focus of the fault diagnosis technology[1-2]. Traditional intelligent fault diagnosis methods built the fault diagnosis model of rotating machinery on the basis of neural network (BP), which incline to cause local minimum problems due to different structure selections[3]. And the general regression neural network (GRNN) algorithm has been studied because of its advantages in approximation ability and fault tolerance[4]. Gai et al.[5] used the GRNN method to carry out fault diagnose of auxiliary inverter of rail transit train. However, it is difficult to determine the smoothing factor and weak adaptive ability for the GRNN method, which may limit its further application. Therefore, as a break-

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through in the field of neural network, deep learning has attracted much attention in recent years because it can well reveal the inherent laws of complex information.

Stack autoencoder (SAE) is a type of the deep learning networks and has the advance ability of modeling, generalization and function expression, so it can solve the problems of traditional methods in feature extraction and health status recognition. Lyu[6] applied the SAE method to fault diagnosis. However, the number of neurons hidden layer is manual and random, which is difficult to get the best diagnosis result. In this paper, an effective fault diagnosis method based on the gravitational search algorithm(GSA)-SAE is proposed to solve the fault diagnosis problem for a turbofan engine. The core idea of the method is to use the GSA optimization algorithm to optimize the number of neurons in each hidden layer of SAE network. According to the optimal neuron number, an effective fault diagnosis model based on GSA-SAE method is built to improve the accuracy of fault diagnosis for aero engines, thus avoiding the influence of manual parameter selection on model.

1 Methodology

1.1 SAE network

SAE network is a deep network model composed of multi-layer sparse autoencoder and regression classification layer[7]. The sparsity constraint is added to the sparse self-encoder, which makes the SAE network have the capabilities of excellent training learning and feature extraction.

(1) Sparse autoencoder

Sparse autoencoding is to add sparse constraints to neurons in the hidden layer. The autoencoder is a nonlinear feature extraction model, including input layer, hidden layer and output layer. The hidden layer is used to encode the input from the input layer and reconstruct the input in the output layer by decoding[6,8-10]. The structure of autoencoder is shown in Fig.1.

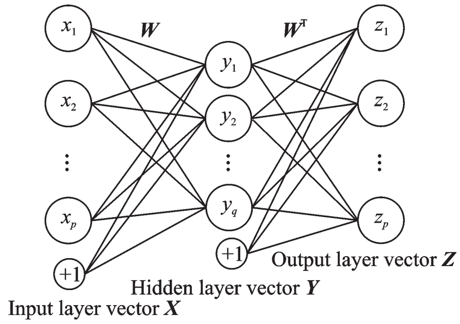

Fig.1 Schematic diagram of autoencoder

The autoencoder is a typical symmetric neural network with unsupervised learning. Fig.1 shows a three-layer autoencoder with a hidden layer. The training of the autoencoder includes the encoding process and the decoding process. The encoding process is to transform the high-dimensional features of the input data into the low-dimensional features of the hidden layer through the activation function in Eq.(1). In the decoding process, the feature representation of the hidden layer is reconstructed by the activation function as the output target through Eq.(2).

$$\boldsymbol{Y}=\sigma(\boldsymbol{W}\boldsymbol{X}+b) \tag{1}$$

$$\boldsymbol{Z}=\sigma(\boldsymbol{W}^{\mathrm{T}}\boldsymbol{Y}+b') \tag{2}$$

where $\boldsymbol{W}$ is the weight matrix from the input layer to the hidden layer, b the hidden layer threshold, σ the sigmoid activation function, $\boldsymbol{W}^{\mathrm{T}}$ the weight matrix from the hidden layer to the output layer, and b' the output layer threshold.

In order to prevent the autoencoder from the over fitting data, we can add a sparse constraint in the network so that the average activation value ρ_j of hidden layer neuron j is close to 0 and ρ is the sparse parameter. In order to restrain ρ_j deviating from ρ, KL divergence can be selected to limit, shown as

$$\sum_{j=1}^{s}\mathrm{KL}(\rho|\rho_j)=\sum_{j=1}^{s}\left[\rho\lg\frac{\rho}{\rho_j}+(1-\rho)\lg\frac{1-\rho}{1-\rho_j}\right] \tag{3}$$

where s is the total number of hidden layer neurons, j the j-th neuron of hidden layer, and $1\leqslant j\leqslant s$. The overall loss function of sparse autoencoder is shown as follows

$$J_{\mathrm{all}}(\boldsymbol{W},b)=J(\boldsymbol{W},b)+\beta\sum_{j=1}^{s}\mathrm{KL}(\rho|\rho_j) \tag{4}$$

$$J(\boldsymbol{W},b)=\left[\frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\|\boldsymbol{X}-\boldsymbol{Z}\|^{2}\right)\right]+\left[\frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_l+1}(W_{ji}(l))^{2}\right] \tag{5}$$

where β is the sparse penalty coefficient, m the total number of samples, n_l the number of network layers, s_l the number of neurons in the l layer, and λ the weight attenuation coefficient.

(2) Regression classification layer

Softmax regression classification layer is an extended form of softmax regression model, which can be used to solve multiple classification problems. And it is a supervised learning algorithm. Therefore, softmax regression is used to construct a classifier to classify the features extracted by SAE[11] in this paper.

The task of softmax regression classification layer is to make a classification according to corresponding functions. Assume that there is a training sample set and the fault type code of gas path is the number of fault type. For the input of test samples, their probabilities of belonging to each fault type can be calculated by softmax regression layer.

1.2 Gravitational search algorithm

GSA is an optimization algorithm based on the law of gravity and the Newton's second law[12]. The optimal solution based on GSA can be found by the change of the position of particles in the population. That is to say, with the continuous iteration, particles will move continuously in the search space by the gravitational force between particles. When the particle moves to the optimal position, the optimal solution is found[13].

In GSA, two variables (i.e. position and velocity) of particles are firstly initialized, and the position represents the solution of the problem[14]. For example, there are N particles in the population, the position and velocity of the i-th particle (i.e., individual) in d-dimensional space are expressed as follows

$$X_i=(x_i^1,\cdots,x_i^d)\quad i=1,2,\cdots,N \tag{6}$$

$$V_i=(v_i^1,\cdots,v_i^d)\quad i=1,2,\cdots,N \tag{7}$$

where x_i^d and v_i^d represent the position component and velocity component of particle i in the d-dimension, respectively. The mass and gravity of each particle can be determined by evaluating the objective function value of each particle. Then, the acceleration can be calculated, and the velocity and position are updated[15].

(1) Calculating mass of particles

The mass of particle i can be defined as follows

$$m_i(t)=\frac{\mathrm{fit}_i(t)-\mathrm{worst}(t)}{\mathrm{best}(t)-\mathrm{worst}(t)} \tag{8}$$

$$M_i(t)=\frac{m_i(t)}{\sum_{i=1}^{N}m_j(t)} \tag{9}$$

where $\mathrm{fit}_i(t)$ and $M_i(t)$ denote the fitness function value and mass of the i-th particle at the t-th iteration, respectively, $\mathrm{best}(t)$ and $\mathrm{worst}(t)$ the best fitness function value and the worst fitness function value of all particles in the t-th iteration. The specific definitions are as follows

$$\mathrm{fit}_i(t)=f(x_i(t))\quad i=1,2,\cdots,N \tag{10}$$

$$\mathrm{best}(t)=\min_{j\in\{1,2,\cdots,N\}}\mathrm{fit}_j(t) \tag{11}$$

$$\mathrm{worst}(t)=\max_{j\in\{1,2,\cdots,N\}}\mathrm{fit}_j(t) \tag{12}$$

(2) Calculating gravity

In the d-dimension, the gravitation of particle j to particle i is defined as follows[16]

$$F_{ij}^d=G(t)\frac{M_i(t)\times M_j(t)}{R_{ij}(t)+\varepsilon}(x_j^d(t)-x_i^d(t)) \tag{13}$$

where $M_i(t)$ and $M_j(t)$ represent the mass of particles i and j at time t, $x_i^d(t)$ and $x_j^d(t)$ the position of the i-th and j-th particles in the d-dimension, $R_{ij}(t)$ represents the Euclidean distance between the particles i and j, $R_{ij}(t)=\left|X_i(t),X_j(t)\right|$, ε is a constant to prevent the denominator from being zero, $G(t)$ the coefficient of universal gravitation at the time of iteration t, and the formula is as follows

$$G(t)=G_0\mathrm{e}^{-\alpha\frac{t}{T}} \tag{14}$$

where G_0 and α represent two constants, t is the number of iterations of the current group, and T the total number of iterations of the algorithm.

In the d-dimension, the resultant force on the particle can be written as follows

$$F_i^d(t)=\sum_{j\in k_{\mathrm{best}},j\neq i}^{N}rF_{ij}^d(t) \tag{15}$$

where r denotes a random variable with uniform distribution between $[0,1]$, k_{best} represents the number of particles with the highest particle mass and decreases linearly with the number of iterations. The initial value is N and the final value is 1.

(3) Calculating acceleration

According to the Newton's second law, the acceleration equation of particles in the second dimension is

$$a_i^t(t)=\frac{F_i^d(t)}{M_i(t)} \tag{16}$$

(4) Updating speed and location

The mass, force, acceleration, velocity and position of particles in the population can be calculated according to Eqs.(17) and (18).

$$v_i^d(t+1)=r\times v_i^d(t)+a_i^d(t) \tag{17}$$

$$x_i^d(t+1)=x_i^d(t)+v_i^d(t+1) \tag{18}$$

Through the analysis of GSA algorithm, we can see that the particles in the population move under the attraction. The particles with smaller mass have longer steps under the same attraction, while the particles with larger mass have shorter steps. The longer step of particles is helpful to the global search. Meanwhile, it can prevent particles from falling local optimum. Instead, the shorter step of particles is helpful to the local search and can improve the convergence accuracy of the algorithm. Finally, the particles gradually converge to the optimal position to achieve the purpose of optimization.

2 Fault Diagnosis Scheme of Aero Engines

2.1 Fault diagnosis scheme based on GSA-SAE

A special data sensor network is used to collect the relevant parameters of the gas path system of a turbofan engine. The data are standardized and preprocessed, which are divided into training sample set and test sample set. The GSA optimization algorithm is used to optimize and determine the number of neurons nodes in each hidden layer of SAE network to obtain the optimal SAE network, thus avoiding the impact of manual setting the number of neurons nodes in SAE network. In this way, a fault diagnosis model of the gas path system of a turbofan engine is established using the training sample set. Furthermore, the fault diagnosis technology is studied, and its scheme of the gas path system based on GSA-SAE is shown in Fig.2.

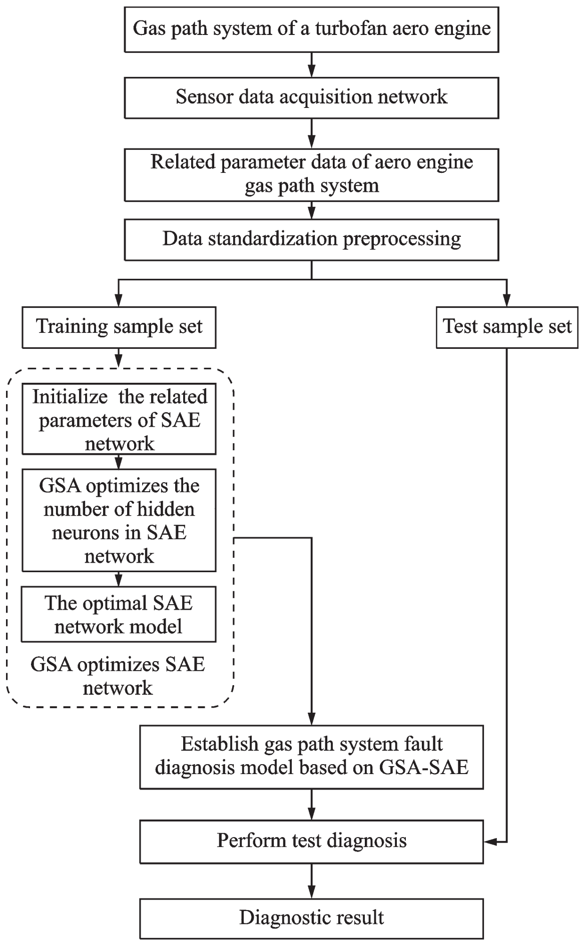

Fig.2 Fault diagnosis scheme of an aero engine based on GSA-SAE

2.2 Optimization of SAE network based on GSA algorithm

The core idea of GSA optimization algorithm is: Firstly, the number of neurons in input layer and output layer of SAE network is determined; Secondly, the initial population is generated randomly, that is, the number of neurons in each hidden layer of SAE network is randomly initialized. On this basis, the number of neurons in each hidden layer of SAE network is optimized by a series of operations such as constantly updating the speed and position of particles until the optimization conditions are met. Therefore, the number of neurons in each hidden layer of SAE network can be finally determined.

The end conditions of the optimization process are that: Whether the number of iterations reaches the set value or whether the value of fitness function meets the requirements. If the optimization condition is satisfied, the search is stopped and the optimization algorithm is finished. The optimal number of neurons in each hidden layer of SAE network can be obtained.

The specific process of GSA algorithm to optimize SAE network is shown in Fig.3.

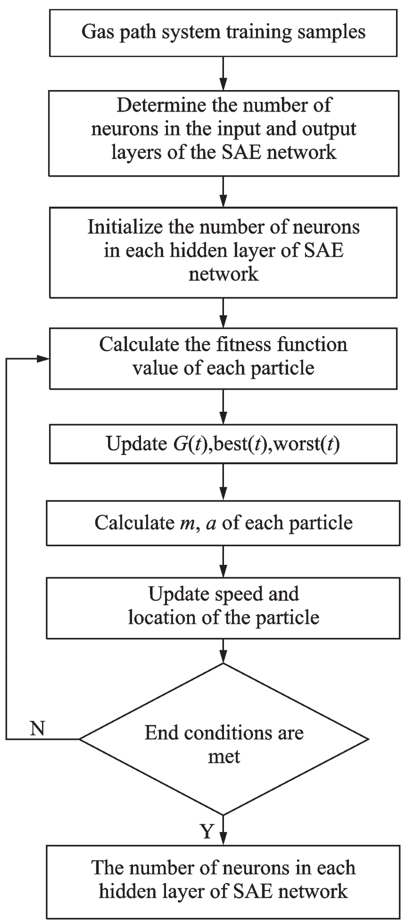

Fig.3 Process of optimizing the number of neurons in each hidden layer of SAE network

3 Fault Diagnosis Steps

The above fault diagnosis strategies are used to diagnose the gas path system of a turbofan engine. The specific steps are as follows:

Step 1 Standardize and preprocess the collected data.

Step 2 Divide the standardized data into training data set and test data set.

Step 3 Set the number of neurons in the input layer and output layer of SAE network and determine the structure of SAE network according to the actual needs.

Step 4 Initialize the number of neurons in each hidden layer of SAE network.

Step 5 Optimize the number of neurons in each hidden layer of SAE network using GSA algorithm, and determine the number of neurons in each hidden layer of SAE network.

Step 6 Establish the optimal fault diagnosis model based on SAE network using training sample set data.

Step 7 Take the test data set as the input of the optimal SAE network, obtain and analyze the diagnosis results.

4 Experimental Verification

4.1 Data collection

In order to verify the effectiveness of the method proposed in this paper, the monitoring data of 17 parameters of the turbofan engine in flight status are used as data samples in experiment, including total inlet air temperature, high-pressure rotor speed, low-pressure rotor speed, turbine pressure ratio, total inlet air temperature of high-pressure compressor, outlet air pressure of high-pressure compressor, total gas temperature after low pressure turbine combustion, oil pressure difference, oil return temperature, high pressure speed increase rate, cabin pressure, adjustable blade angle of compressor, engine casing vibration, nozzle throat diameter, adjustable blade angle of fan, afterburner connotation of fuel flow measurement valve displacement, and afterburner fuel flow measurement valve displacement.

Due to the different dimensions of the parameters, it is necessary to carry out standardization and preprocess in order to improve the accuracy of fault diagnosis.

Select 560 samples as the training set (including 320 normal samples, 140 samples with afterburner fault, and 100 samples with fake breath fault) and 225 samples as test set (including 128 normal samples, 57 samples with afterburner fault, and 40 samples with fake breath fault). The number of training samples and test samples for each state is shown in Table 1.

Table 1 The number of training samples and testing samples for each state of aero engines

Number	Category	Training sample	Test sample
1	Health status	320	128
2	Afterburner fault	140	57
3	Fake breath fault	100	40

4.2 Verification and result analysis

In order to verify the effectiveness of the proposed method and simplify the complexity of the network, a stack autoencoding network with two hidden layers is designed. The number of neurons in the two-layer hidden layer of SAE network model is optimized by the GSA optimization algorithm. The optimal numbers of neurons in the two hidden layers of SAE network model are 47 and 47, respectively. Other parameters of SAE network model are set as follows: The maximum number of iterations is set to 1 000, the learning rate is set to 0.01, the sparsity parameter is 0.1, the weight attenuation coefficient is 0.002, and the weight of sparse penalty term is 3. The network structure parameters of GSA-SAE model are shown in Table 2.

Table 2 Structure parameters of GSA-SAE network model

Network structure	The number of neurons
Input layer	17
The first layer	47
The second layer	47
Output layer	3

According to the above parameters, the optimal fault diagnosis model of GSA-SAE can be obtained. And 225 test samples are used for fault diagnosis test study.

To compare the results of different methods, SAE network, GRNN and BP models are built using the same test set, respectively. The engine states corresponding to the output layer neurons of each diagnosis network model are shown in Table 3.

Table 3 Aero engine states corresponding to neurons in output layer of fault diagnosis model

Status of aero engine	Diagnostic network output
Health status	1 0 0
Afterburner fault	0 1 0
Fake breath fault	0 0 1

The same test set data are used as the input of GSA-SAE, SAE, GRNN and BP network fault diagnosis models. The different diagnosis results are shown in Table 4.

Table 4 Accuracy of fault diagnosis based on different models

Fault diagnosis model	Diagnostic accuracy/%
GSA-SAE	98.222
SAE	95.556
GRNN	91.110
BP	85.330

The main parameters of different fault diagnosis models are set as follows:

(1) SAE model: The number of neurons in the input layer is 17, the number of neurons in the first hidden layer is 70, the number of neurons in the second hidden layer is 70, and the number of neurons in the output layer is 3.

(2) GRNN model: The number of neurons in the input layer is 17 and the number of neurons in the output layer is 3. The value of smoothing factor is 0.14.

(3) BP model: The number of neurons in the input layer is 17 and the number of neurons in the hidden layer is 35. The activation function of the hidden layer is the Sigmoid function, and the number of output neurons is 3.

From Table 4, it can be seen that the GSA-SAE model has the best diagnosis results with an accuracy of 98.222%. It is obviously higher than SAE, GRNN and BP network model, which verifies the effectiveness of the GSA-SAE method.

5 Conclusions

The accuracy of fault diagnosis for aero engines is not high in practical application. In this paper, an effective fault diagnosis method based on GSA-SAE is proposed for a turbofan engine. Firstly, the monitoring data of 17 parameters are preprocessed. After preprocessing, the data of 17 parameters are divided into training sample set and test sample set. Then, the SAE fault diagnosis model is constructed. In order to solve the problem of manual setting the number of neurons in each hidden layer of SAE network, this paper proposes a GSA optimization algorithm to optimize the SAE network to find and obtain the optimal number of neurons in each hidden layer of SAE network. On this basis, the optimal fault diagnosis model of aero engines based on GSA-SAE is established. The validity of the optimal GSA-SAE model is verified using collected aero engine data. In this paper, the same training sample set and test sample set are used to build different fault diagnosis models and carry out simulations in order to show the advantages of the proposed GSA-SAE method. The results show that the accuracy of the proposed GSA-SAE fault diagnosis method is significantly higher than that of SAE, GRNN and BP network models. Based on the proposed method, the problem that the number of neurons in each hidden layer of SAE network usually depends on manual setting has been well solved, which effectively improves the performance of fault diagnosis.

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Author contributions Prof. **CUI Jianguo** designed the technical solution, and revised the article. Ms. **TIAN Yan** designed the fault diagnosis method and wrote the first draft of the article. Mr. **CUI Xiao**, Dr. **TANG Xiaochu**, Mr. **WANG Jinglin**, Dr. **JIANG Liying** and Dr. **YU Mingyue** tested and verified the fault diagnosis method. All authors commented on the manuscript draft and approved the submission.

Competing interests The authors declare no competing interests.

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基于GSA-SAE的航空发动机故障诊断方法

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摘要:航空发动机的健康状态对飞机的飞行安全至关重要,而航空发动机实际工作时常常由于其结构复杂、工作环境恶劣等因素难以对健康状态进行有效的故障诊断。本文提出了一种基于引力搜索方法(Gravitational search algorithm, GSA)和堆栈自动编码器(Stack autoencoder ,SAE)的航空发动机故障诊断方法,并对某型涡扇航空发动机进行了故障诊断技术研究。首先,对获取的某型涡扇航空发动机进口空气总温、高压转子转速、低压转子转速、涡轮落压比、高压压气机进口空气总温和高压压气机出口空气压力等17个参数的数据进行预处理,创建SAE故障诊断模型架构。为解决SAE网络各隐含层神经元数目需要人为设置而导致不能获得最佳诊断效果问题,提出了采用GSA优化算法对SAE网络进行优化,寻找并获取最佳SAE网络各隐含层神经元个数。在此基础上,创建基于GSA-SAE的最优航空发动机故障诊断模型,并由获取的航空发动机相关参数数据对创建的最优GSA-SAE故障诊断模型的有效性进行了试验验证。结果表明,本文提出的基于GSA-SAE的航空发动机故障诊断方法能够有效地解决SAE网络各隐层神经元数目由于依靠人为设置而导致故障诊断效果不佳的问题,避免了人为因素的干扰与影响,具有良好的故障诊断效能。GSA-SAE模型的故障诊断准确率高达98.222%,优于SAE、广义回归神经网络(General regression neural network,GRNN)和反向传播 (Back propagation, BP)诊断模型的故障诊断准确率。

关键词:航空发动机;故障诊断;引力搜索方法优化算法;SAE网络