Journal of Computers Vol. 33 No. 3, June 2022, pp. 59-71
doi: 10.53106/199115992022063303005

Stall Warning Algorithm of Axial Compressor Based on SSA-DBN

Xiao-Hong Qiu*, Jia-Li Chen, Zi-Ying Ao

Department of Software Engineering, Jiangxi University of Science and Technology, Nanchang 330013, China
chenjiali19951221@163.com

Received 13 July 2021; Revised 14 November 2021; Accepted 14 December 2021

Abstract. To solve the problem of stall warning for axial compressors, this paper proposes a stall warning algorithm based on the sparrow search algorithm, which optimizes the deep belief network. The deep belief network is trained by using deep learning to extract the FFT spectrum of compressor stall experiment data directly as the feature vector. To improve the accuracy of DBN classification, parameters of hidden layer nodes n and initial weights w of DBN were optimized by SSA algorithm, and stall warning algorithm model of SSA-DBN axial-flow compressor was established. The experimental results of the algorithms show that the stall data at each speed is at least 0.1 ～ 0.3s in advance for early warning. This method is 0.075~0.281s ahead of the various models from the past to the present, and noise is superimposed on the experimental data to verify the Robustness of the way, better surge warning margin performance, and engineering practicability.

Keywords: deep belief network, sparrow search algorithm, parameter optimization, SSA-DBN, axial compressor

1 Introduction

The rotating stall of the compressor can easily lead to surging, resulting in broken blades and damage to the internal structure of the compressor, which in turn affects the safety and performance of the compressor, and even reduces the economic benefits of the compressor [1]. Therefore, how to accurately capture the compressor instability signal and provide an effective early warning plan accordingly have become the focus of attention of many researchers around the world [2]. Many types of Research have been done on the rotating stall of the axial compressor. For example, Day [3] and McDougall et al. [4] have found two separate instability precursors through experiments, namely the tip type and the modal wave type, which provide two different stall warning methods. Prominent achievements include Wavelet energy [5], Chaotic time series analysis [6], Wavelet analysis [7], auto-correlation coefficient [8], Multi-resolution wavelet analysis [9], etc. They discussed the characteristics of the compressor and explored the stall detection method. However, these stall detection methods depend on stall signal, and the warning margin is not enough. Analysis of the variance [10] can detect the presence of compressor disturbance stall. Still, this kind of method is susceptible to external factors and depends on the operating speed of the compressor, so it is necessary to determine stall according to different thresholds. Many ways have been proposed, including short-term energy [11], modal wave theory [12], fluctuating pressure change rate [13], theoretical study on the amplitude and frequency [14], etc. And other research pointed out that the compressor disturbance stall precursor can be detected. Still, this type of method is susceptible to external factors and depends on the working speed of the compressor. It is necessary to judge whether the stall is stalled according to different thresholds or not. Li et al. [15] used the cross-correlation analysis to warn the compressor stall effectively, but it is susceptible to external noise. The compressor under actual total intake is also more complicated, and there are specific problems in practicability. Liu et al. [16] used the spatial Fourier transform to detect the spike-type stall precursor disturbance effectively. Li et al. [17] further studied the spike-type stall precursor and controlled the stall actively, but the various speed modes are highly complex. These research and studies can detect stall signals in experiments, but these methods have not widely used in practical engineering. Therefore, reliable and effective stall warning methods are essential in compressor stall warning.

In the previous studies, Methling et al. [18] discussed the possibility of using an artificial neural network to identify the initial surge stall detection of the compressor. The characteristics of distorted stall precursor of the compressor are detected by neural network modeling. The most significant disadvantage of this method is that when it is used for modal type judgment. It needs to adopt a time-domain modal matching method to establish modal library, so the timeliness is not vital. The above methods used for compressor signal identification can neither extract effective features nor find a standard value that can distinguish normal operation, early warning oper-

* Corresponding Author

ation and stall operation. The warning of the compressor cannot be judged from the operation near the stall line. Lin [19] uses neural network modeling to detect the characteristics of the compressor distortion stall precursors. The biggest shortcoming of that when this method is used for modal judgment, the time domain modal matching method needs to be used to establish a modal library, which is not very time-sensitive. The above techniques is used for compressor signal recognition, which can neither extract compelling, practical features nor find a common value that can distinguish regular process, early warning operation and stall operation. It cannot judge the compressor early warning status from the operating conditions near the stall line.

The neural network has the advantage of solid characteristics learning ability, and it is seldom used in the research of compressor stall early warning. Therefore, this paper takes the experimental data of dynamic pressure stall at the output of a multi-stage high-speed compressor as an example. From the perspective of deep learning, combined with the advantages of deep belief network (DBN) in feature extraction and processing of high-dimensional data, an SSA-DBN-based axial compressor stall early warning algorithm is proposed. This method extracts features from the disturbing data when the compressor stalls and extracts the FFT spectrum as the feature vector classifies the compressor stall pressure data. To improve the accuracy of DBN classification, the Sparrow Search Algorithm (SSA) is used to optimize the weight parameters w and the hidden layer nodes n of DBN, which effectively improves the classification accuracy of DBN and achieves compressor stall warning.

The first part describes the background of the axial flow compressor and the research status at home and abroad. The second part introduces the deep belief network and sparrow search algorithm. In the third part, the stall warning method of SSA-DBN axial compressor is proposed. The sparrow search algorithm is used to optimize the weight and node number of the hidden layers of the deep belief network, and the optimal network structure is obtained. In the fourth part, the simulation data provided by airlines are preprocessed and then tested to get stable and reliable results. Other methods are used to experiment with the same data, and after comparison, it is found that the method proposed in this paper is more advantageous. The fifth part is the summary of the work.

2 Related Work

2.1 Deep Belief Networks

In this section, we introduce Deep Belief Networks (DBN). DBN is an unsupervised deep neural network fast learning algorithm proposed by Hinton et al. [20] in 2006. DBN is a probability generation model that adjusts the parameters between its neurons through training. It makes the whole DBN generate training data according to the trend of maximum probability, forms high-level abstract features, and improves the performance of model classification. DBN can be used not only for feature recognition but also for feature classification, and are used in various fields, including fault detection and diagnosis [21-23].

In this paper, the two-layer restricted Boltzmann machine and the Softmax classification layer are taken as examples to construct a DBN model that can finally be implemented in practical applications. The model construction is shown in Fig. 1. V1~vm represent the explicit layer neurons, h1~hn, h1~hk express hidden layer neurons, y1~yp represent samples with known labels, and o1 and o2 represent the output of the classification results.

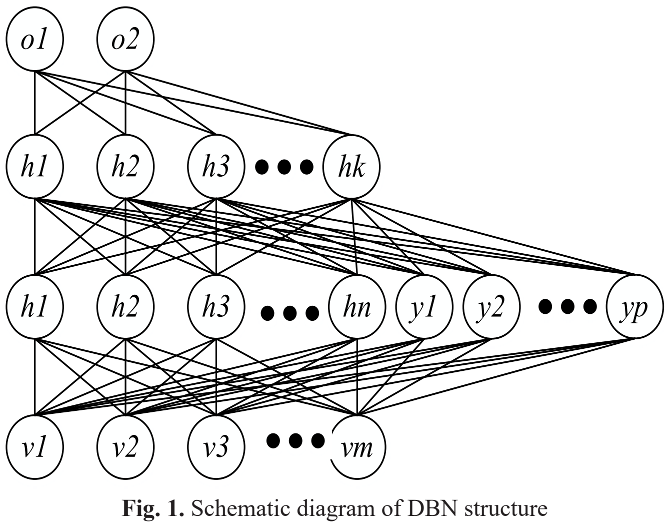

Fig. 1. Schematic diagram of DBN structure

The process of training RBM is to find the optimal weights of the connection between the visible layer nodes and the hidden layer nodes. Here we use the classic learning algorithm, contrast divergence (CD) algorithm, as an example to update the weights. The RBM weight update steps are as follows.

Step 1: Firstly, sample the training sample set, assuming that each sampling record is marked as X.

Step 2: Secondly, input X into the visual layer $v^{(0)}$ and calculate the probability that the record makes the hidden element open as formula (1).

$$P(h_j^{(0)} = 1 | v^{(0)}) = \sigma(W_j v^{(0)}) . \quad \textbf{(1)}$$

Step 3: Then, reconstruct the visible layer, and extract a sample of the hidden layer from the calculated probability distribution as shown in formula (2).

$$h^{(0)} \sim P(h^{(0)} | v^{(0)}) . \quad \textbf{(2)}$$

Step 4: Next, calculate the activation probability of hidden elements, based on extracting samples from the explicit layer and using reconstructed clear layer neurons to calculate as formula (3).

$$P(v_i^{(1)} = 1 | h^{(0)}) = \sigma(W_i^T h^{(0)}), v^{(1)} \sim P(v^{(1)} | h^{(0)}) . \quad \textbf{(3)}$$

Step 5: Finally, the weight w is updated according to the correlation difference between the hidden layer neurons and the visible layer neurons, as shown in formula (4).

$$P(h_j^{(1)} = 1 | v^{(1)}) = \sigma(W_j v^{(1)}), W \leftarrow W + \lambda(P(h^{(0)}=1 | v^{(0)}) v^{(0)T} - P(h^{(1)} = 1 | v^{(1)}) v^{(1)T}) . \quad \textbf{(4)}$$

In the formula, v represents the graphic element, m and n represent the number of detailed elements and hidden elements, the superscript in the procedure represents the sampling step. And $v^{(0)} h_j^{(0)}$ represents the exact layer and the first sampling of the hidden layer, w represents the connection weight between layers. After it is trained, it can determine the state of the hidden element corresponding to a new record in the input layer.

2.2 Sparrow Search Algorithm

In this section, we introduce Sparrow Search Algorithm (SSA). SSA is a new swarm intelligence optimization algorithm that it proposed by Xue et al. [24] based on the foraging behavior and anti-predation behavior of sparrows in 2020. In the process of foraging for sparrows, it is divided into discoverers and followers. The discoverers in the population are responsible for finding food and providing foraging areas and directions for the entire sparrow population, while followers use the discoverers to obtain food. To get food, sparrows usually use two behavioral strategies, the discoverer and the follower, to forage. To increase their predation rate, individuals in the population will monitor the behavior of other individuals in the group and compete with high-intake companions for food resources. In the mathematical model [25], the discoverer with a better fitness value of the SSA algorithm will prioritize food during the search process. Because the discoverer is responsible for finding food for the entire sparrow population and providing foraging directions for all followers, the discoverer can obtain a more extensive foraging search range than the followers. The advantage of this algorithm is that it has strong global search ability, fast optimization speed, and fast convergence speed.

Suppose that the sparrow population is represented by a mathematical model as.

$$Y = \begin{bmatrix} y_1^1 & y_1^2 & \cdots & y_1^d \\ y_2^1 & y_2^2 & \cdots & y_2^d \\ \cdots & \cdots & \cdots & \cdots \\ y_m^1 & y_m^2 & \cdots & y_m^d \end{bmatrix} . \quad \textbf{(5)}$$

In the above formula (5), m represents the number of sparrows; d represents the dimension of the optimized variable.

Then the fitness value of all sparrows is expressed by a mathematical model as.

$$F_Y = \begin{bmatrix} f([y_{1,1} & y_{1,2} & \cdots & y_{1,d}]) \\ f([y_{2,1} & y_{2,2} & \cdots & y_{2,d}]) \\ \vdots & \vdots & \vdots & \vdots \\ f([y_{m,1} & y_{m,2} & \cdots & y_{m,d}]) \end{bmatrix}. \tag{6}$$

In the above formula (6), the value of each row F_Y is the fitness value of the individual.

In the search process, generally, the sparrows with higher adaptability will get food first. As the leader of the sparrow population, the explorer is responsible for searching for food and providing directions for searching for food, so the explorer has the more extensive range of food searches.

When there is no predator around the sparrow population, the explorer can search for food at will. If a predator is found around, the explorer will lead his followers to a safe place.

The position of the explorer is represented by a mathematical model.

$$Y_{i,j}^{t+1} = \begin{cases} Y_{i,j} \bullet \exp\left(-\dfrac{i}{\alpha.iteration_{\max}}\right), R_2 < ST \\ Y_{i,j} + Q.L, R_2 \geq ST \end{cases}. \tag{7}$$

In the above formula (7), t is the current number of iterations. $iteratin_{\max}$ is the maximum number of iterations. $Y_{i,j}$ is the position information of the i the sparrow in the j the dimension. α is a random number, $\alpha \in (0,1]$. $R_2 \in (0,1]$. ST represents a safe value, $ST \in (0.5,1]$. And Q represents a normal distribution of the random number. L is a $1 \times d$ matrix, where all elements in the matrix are 1.

If $R_2 < ST$, it means that there are no predators around the sparrow population. Otherwise, there are predators around the sparrow population.

In the entire sparrow population, the proportion of explorers and followers is certain. Only by finding good food, can one become an explorer and vice versa. The foraging environment and range of the followers of the sparrow population are relatively poor. However, they will always pay attention to the explorer's situation and compete with the explorer for food. If the grab is successful, they will obtain the explorer's food instead of going farther to search for food.

And the position of the follower is represented by a mathematical model.

$$Y_{i,j}^{t+1} = \begin{cases} Q.\exp(\dfrac{Y_{worst} - Y_{i,j}^t}{i^2}), j > m/2 \\ Y_P^{t+1} + \left|Y_{i,j} - Y_P^{t+1}\right|.A^+, j \leq m/2 \end{cases}. \tag{8}$$

The above formula (8): Y_{worst} represents the global worst position; Y_P represents the best position among the current discoverers; A represents a 1xd matrix, where each element in the matrix is 1 or -1, and $A^+ = A^T(AA^T)^{-1}$.

If $i > m/2$, it means that the followers did not get food this time and needed to search for food farther away.

In the entire sparrow population, suppose that vigilance accounts for 10% to 20% of the total. The initial position of the vigilant is randomly distributed in the population. If the alert person realizes that there are predators around, the outer sparrows will fly quickly and safely to obtain a better environment for searching for food. The inner sparrows will move around in the safe area to reduce the probability of predation.

The vigilant is expressed in a mathematical model as.

$$Y_{i,j}^{t+1} = \begin{cases} Y_{best}^{t} + \beta \cdot \left| Y_{i,j}^{t} - Y_{best}^{t} \right|, f_i > f_b \\ Y_{i,j}^{t} + L \cdot \left(\dfrac{\left| Y_{i,j}^{t} - Y_{worst}^{t} \right|}{(f_i - f_w) + \varepsilon} \right), f_i = f_b \end{cases} . \quad \mathbf{(9)}$$

In the above formula (9): Y_{best} is the current global optimal position. β is the step size and obeys the standard normal distribution. L represents a random number, f_i is the fitness value of the present sparrow individual; f_b is the current global best fitness; f_w is the current global worst fitness value; ε is a constant to avoid 0 in the denominator.

When $f_i > f_b$, it means that the outer sparrow has found a predator, otherwise, the middle sparrow has found a predator.

3 Proposed Methods

We proposed a Sparrow Search Algorithm to optimize the Deep Belief Network (SSA-DBN). The specific optimization steps of SSA-DBN are as follows:

(1) Set n to the total number of sparrows in the SSA algorithm. Set the maximum iteration includes the proportion of discoverers, the proportion of followers, and the value range of W and H_{nodes}. Randomly initialize sparrow population;

(2) Calculate the fitness of each sparrow and sort it to define the population to which each sparrow belongs;

(3) Update the position of each sparrow population according to formula (7-9);

(4) Compare the fitness before and after the update, keep the better fitness and continue to update;

(5) Determine whether the number of iterations. If it is not iteration, skip to (2) to continue until it is iteration and terminate the operation;

(6) The position of the optimal fitness obtained is the weight W and H_{nodes} of DBN.

The stall warning process of the SSA-DBN axial compressor based on FFT extraction features is as follows:

(1) Perform Oneshot coding on the wall pressure signal of the axial flow compressor and randomly divide it into training samples, verification samples, and test samples;

(2) Perform Fourier transform on the training samples, verification samples, and test samples, extract the FFT spectrum as the feature vector for stall warning, and then normalize the feature vector as the input value of the network;

(3) Use SSA-DBN to perform stall warning judgment on the obtained input value.

The overall flow diagram is shown in Fig. 2.

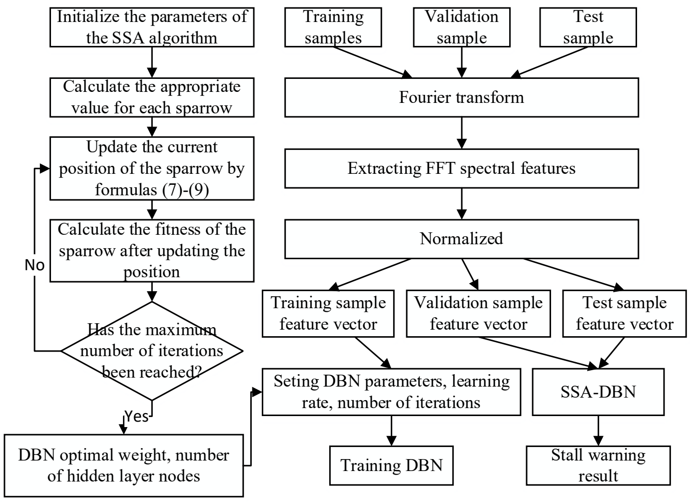

Fig. 2. Schematic diagram of the SSA-DBN model process

SSA-DBN algorithm is shown in Table 1 below.

Table 1. SSA-DBN algorithm

SSA-DBN Algorithm
FUNCTION bestX,Covergence_curvel
Clear all variables
Define sparrow number of population (pop)
Define maxinum number of iterations
Define the population size of producers accounts for “P-percent”percent of the total
Initialization
For i->pop
fit(i)=fitness(hiddenum,X(i,))
bestX=X
end
pFit=fit
pX=x
fMin=fit(1)
bextX=x(i,:)
For t->M
Explorer location updated
Followers location updated
Peripheral sparrow position changed
A change in the position of a sparrow in a population
fit(sortIndex(b(j))=fitness(hiddenum,x(sortIndex(b(j))
end
For i->pop
if fit(i)<pFit(i)
pFit(i)=fit(i)
pX(i,:)=x(i,:)
end
pFit(i)<fMin
fMin=Pfit(i)
bestX=pX(i,:)
end
end
Convergence_curve(t)=fMin
end of function

4 Experiment Results

4.1 Experiment Data

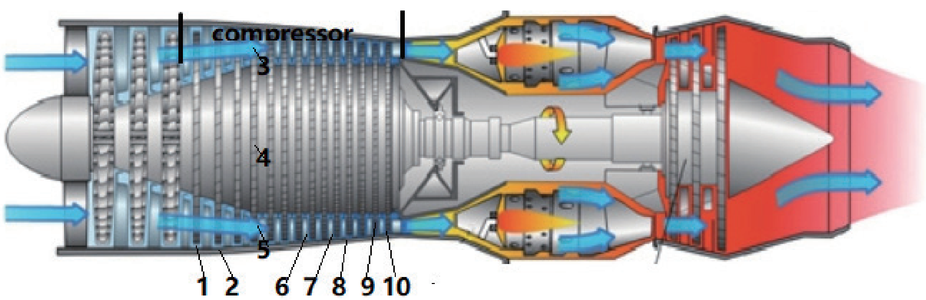

Fig. 3. Compressor

Fig. 3 is a compressor diagram, and 1-10 is the sampling point for the compressor pressure signal. Taking two models of high-speed multi-stage compressors as the experimental objects, the sampling rate of the experimental data of one model is 6kHz. The experiment selects the pressure signal data of the multi-stage axial compressor speeds of 70%, 75%, 80%, 90%, 95%, 98% and changes the angle of the blade fan. The pressure signal data speeds of 80%, 85%, 90%, 95%, 98% of the blade fan pressure. The sampling rate of the experimental data of another model is 10kHz, and the experiment selects the pressure signal data of the multi-stage axial compressor under normal conditions and changing the angle of the blade or changing the speeds of 50%, 60%, 70%, 75%, 80%, 85%, 90% of the blade pressure.

Due to limited space, only a few examples are shown. Through experimental analysis, the signal characteristics of the first-stage air inlet of the axial compressor are the most sensitive. The signal characteristics of the second, third, and fourth stage channel are similar to the signal characteristics of the first stage inlet. However, the stall signal characteristics of the rear inlet will be more and more delayed. Due to the length of the paper, only two sets of signals are shown. As shown from Fig. 4 and Fig. 5, the stall signal of the first stage inlet of the compressor is earlier than that of the last stage inlet. Therefore, the first stage inlet is selected for experimental data, and the data of the previous stage inlet is used as reference.

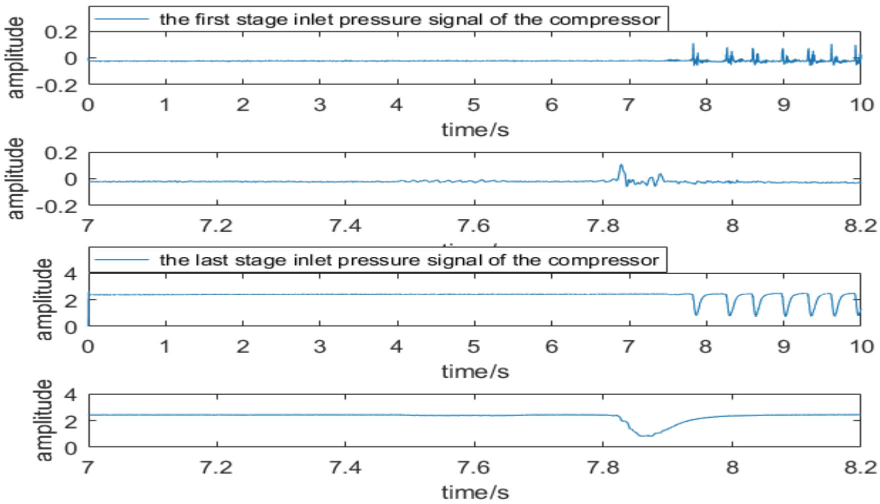

Fig. 4. The first and last stage air inlet pressure signals and partially enlarged diagrams at 70% speed

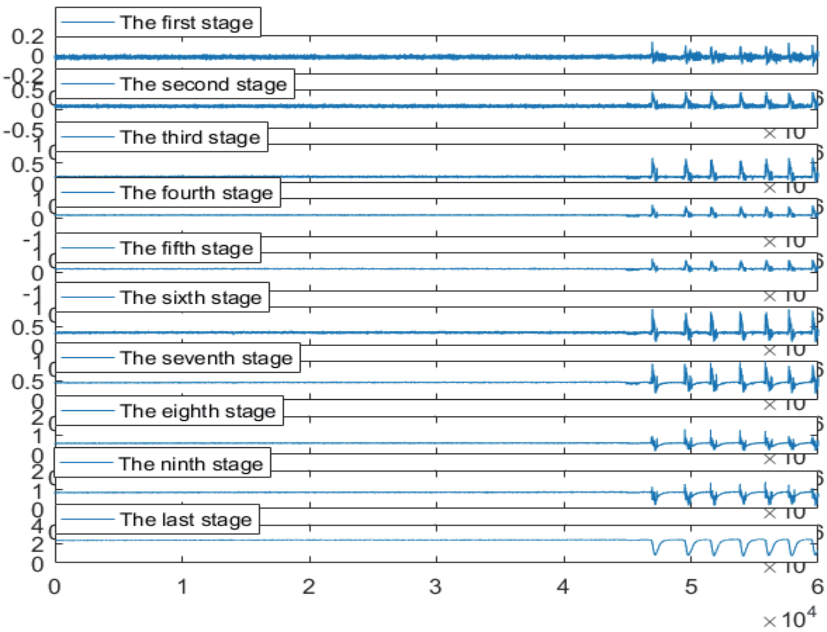

Fig. 5. The pressure signal of each stage of the air inlet at 70% speed

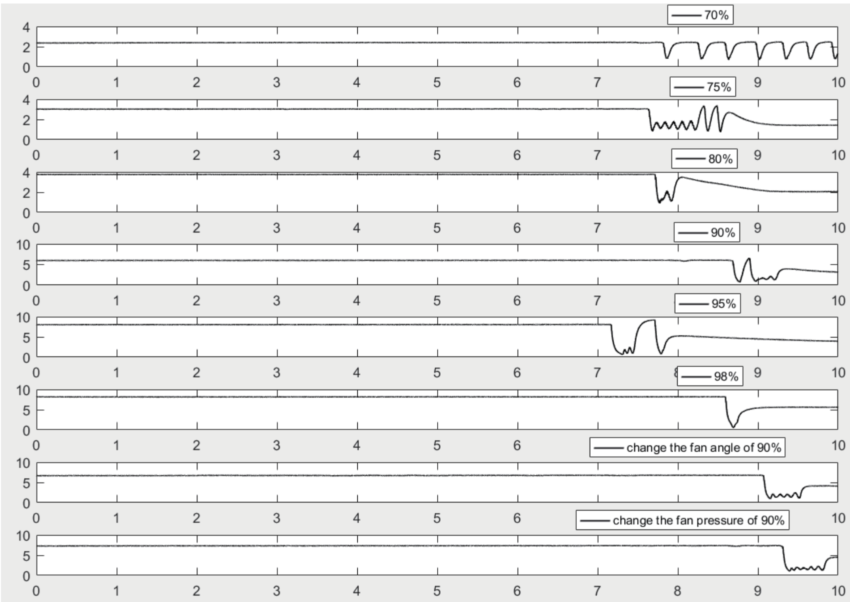

Fig. 6. Different levels of inlet pressure signals

As shown in Fig. 6, we use compressor speeds of 70%, 75%, 80%, 90%, 95%, 98%, change the blade fan angle speed to 90%, change the blade fan pressure speed to 90%. Table 2 shows the data classification, including normal operation state and stall operation state. The stall operation state includes the small disturbance state before the stall.

The Fast Fourier transform (FFT) transformation processing of signal pressure data. At the time of sampling, perform FFT transformation.

$$x(n) = \sum_{t=1}^{N} x(t) e^{-\frac{2j\pi tn}{N}}, (t = 1, 2, ..., N) \quad . \tag{10}$$

The absolute value of $x(n)$ is the amplitude of the corresponding frequency points nN/fs , and the frequency interval is fs/N .

In this paper, 1024 points are selected for FFT transformation. The eigenvalues are sampled and extracted by using the above formula (10).

Table 2. Data

Classification	Normal operation state (point)	Stall operating state (Contains forewarning of the stall)
n^r=70%	1~45000	45001~60000
n^r= 75%	1~45000	45001~60000
n^r= 80%	1~45000	45001~60000
n^r= 90%	1~50000	50001~60000
n^r= 95%	1~42000	42001~60000
n^r= 98%	1~50000	50001~60000
Change the fan angle n_r= 90%	1~54000	54001~60000
Change the fan pressure n_r= 90%	1~54000	54001~60000
Another type of compressor n_r=50%	1~50000	50000~130000

4.2 Experiment Results

The experimental environment was performed in Matlab2016a on a 2.30Hz Intel i5-6300H processor and 8GB memory computer.

Taking the data of 70% rotational speed of an axial compressor as an example, several other methods are compared. The results are shown in Table 3.

Table 3. A comparison of several other methods

Accuracy	SVM	KNN	BP	DBN	SSADBN
Average training accuracy (%)	52.50	99.15	98.76	97.86	100.00
Average test accuracy (%)	47.37	99.02	99.34	100.00	100.00

A brief comparison of the different models is presented in Table 4. The accuracy of the SSA-DBN model is much higher than that of the DBN model, which shows that the SSA optimization DBN algorithm has a significant effect.

Through experiment analysis, the SSA-DBN model has higher classification accuracy compared with the DBN model. This shows that there is no probability of misjudgment, so it has got the axial flow. The effect of compressor early warning and realized early warning. Among them, the maximum number of iterations of DBN is 100 times. To make the experiment more convincing, 30 experiments were carried out for the following two models.

Table 4. Comparison of classification accuracy under the two methods

Method	DBN		SSA-DBN	
Rotating speed	***Training accuracy***	***Test accuracy***	***Training accuracy***	***Test accuracy***
n_r= 70%	97.86%	100.00%	100.00%	100.00%
n_r= 75%	86.78%	90.00%	99.64%	100.00%
n_r= 80%	83.92%	77.50%	100.00%	100.00%
n_r= 90%	85.35%	77.50%	98.93%	92.50%
n_r= 95%	84.64%	85.00%	100.00%	100.00%
n_r= 98%	57.86%	40.00%	94.64%	90.00%
Change the fan angle n_r= 90%	91.07%	85.00%	100.00%	100.00%
Change the fan pressure n_r= 90%	92.50%	90.00%	100.00%	100.00%
Another type of compressor n_r= 50%	86.42%	85.00%	95.00%	95.00%

Take the data of 95% rotational speed of axial flow compressor as an example. The fitness evolution curve of SSA optimized DBN and the training accuracy and test accuracy charts of SSA-DBN were studied. Fig. 7 and Fig. 8 are graphs of the training accuracy and test accuracy of the DBN model of the compressor at 95% speed. Fig. 9 is the convergence diagram of the number of iterations of the SSA algorithm to optimize the DBN network. The optimal value is obtained after six iterations, and the error rate of SSA-DBN is zero. Fig. 10 and Fig. 11 are graphs of the training accuracy and test accuracy of the SSA-DBN model with a compressor at 95% speed.

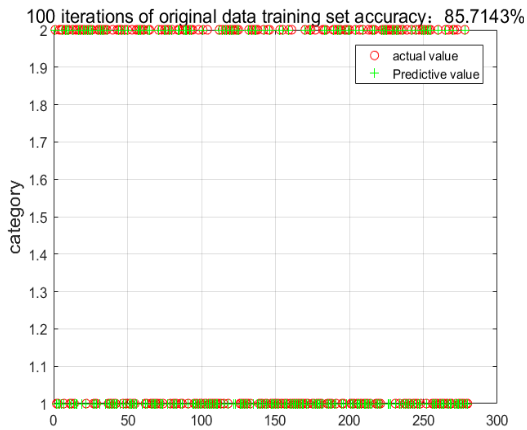

Fig. 7. The accuracy of the single classification training set in the DBN model at 95% speed

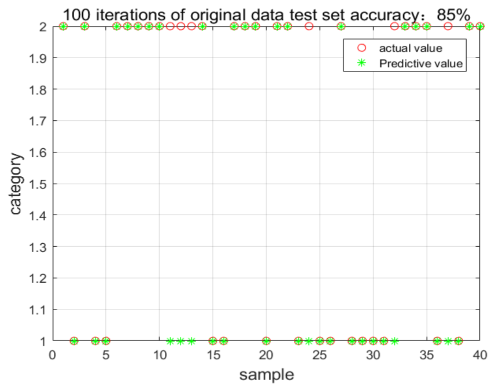

Fig. 8. The accuracy of the single classification test set in the DBN model at 95% speed

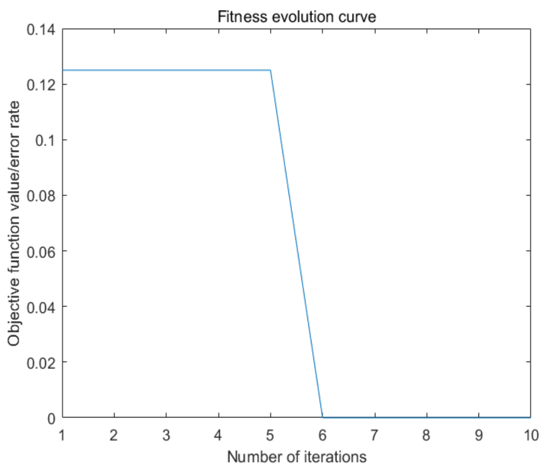

Fig. 9. The fitness evolution curve of SSA optimized DBN

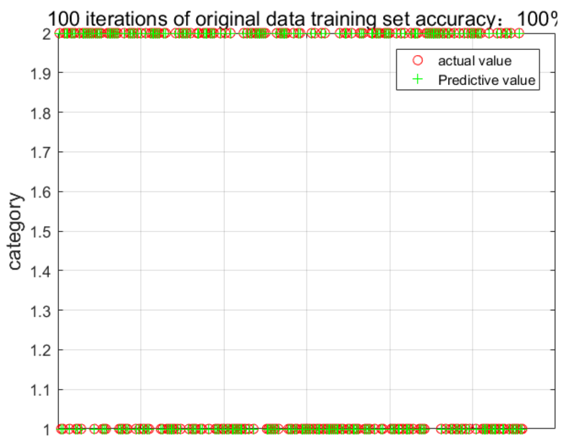

Fig. 10. The accuracy of the single classification training set in the SSA-DBN model at 95% speed

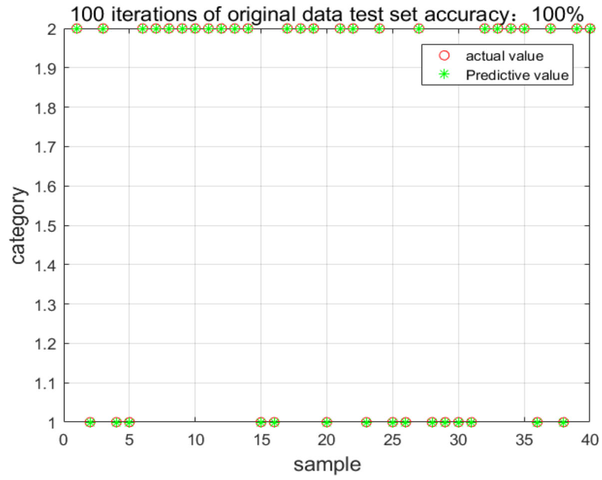

Fig. 11. Accuracy of single classification test set in SSA-DBN model at 95% speed

Without an optimized deep belief network, the accuracy of the training set and test set is only 85%. Optimized deep belief network, the accuracy of the training set and test set can reach 100%. Moreover, the optimized deep belief network can train data faster. Therefore, the optimal weight and the number of hidden layer nodes are fundamental parameters for deep belief networks.

4.3 Comparison with Related Works

It is proved that the algorithms proposed are very effective, and achieve stall warnings in advance. The first column is the stall point at each speed. The stall warning time at each rate is shown in Table 5, and the stall warning calculation is compared with other methods. It can be seen from the data in the table that the SSA-DBN form is earlier 0.075~0.281s than the frequency band energy method, short-term energy method, and variance method. It proves that the SSA-DBN way has significant effects in the early warning of the axial compressor stall and has a better stall warning margin.

The SSA-DBN method uses the frequency spectrum of Fourier transform of compressor pressure data as the characteristic vector of DBN network input. There is no need to set a threshold to determine whether the compressor is stalling. Other methods rely on thresholds. The neural network trained by this method is suitable for different speeds of the same type of compressor. But the bigger the training data, the wider the scope. Other methods need different thresholds to judge different speeds of a unified type compressor.

Table 5. Stall warning timetable of different methods

Early warning method	n_r =70%	n_r =75%	n_r =80%	n_r =90%	n_r =95%	n_r =98%
Stall point time	7.860s	7.684s	7.772s	8.775s	7.311s	8.693s
Frequency band energy method [26]	7.824s	7.656s	7.732s	8.700s	7.184s	8.608s
Short-term energy [11]	7.833s	7.650s	7.733s	8.700s	7.183s	8.608s
Analysis of variance [10]	7.858s	7.675s	7.750s	8.709s	7.192s	8.617s
Fluctuating pressure change rate [13]	7.842s	7.666s	7.750s	8.708s	7.183s	8.617s
SSA-DBN method	7.585s	7.585s	7.585s	8.419s	7.085s	8.419s

5 Conclusions

In summary, it provides a new idea for the study of the stall warning method of axial compressor. The data prediction problem is transformed into a data classification problem. A deep belief network is used to identify stall warning of axial compressor. The experimental results show that the stall data at each speed can be warned at least 0.1~0.3s in advance. Compared with other methods, it is 0.075~0.281s earlier. This method is suitable for stall warning of the same type of axial compressor at different speeds. The most important feature of this method is that it saves time without data filtering and feature selection. Fourier transform is straightforward and can be modeled directly by spectral components without setting parameters. The sparrow search algorithm optimizes the structural parameters of the deep belief network and obtains the optimal weight and hidden layer node number. Work of Future: 1. Three types of compressor stall signal recognition (regular operation, stall precursor operation, stall operation) will be studied. 2. More other types of axial compressors will be verified to make the proposed algorithm universal. 3. To make stall warning algorithm has practical solid engineering value. 4. Multi-mode information fusion research will be carried out to mix different information. A maximum pattern information fusion algorithm is proposed to detect stall precursors more quickly.

This method reduces the failure rate of aero-engine, improves the safety and reliability of the engine, and has important scientific significance and engineering application value. It provides vital technology reserve for developing advanced anti-surge devices and developing active instability control, and the most important thing is to bring higher economic benefits to the country.

Acknowledgement

This work was supported by the Natural Science Foundation of Jiangxi Province (20181BAB202018), Jiangxi University of Science and Technology postgraduate teaching reform project (YJG2018015).

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