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Internal Combustion Engine in Agricultural Machinery Field Relying on Artificial Fish Swarm Algorithm

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Abstract: In the field of agricultural machinery, as the power source for the operation of mechanical equipment, the internal combustion engine (ICE) is the key assembly component of mechanical equipment. Due to its high thermal efficiency and strong power, it is widely used in agriculture, industry and other fields. However, the ICE has complex structure and poor working conditions, so it is very easy to fail in actual work. Once the key components of the equipment fail, the production is likely to be interrupted, causing significant economic losses and even catastrophic consequences. Therefore, this paper studies and analyzes the application and realization of ICE in agricultural machinery field (AMF) relying on AF swarm algorithm (AFSA). This paper briefly analyzes the ICE in the field of agricultural machinery and the basic AFSA, and discusses the concrete realization and steps of the AFSA; by analyzing the parameters of AFSA, the application and realization of ICE in AMF relying on AFSA are studied, which is of great significance to the development of ICE in AMF.

1. Introduction

Due to the complex structure of ICE power system in the field of agricultural machinery, a wide variety of signals, multiple signal transmission channels, serious coupling, prominent nonlinear characteristics and other characteristics, it is difficult to extract machine signal information. The vibration signal of ICE contains rich equipment status information. Through the measurement and analysis of its surface vibration signal, its working status and fault nature can be judged. That is to say, it is feasible to extract time-domain, frequency-domain and time-frequency domain feature vectors from vibration signals as the judgment basis of mechanical operation state. However, due to the nonlinearity of the vibration signal and the different sensitivity and regularity of each extracted characteristic parameter to the equipment status, in order to comprehensively and accurately evaluate the health status of the mechanical equipment in the equipment fault diagnosis, this paper studies and analyzes the application and practice of the ICE in the AMF relying on the AFSA.

Many scholars at home and abroad have done a lot of research work on the application and realization of ICE in the field of agricultural machinery, and have also made certain achievements. However, in general, the research and application of these theories are still in an initial stage, and the theory and technology of ICE fault diagnosis for non Gaussian, non-stationary and nonlinear signal processing still have a great room for development and improvement. At present, most ICEs focus on the monitoring of state parameters, including the monitoring of temperature, pressure and other state parameters, and the monitoring system based on these physical parameters [1]. Although it can monitor the running state of the ICE, because the changes of these parameters are not obvious at the beginning of the mechanical failure, it is difficult to predict and judge the failure according to the changes of the monitored state parameters. In addition, there are few monitored physical state parameters of the ICE, and some parameters are consistent when the failure occurs, so it is impossible to judge the failure of the ICE based on these parameters, Therefore, it is necessary to improve the fault identification method of ICE and improve its condition monitoring means [2].

In this context, one of the key problems to be solved in the fault diagnosis of ICEs is how to effectively analyze and reprocess the mechanical dynamic vibration signals with nonlinear and non-stationary characteristics in real time, which is also an important scientific problem to be solved in the field of fault diagnosis. To sum up, this paper proposes an improved method relying on AFSA, which lays a theoretical foundation for improving the fault diagnosis level of complex mechanical equipment such as ICEs, improving the mechanical fault detection technology, and provides method support for practical engineering applications, thus providing a theoretical basis and scientific basis for improving the efficiency of ICE condition monitoring and the accuracy of fault diagnosis [3-4].

2. AFSA and Analysis of ICE in AMF

2.1. ICE in AMF

Mechanical condition monitoring and fault diagnosis technology plays an important role in the engineering field, especially for large and complex mechanical equipment, it is difficult to accurately grasp its operating state by intuition alone, and the fault diagnosis method provides effective fault information to the staff at the initial stage of the fault occurrence, reducing the loss caused by the fault; At the same time, failure detection and judgment without disassembly can be realized, which improves the maintenance efficiency. Therefore, it is necessary to study fault detection and diagnosis methods for complex mechanical equipment such as ICEs to improve mechanical maintenance efficiency, save production costs and improve economic benefits [5-6].

As shown in Figure 1, the fault diagnosis of ICE mainly includes three steps. Measure the fault signal; Extract fault features; Fault identification and diagnosis. The most critical step is fault feature extraction. Due to the large number of ICE components, complex structure, variable operating conditions, complex surface vibration signal components and strong nonstationarity and nonlinearity, simple time-domain or frequency-domain characteristics cannot meet the requirements for the identification of ICE fault modes, which has caused great difficulties in the extraction of ICE fault characteristics [7].

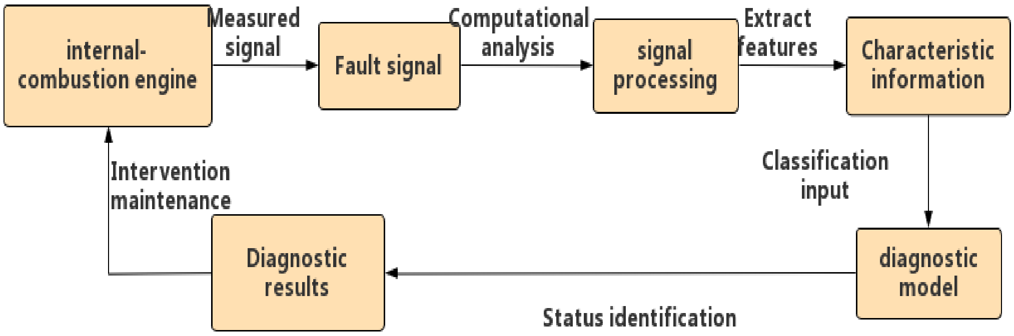

Figure 1. Basic process of fault diagnosis

2.2. Basic AFSA

AFSA adopts an object-oriented approach, encapsulating some data information and a series of behaviors into entities. The living space of the AF is the solution domain of the problem. The position of the AF at the next moment is jointly determined by the state of the previous moment and the state of its environment. At the same time, the individual behavior of the AF will also affect the swimming trajectory of other AF partners [8-9]. A single AF can not directly perceive the location of food. In order to find the place where food exists as soon as possible, the individual fish must cooperate with each other in a cooperative way. In the process of cooperation between AF, there are four different behaviors.

Feeding behavior: This is the most basic behavior of AF, and it is also a form of fish hunting for food. The amount or concentration of food is the rule of the movement direction of individual fish. AF will constantly explore and move towards the place with high food amount or concentration.

Herding behavior: This is a unique way of survival for fish. A large number of fish may encounter some uncontrollable adverse factors in their survival and foraging, and gather together to hunt for food or avoid natural enemies [10].

Tail chasing behavior: In the process of fish searching for food, when one fish finds a place with enough food, it will attract its nearby AF partners to quickly approach.

Random behavior: The fish moves randomly in the water irregularly in order to further expand the search scope and find food and AF partners [11].

The typical behaviors of the AFSA will be converted with the changes of the swimming and environment of the AF, making the fish swarm algorithm have the following characteristics:

The algorithm has strong applicability to the properties of the objective function, and most of the problems to be optimized can obtain the global optimal solution through the algorithm; The algorithm has little relationship with the setting of initial values, and the fixed or randomly generated initial parameter values have little influence on the iterative results; The algorithm does not require high parameter range and dimension in the optimization problem, and the allowable range is large; To some extent, the algorithm can better prevent the algorithm from falling into the local optimal solution, and the probability of obtaining the global optimal solution is high; The algorithm has the ability to obtain a good target solution after a short iteration; The execution behavior of the algorithm can be combined at will [12-13].

2.3. Specific Implementation and Steps of AFSA

During the implementation of the algorithm, the behavior evaluation is used to select which behavior the AF performs, the bulletin board is set to record the global historical optimal position of the AF, and finally the termination condition of the algorithm is set to terminate the algorithm. Behavior evaluation: according to the nature of the problem to be optimized and whether the problem is a maximum problem or a minimum problem, set the food concentration function, calculate the food concentration value at the initial position of the AF in this iteration, then execute the above three behaviors respectively, calculate the fitness value corresponding to the position after each behavior moves, compare the fitness change values of different behaviors, and select the behavior leading to the best direction in the alternative rows [14-15].

Bulletin board: bulletin board is used to record the global historical optimal position and corresponding fitness value in the process of AFSA iteration. When the algorithm is initialized, the optimal AF among the initial N AF will be marked on the bulletin board [16]. After running the algorithm once, compare the fitness value corresponding to the position of each AF after executing the behavior with the data on the bulletin board. If the value is better than the value on the bulletin board, use the position and the corresponding fitness value to update the bulletin board. Otherwise, keep the bulletin board unchanged.

Termination conditions: When the problems handled in the contemporary era are different, the termination conditions of the algorithm will also be different. Usually, a fixed number of iterations are manually set, or the accuracy and error of the target algorithm are set. If the algorithm meets the termination condition, output the global historical optimal position on the bulletin board; otherwise, re execute the three behaviors of the fish school to continue iteration until the termination condition is met [17-18].

3. AFSA

3.1. Model of AFSA

The AI mode based on biological behavior is different from the classical AI mode. It is based on the bottom-up design method. First, the behavior perception mode of a single entity is designed, and then individuals or groups are placed in the environment to solve problems in their interaction with the environment. Its intelligence features are: embeddedness, materialization, autonomy and salience. Autonomous entities usually do not have advanced intelligence, but their cluster activities show activities that can only be achieved by advanced intelligence. This phenomenon is called cluster intelligence. Only when social creatures cooperate with each other to carry out certain activities, will swarm intelligence phenomenon occur, such as insects, birds, fish, microorganisms, etc.

The AF is an abstraction of the individual biological fish, which contains the behavior characteristics of the fish and its response to the environment. The AF can receive environmental information through its senses and respond to the information accordingly. At the same time, the individual AF can also influence the behavior of other AF through its own behavior. The AF perceives the environment through its own "vision". Due to the complexity of the biological fish vision system, the concept of "vision" is adopted in the visual bionics of AF. The more times the AF tries, the more comprehensive the AF can understand the environmental information within the field of vision, which is helpful to make correct behavior decisions. Of course, the number of patrols cannot be increased indefinitely, which is not in line with the actual behavior of biological fish.

3.2. Behavior Mode of AF

There are N AF in a d-dimensional search space. The state position of the AF is represented by the vector X=(x1, x2,..., xd). ‖ xi xj ‖ represents the space distance between two pairs of AF individuals. The crowding degree of the AF population in the search space is determined by the crowding degree factor σ The food concentration at the location of AF is Y=f (X). The four behavior modes of AF are the core idea of AFSA model.

3.2.1. Feeding Behavior

The foraging process of AF is to simulate the process of biological fish finding food and swimming towards food. The current state of AF i is Xi, and a new state Xj is randomly selected within its field of vision, which is expressed as:

$$X_{i} = X_{i} + Visual * Rand() \tag{1}$$

Rand() is a random number between - 1 and 1 with uniform distribution. If the food concentration at state Xj is higher than that at state Xi, AF i moves one step towards state Xj, which is the foraging behavior of AF, as shown in equation (2).

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

If the state Xj is not better than the state Xi, continue to try to select a new state Xj. Try numtry repeatedly after reaching the maximum number of foraging times, the foraging behavior of the AF fails and executes random behavior.

3.2.2. Parameter Analysis of AFSA

Although the parameters of the AFSA have some robustness, the reasonable setting of parameters can maximize the performance of the algorithm. The analysis of the mechanism of the algorithm parameters is the basis for improving the algorithm and its performance.

The larger the size of the AF population, the higher the density of the AF individuals in the optimization space, and the greater the probability of the AF reaching the optimal solution, promoting it to get rid of the interference of local extreme values. During the implementation of the algorithm, the larger the AF population, the denser the distribution of AF individuals in the optimization space, and the more comprehensive the understanding of the optimization space. On the premise that other conditions remain unchanged; the higher AF density can not only promote the local search of the AF, but also fully understand the overall situation, improve the global convergence and accuracy of the algorithm, but also increase the operation storage space and improve the complexity of the algorithm. In the process of practical application, under the premise of meeting the accuracy requirements, smaller AF populations should be used. The algorithm parameters are set as: Visual=2, step=1, try_ num=10, ITtime=10, σ= 0.618, the population size is N=10, 40, 60 respectively, and 10 comparative studies are conducted independently. The test results are shown in Table 1.

Table 1. Simulation comparison of different population size

Population size	Optimal value	Time	Worst value	Time	average value
10	0.9988	0.059265	0.9888	0.063085	0.99527
40	1.0000	0.157109	0.9972	0.161015	0.99918
60	1.0000	0.324970	0.9991	0.272316	0.99966

It can be seen from Table 1 that with the expansion of the AF population, the accuracy of the optimal solution is improved, but the complexity of the algorithm increases, and the algorithm time consumption increases within the same number of iterations.

4. Application and Realization of ICE in AMF Relying on AFSA

4.1. ICE Bench Test and Data Set Acquisition

The AFSA is to analyze and study the data as the research object. The data used in this study are obtained from the ICE test records. This chapter discusses the acquisition of the research object. This chapter will describe the source of the data set required by the model in terms of the test bench and equipment, the fuel used for the test, and the test plan.

Test bench design and equipment selection

Test bench. The engine test bench is the basis for engine test. The establishment of the test bench and the selection of the matching equipment related to the bench are particularly important. This research mainly focuses on the correlation analysis of oil products and ICE performance. The research needs to be applicable to the market. According to the research needs and the research on mainstream engine types at home and abroad, 2.0T engine is selected for experimental research.

Measurement and control platform and equipment. The performance of the oil and ICE studied in this test should be applicable in the actual vehicle. Therefore, ECU control is adopted in the control strategy during the test, and the cross matching test of the oil and ICE performance is conducted by debugging the engine adjustment parameters (such as injection time or ignition advance angle) in combination with INCA7.1 software, so as to carry out the research of oil engine coordination. During the test, dry and wet thermometers and atmospheric pressure gauges are required to monitor and record the atmospheric temperature, humidity and pressure. The engine bench oil temperature, oil pressure, intake and exhaust pressure, cooling water temperature and intake and exhaust temperature are collected by the pressure sensor and temperature sensor respectively, and transmitted to the electric dynamometer bench monitoring system to control the real-time state of the engine through the monitoring of various indicators. During the test, the intercooler temperature and pressure shall be monitored to ensure that the engine operates normally during the test.

4.2. Selection of Correlation Dimension Parameters

In this paper, the ex factory valve clearance setting of the diesel engine is taken as a normal parameter, and the valve clearance deviating from this value is taken as a fault parameter. The ex factory valve clearance of the diesel engine used in the experiment is set as: inlet valve clearance 0.3mm, outlet valve clearance 0.5mm; Fault valve clearance is set as: inlet valve clearance 0.4mm, outlet valve clearance 0.6mm. Table 2 shows 7 states of valve clearance of diesel engine. The valve clearance of cylinders 1~6 occurs successively. This paper calculates the optimal time delay and embedding dimension of cylinder head vibration signal after noise reduction under different states of valve clearance of seven diesel engines, as shown in Table 3 and Figure 2.

Table 2. Seven valve clearance states

States	Valve clearance (mm)	1 cylinder	2 cylinder	3 cylinder	4 cylinder	5 cylinder	6 cylinder
1	intake valve(IV)	0.4	0.3	0.3	0.3	0.3	0.3
	Air outlet valve	0.6	0.5	0.5	0.5	0.5	0.5
2	IV	0.3	0.4	0.3	0.3	0.3	0.3
	Air outlet valve	0.5	0.6	0.5	0.5	0.5	0.5
3	IV	0.3	0.3	0.4	0.3	0.3	0.3
	Air outlet valve	0.5	0.5	0.6	0.5	0.5	0.5
4	IV	0.3	0.3	0.3	0.4	0.3	0.3
	Air outlet valve	0.5	0.5	0.5	0.6	0.5	0.5
5	IV	0.3	0.3	0.3	0.3	0.4	0.3
	Air outlet valve	0.5	0.5	0.5	0.5	0.6	0.5
6	IV	0.3	0.3	0.3	0.3	0.3	0.4
	Air outlet valve	0.5	0.5	0.5	0.5	0.5	0.6
7	IV	0.3	0.3	0.3	0.3	0.3	0.3
	Air outlet valve	0.5	0.5	0.5	0.5	0.5	0.5

Table 3. Results of good delay and embedded dimension

	State1	State2	State3	State4	State5	State6	State7
Time delay	5	5	5	6	5	7	5
Embedded dimension	6	9	11	28	19	30	39

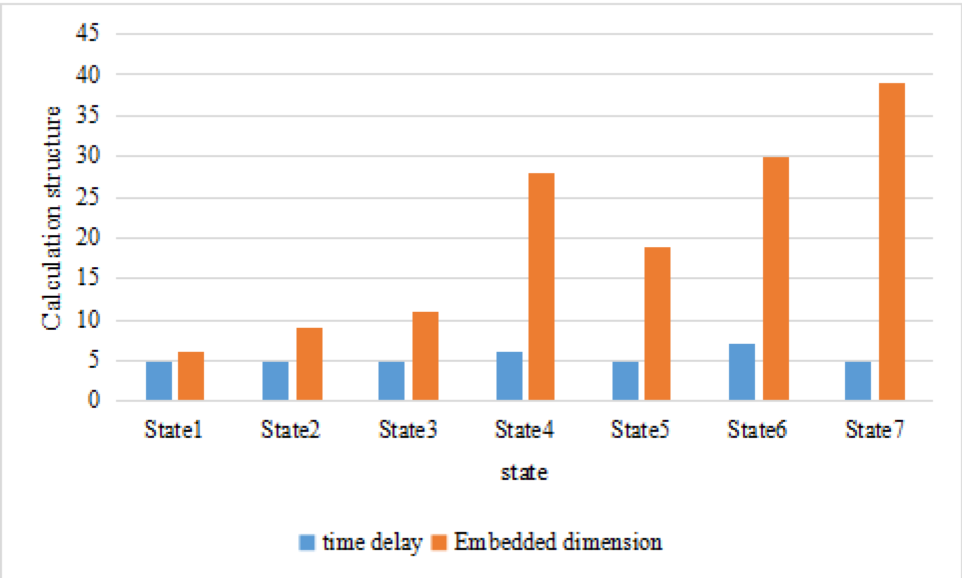

Figure 2. Calculation results of delay and embedded dimension

The experimental process and data feature extraction and recognition process include: noise reduction preprocessing, single channel extraction of vibration source signal, local mean decomposition to obtain PFs, calculation of each PFs feature value, input the obtained feature data into SVM state recognizer, and classify and identify different diesel engine valve clearance states. The statistical characteristics include: mean, standard deviation, root mean square, skewness, kurtosis; the characteristics of frequency energy include: wavelet entropy, wavelet energy; The correlation characteristic is correlation coefficient, and the fractal characteristic is correlation dimension. The extracted features are divided into two categories. The first category is mathematical statistical features; The second type is special characteristics, namely frequency energy characteristics, fractal characteristics and correlation coefficients.

It can be seen from the above chart that different classifiers have different classification accuracy when the feature quantity of the input classifier is different. When the mathematical statistical characteristics are input, the classification accuracy of the AFSA is the lowest 82.221%; When special features are input, the highest accuracy of the classifier is 99.2147%. The results show that the AFSA is superior to other algorithms in training speed and diagnostic accuracy.

5. Conclusion

In this paper, based on the AMF, the correlation analysis of ICE performance is studied and discussed by using AFSA, and the ICE model in the AMF of AFSA is constructed, and the model is verified and applied. However, there are still many research contents to be further discussed in this paper. Based on the correlation analysis of ICE performance in the field of agricultural machinery, this paper focuses on the content of typical components in the oil products, so more research can be done on the carbon chain length and hydrocarbon ratio in the oil products in the later stage; In this paper, only the AFSA is selected for the research on the application and implementation of ICEs in the field of agricultural machinery. In the later research, different types of intelligent algorithms can be used as much as possible, and the differences between different algorithms can be compared to find the best algorithm for correlation analysis.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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