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*Research Article*

# Online Monitoring of Automotive Engine Lubricating Oil Based on Internet of Things Technology

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In order to realize the online monitoring of automotive engine lubricating oil, a method based on Internet of Things technology is proposed. This method uses the self-organizing neural network of the Internet of Things to fuse the original multidimensional feature data to obtain the fusion value. The Parzen window method is used to formulate the limit value of fusion value, and the samples are divided into three states: normal, warning, and abnormal. Weka software is used to extract rules from oil data. This method can identify different wear state information from oil spectral data, extract knowledge rules, and use them to build the knowledge base of automobile engine wear diagnosis system, so as to realize the automation and intelligence of automobile engine fault diagnosis based on lubricating oil spectral wear data. The measurement method of the lubricating oil sensor is mainly to comprehensively reflect the relationship between oil quality and electrical signal, so as to effectively provide users with reliable information. After many studies, it is concluded that the conductivity of lubricating oil has a good linear relationship with its acid value, metal particles, moisture content, and the change of additive content. Measuring the change of conductivity is an effective means to detect the change of lubricating oil quality. The experimental results show that using the extracted knowledge rules to verify the state of samples, the recognition rate is 97.47%. In order to more fully explain the difference between important element fusion and all feature fusion, all features are extracted. At the same time, the fault diagnosis and recognition rate of all features is not high, only 62.39%. It is proved that the Internet of Things technology can effectively realize online monitoring of the automotive engine lubricating oil.

## 1. Introduction

The oilfield has main production equipment such as water injection pump, oil transfer pump, natural gas compressor, and generator set, which has the characteristics of continuous operation, large impact load, high working temperature, and fast movement speed. Once these major key equipment fails, it will cause huge economic losses to the oilfield and even endanger personal safety. Therefore, there are strict requirements for the safety performance and operation reliability of the equipment. At present, relying on the lubrication station and laboratory, the oilfield has carried out offline physical and chemical analyses and element analysis of the lubricating oil for generator sets, water injection pumps, natural gas compressors, and other equipment, which has played a positive role in finding the inducement of equipment failure in time, the development of early failure and ensuring the safe and reliable operation of equipment. However, this detection method is not intelligent and cannot be interconnected. It can only give isolated detection results, and the effect of guiding equipment maintenance is not obvious. Especially in the environment where the oilfield vigorously develops the Internet of Things technology and establishes a digital oilfield, this oil monitoring system is separated from the whole oilfield digital system and becomes an information island. It is a short board for building an intelligent digital oilfield system. Therefore, the construction of lubricating oil online monitoring to monitor and evaluate the lubrication and wear status of oilfield equipment in real time is

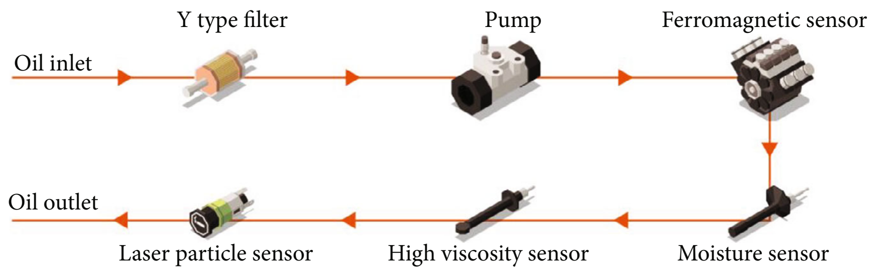


Figure 1: Sensor layout diagram of gear oil online monitoring module.

an effective means to realize predictive maintenance and active maintenance, which is of great significance to ensure the safe, economic, and efficient operation of equipment [1].

Lubricating oil online monitoring technology is to continuously detect the physical and chemical parameters and wear particles of lubricating oil by installing various sensors on the equipment. Generally, the technical method of trend analysis is used to determine the service status of lubricating oil and equipment. It has the characteristics of real-time, continuity, synchronization, rapid analysis, high degree of automation, and informatization. The moisture in lubricating oil will make the oil emulsified and oxidized and reduce the viscosity and oil film strength, and the formation of lubricating oil oxides and polluting impurities will reduce the fluidity of lubricating oil and lead to the increase of viscosity. Moisture and viscosity are an important basis for measuring the lubricating ability of oil. Ferromagnetic and nonferromagnetic wear elements in lubricating oil exist in the form of particles. Monitoring their quantity is of great significance to judge the equipment wear of nonferrous and metal parts. When the oil is aged or polluted, the content of polar molecules and particles in the oil changes, and the dielectric constant of the oil also changes. At the same time, due to friction and wear, worn metal particles and other highly conductive compounds will also change the dielectric constant of the lubricating oil [2]. By monitoring the dielectric constant and AC impedance of lubricating oil, the information of oil quality and wear fault can be reflected. For the main drive gear oil, the main monitoring indicators are temperature, viscosity, moisture, dielectric constant, ferromagnetic particles, and pollution degree. Therefore, the high viscosity sensor, moisture sensor, ferromagnetic sensor, and laser particle sensor are designed in the main bearing gear oil online monitoring module to collect the above indicators in real time. The sensor arrangement is shown in Figure 1.

According to the actual working conditions of the equipment, the three-dimensional six index system of lubricating oil online monitoring is determined, namely, physical and chemical indexes, wear index, and comprehensive quality index. Physical and chemical indexes include moisture and viscosity. Wear indicators include ferromagnetic particles and nonferromagnetic particles. The comprehensive quality indexes include dielectric constant and AC impedance. The three indexes compensate each other, which can scientifically and reasonably determine the working state of lubricating oil and the wear state of equipment [3].

## 2. Literature Review

According to relevant statistics, more than 50% of the malignant faults of mechanical equipment are caused by lubrication failure and excessive wear. Therefore, the research and application of oil online monitoring and diagnosis technology has important practical significance. At present, many scholars have done more research on the application of oil monitoring technology. Singh et al. mainly studied oil detection technology [4]. Fan et al. mainly introduced the application of oil detection technology in equipment fault diagnosis [5]. Wang et al. introduced the application of offline detection technology in shield. However, with the continuous improvement of automation and integration of shield and the increasing number of shield, the detection technology based on offline detection can not meet the needs of long-term continuous monitoring of modern equipment [6]. Yi et al.'s analysis of the transport fleet (6.4 L, 6.7 L engines) using conventional mineral oil (15 W-40) and fully synthetic oil (5 W-40) shows that the current 5000 mile oil change interval can be extended. Moreover, there are significant differences in oil performance and chemical degradation between 6.4 L and 6.7 L engines. The approximate life of 6.41 engine oil is 8000 miles (about 12800 km), while the approximate life of 6.7 L engine oil is 12500 miles (about 20000 km) [7]. Bo and Qin studied the oil change cycle of vehicle lubricating oil. Sg15W-40 general internal combustion engine oil is selected to conduct tracking test on five civil cars. The collected oil samples are analyzed for physical and chemical properties. Combined with statistical analysis method, it is obtained that the failure mileage of lubricating oil is 7600 km at 90% confidence level [8]. Zhao et al. conducted several groups of driving tests on sf5W-30 engine oil, studied the oil change cycle of sf5W-30 engine oil by using pressure differential scanning calorimeter (PDSC) and infrared spectrometer, and took the vulcanization value in the lubricating oil as the oil change index. When the vulcanization value in the lubricating oil reaches the set threshold (25 A/cm), the running mileage of the driving test vehicle is 9000-9400 km, and this is the engine oil failure time [9]. For Ashwini et al., according to the differences of vehicle operating conditions, different vehicle models are selected for driving test, and the viscosity, flash point, fuel dilution, and other indexes of engine oil (sm5w-30) with different operating mileages are tested. The test results show that after the five test vehicles run for 10000 km, the vehicle runs without abnormality, and the oil still has good oxidation stability, cleaning dispersion capacity, and lubrication performance [10]. Wang et al. based on Jiefang

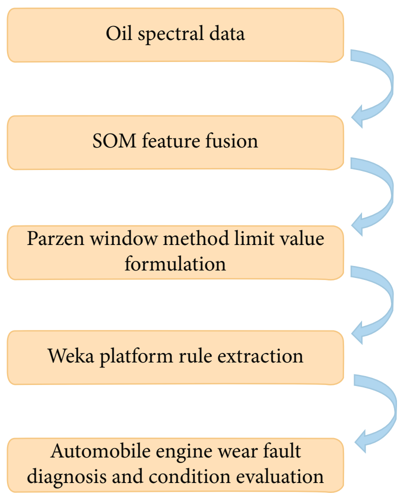


Figure 2: Flow chart of knowledge acquisition method.

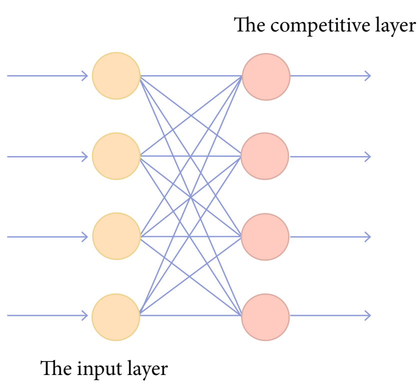


Figure 3: Structure of the self-organizing neural network.

J6 heavy tractor carried out the technology development and research on $1 \times 10^5$ km long oil change cycle of e410w-40 engine oil. Combined with bench test, driving test, and engine disassembly test, it shows that all indexes of lubricating oil are within the range specified in the national standard, and the wear of engine parts is also within the normal range, and in August 2015, China First Automobile Co., Ltd. took the lead in applying this long oil change cycle technology in China [11]. Yuldashev et al. believe that developing a sensor that can facilitate the real-time online monitoring of lubricating oil installed on the vehicle should not only monitor the deterioration degree and pollution of lubricating oil but also accurately remind the best time to replace new oil. When the lubricating oil deteriorates to the extent that it will harm the engine or exceed the predetermined threshold of parameter indicators, it will send an alarm to the user in time to remind the user to replace the lubricating oil. At present, it is a very urgent work for people. The development of this sensor should have the following characteristics: fast analysis speed, low cost, real-time monitoring, accurate judgment, simple operation, etc., so that each user can easily master its operation method [12]. Zhang et al. believe that at present, oil detection technology is mainly applied in engineering technology, large mining enterprises, petroleum oil detection, and other fields. The main method is to extract a certain amount of samples from its equipment and send them to the oil detection center, and then, professionals will detect and analyze the oil products of the oil samples to determine their pollution degree and deterioration status, so as to provide reference for its equipment to replace oil and diagnose faults [13].

Based on the current research, this paper proposes a method based on Internet of Things technology. This method uses the self-organizing neural network of the Internet of Things to fuse the original multidimensional feature data to obtain the fusion value. The Parzen window method is used to formulate the limit value of fusion value, and the samples are divided into three states: normal, warning, and abnormal. Weka software is used to extract rules from oil data. This method can identify different wear state information from oil spectral data, extract knowledge rules, and use them to build the knowledge base of automobile engine wear diagnosis system, so as to realize the automation and intelligence of automobile engine fault diagnosis based on lubricating oil spectral wear data. The measurement method of the lubricating oil sensor is mainly to comprehensively reflect the relationship between oil quality and electrical signal, so as to effectively provide users with reliable information. After many studies, it is concluded that the conductivity of lubricating oil has a good linear relationship with its acid value, metal particles, moisture content, and the change of additive content. Measuring the change of conductivity is an effective means to detect the change of lubricating oil quality.

## 3. Wear Fault Diagnosis Knowledge Acquisition Method Based on Oil Spectrum Data Fusion

*3.1. Method and Process.* Figure 2 shows the flow chart of knowledge acquisition method for automobile engine wear fault diagnosis based on oil spectrum data fusion, mainly including feature fusion based on SOM, boundary value formulation based on the Parzen window method and knowledge rule extraction based on Weka platform. The flow chart of knowledge acquisition method is shown in Figure 2.

*3.2. Self-Organizing Neural Network Learning Algorithm.* Self-organizing neural network, also known as self-organizing feature mapping and Koho Nen network, is a neural network with self-organizing ability trained by unsupervised learning. It can conduct self-organizing training and judgment on the input mode and finally divide it into different types. With its low-dimensional organization ability of high-dimensional data, SOM has many successful applications in data mining fields such as classification, clustering, fusion, and prediction [14]. Figure 3 shows the structure of the self-organizing neural network.

SOM's competitive learning algorithm process:

(1) Set the variable and parameter $X[n] = [x_1(n), x_2(n), \cdots, x_N(n)]^T$ as the input vector, or training sample. $W_i[n] =$

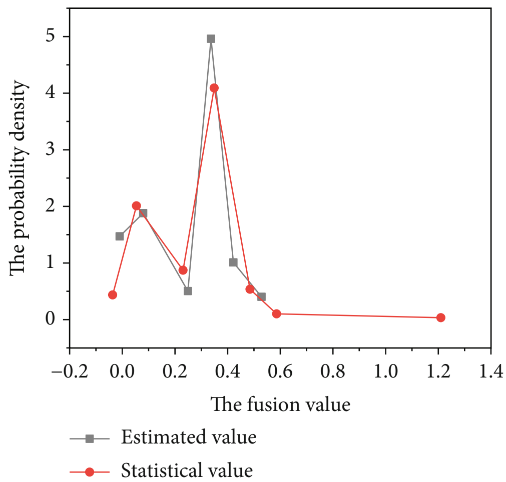


Figure 4: Comparison of probability density function between estimation and statistics.

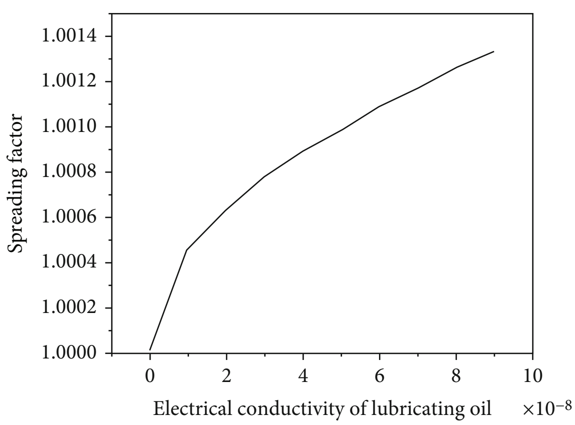


Figure 5: Relationship between the propagation factor and change of lubricating oil conductivity (frequency 10 MHz).

$[w_{i1}(n), w_{i2}(n), \cdots, w_{iN}(n)]^T$ is the weight loss, $i = 1, 2, .., M$. The number of iterations is $K$

(2) Initialization: initialize the weight vector $W_i$ with a small random value. Set the initial learning rate $\eta(0)$. Normalize all input vectors $X$ and initial values $W_i(0)$ of weight vectors:

$$X' = \frac{X}{\|X\|}, \tag{1}$$

$$W_i'(0) = \frac{W_i(0)}{\|W_i(0)\|}, \tag{2}$$

where

$$\|W_i(0)\| = \sum_{j=i}^{N} \left[w_{ij}(0)\right]^2, \tag{3}$$

$$\|X\| = \sum_{i=1}^{N} (x_i)^2. \tag{4}$$

They are the European norm of weight vector and input vector, respectively

(3) Sampling, approximate matching: select the training sample $X'$ from the space and pass the standard of minimum Euclidean distance

$$\left\|X' - W_c'\right\| = \min_i \left\|X' - W_i'\right\|, i = 1, 2, \cdots, M, \tag{5}$$

to select the winning neuron $C$, so as to realize the competition process of neurons

(4) Update: Hebb learning rules are used for excited neurons in the topological neighborhood $N_c(n)$ of winning neurons:

$$W_i'(n+1) = W_i'(n) + \eta(n)\left(X' - W_i'(n)\right). \tag{6}$$

Update the weight vector of neurons, so as to realize the cooperation and update process of neurons

(5) Update the learning rate $\eta(n)$ and topological neighborhood and renormalize the learned weights:

$$N_c(n) = \mathrm{INT}\left[N_c(0)\left(1 - \frac{n}{N}\right)\right], \tag{7}$$

$$W_i'(n+1) = \frac{W_i'(n+1)}{\left\|W_i'(n+1)\right\|} \tag{8}$$

(6) Judge whether the number of iterations n exceeds $K$. If $n \le K$, increase the value of $N$ by 1 and go to step 3. Otherwise, end the iteration process

*3.3. Feature Fusion Based on SOM.* The steps of feature fusion based on SOM are as follows.

*3.3.1. Extract Normal Samples.* Because the weights of the training samples are normal, we need to extract the features of the SOM network through the normal samples. The steps of extracting normal samples are as follows.

(i) Step 1: create a self-organizing neural network. Set the parameters of network training and carry out SOM training for all samples $X$. Among them, the number of output neurons is $m_1 \times n_1$ and the number of training $K_1$. $m_1$ and $n_1$ represent the number of rows and columns of output neurons, respectively

(ii) Step 2: identification of clustering samples. After training, a certain number of samples will be gathered on each output neuron. Therefore, sample identification is carried out with the help of SOM toolbox function in MATLAB [15]

(iii) Step 3: screening of normal samples. Because the topological structure on the neural network structure diagram shows the number of samples corresponding to neuron clustering. The color distribution on the nearest neighbor neuron map reflects the proximity between adjacent neurons. The lighter the color, the closer the distance between two neurons, and the darker the color, the farther the distance between two neurons; At the same time, according to the sample value size on each neuron, the normal sample is extracted and recorded as $y$

*3.3.2. Normal Sample Training.* Carry out SOM network training for normal samples, reset the number of output neurons $m_2 \times n_2$ and the number of network iterations $K_1$, and obtain the weight vector w of normal sample training. Where $m_2$ and $n_2$, respectively, represent the number of rows and columns of output neurons, the number of columns of weight vector $w$ is equal to the sample dimension, and the number of rows is equal to the number of output neurons, i.e., $m_2 \times n_2$.

*3.3.3. Feature Fusion.* Calculate the minimum matching distance d from all samples $x$ to the weight vector $w$ of normal samples, and then fuse a curve to achieve the purpose of feature fusion [16].

$$d = \min_j \left\| X - W_j \right\|, \tag{9}$$

where $j$ is the number of output neurons.

*3.4. Formulation of Limit Value Based on Parzen Window Method.* The traditional limit value formulation methods assume that the oil monitoring data obey the normal distribution, but the distribution law of the actual data is not necessarily normal, and its probability distribution is often unknown. At this time, it is necessary to estimate the probability density function of the data from a large number of data and obtain the probability distribution of the sample according to the probability density function; then, the limit value of wear diagnosis is obtained according to the estimated probability distribution.

To estimate the probability density function,

$$F(x) = P(X \le x) = \int_{-\infty}^{x} p(t)dt. \tag{10}$$

It is necessary to find the solution of linear operator

$$\int_{-\infty}^{\infty} \theta(x-t)p(t)dt = F(x), \tag{11}$$

where

$$\theta(x) = \begin{cases} 1, x > 0, \\ 0, x \le 0. \end{cases} \tag{12}$$

And the solution must also meet the following two conditions:

$$p(x) \ge 0, \int_{-\infty}^{\infty} p(x)dx = 1 \tag{13}$$

In equation (9), the expression of the distribution function $F(x)$ is unknown, but a set of samples $x_1, \cdots, x_l$ are given. According to the probability theory, this group of samples is independent and identically distributed. Now, use sample $x_1, \cdots, x_l$ to construct the empirical distribution function, where $l$ is the number of samples [17].

$$F_l(x) = \frac{1}{l} \sum_{i=1}^{l} \theta(x - x_i). \tag{14}$$

The Parzen window estimation method is a nonparametric estimation method that uses known sample points to estimate the overall probability density distribution, that is, it uses the average value of the density of each point in a certain range to estimate the overall probability density. Due to its solid theoretical foundation and excellent performance, Parzen window technology has become a widely used the nonparametric density estimation method.

Generally, let $x$ be a point in $d$-dimensional space, the total number of samples selected is $n$, in order to estimate the distribution probability density $P(x)$ at $x$, make a hypercube $V_N$ centered on $X$, and its side length is $h_N$; then, the expression of volume is $V_N = h_N^d$. To calculate the number of samples $k_n$ falling into hypercube $V_N$, it is necessary to construct a function so that

$$\phi(u) = \begin{cases} 1, \text{when} \left| u_j \right| \le \frac{1}{2}, j = 1, 2, \cdots, d, \\ 0, \text{other}. \end{cases} \tag{15}$$

If $\phi(u)$ satisfies the condition of equation (13), the number of samples falling into the hypercube is

$$k_N = \sum_{i=1}^{N} \phi\left(\frac{x - x_i}{h_N}\right). \tag{16}$$

Substitute equation (14) into:

$$\widehat{P}_N(x) = \frac{k_N/N}{V}, \tag{17}$$

$$\widehat{P}_N(x) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{V_N} \phi\left(\frac{x - x_i}{h_N}\right). \tag{18}$$

*3.5. Conductivity Is the Main Basis for Evaluating the Quality*

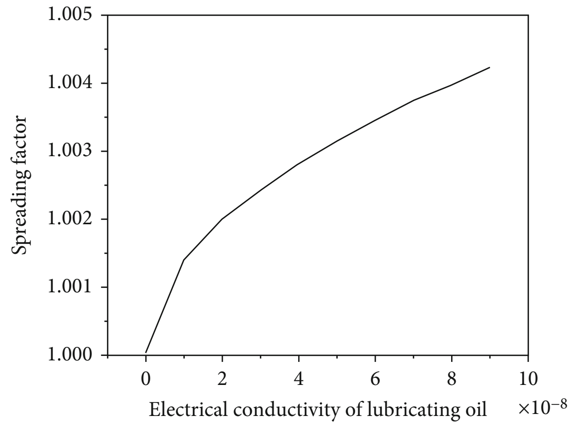


Figure 6: Relationship between propagation factor and change of lubricating oil conductivity (frequency 100 MHz).

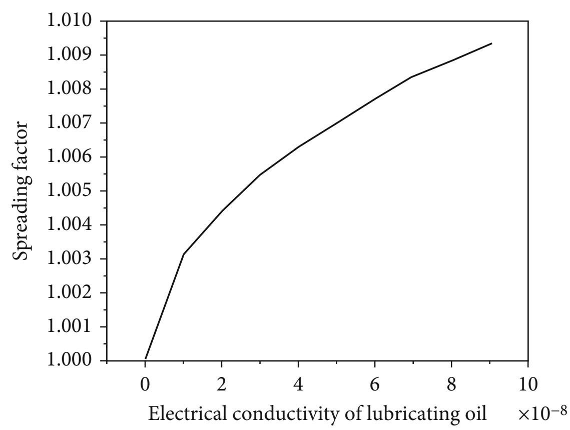


Figure 7: Relationship between the propagation factor and change of lubricating oil conductivity (frequency 500 MHz).

*of Lubricating Oil.* If its composition changes, or there is invasion of external substances, or its own oxidation, etc., they will change the conductivity of lubricating oil. Therefore, as long as we know the change of the conductivity value of the lubricating oil, we can easily judge the quality of the lubricating oil.

As early as 1994, Ford Motor Company had passed the laboratory evaluation and driving test. Finally, it was concluded that the online monitoring of lubricating oil can be done by measuring the conductivity of the lubricating oil. The measurement method of the lubricating oil sensor is mainly to comprehensively reflect the relationship between oil quality and electrical signal, so as to effectively provide users with reliable information. After many studies, it is concluded that the conductivity of lubricating oil has a good linear relationship with its acid value, metal particles, moisture content, and the change of additive content. Measuring the change of conductivity is an effective means to detect the change of lubricating oil quality. In the quality identification of lubricating oil, permittivity and conductivity are two important parameters to evaluate the electrochemical performance of oil. The permittivity of different oil products has little difference; however, the conductivity of different oil products varies greatly due to the change of oil components, generally ranging from 10-7 to 10-15 s/m, with a variation range of about 8 orders of magnitude. Therefore, when evaluating whether the quality of lubricating oil has deteriorated, it can be judged by accurately measuring the conductivity. Therefore, measuring conductivity will be a comprehensive way to reflect the change of lubricating oil quality. Therefore, this paper will study the theoretical method based on the physical quantity of conductivity and preliminarily design the online lubricating oil sensor [18].

*3.6. Extraction of Wear Element Rules Based on Weka Platform.* The knowledge rule extraction of engine wear elements is mainly carried out with the help of Weka platform. Weka is a comprehensive data mining system developed by Waikato University in New Zealand. It not only provides a variety of data mining methods (classification, clustering, association rules, etc.) but also provides data preprocessing functions suitable for any data set and a variety of algorithm performance evaluation methods. The rule extraction function of Weka software relies on the decision tree classification algorithm, namely, C4.5 algorithm. It is a guided inductive learning algorithm, which inherits all the advantages of ID3 algorithm and improves it. It is especially suitable for occasions with large amount of mining data and high requirements for relative efficiency and performance.

## 4. Experimental Results and Analysis

In order to verify the effectiveness of this method, 2089 oil spectral data of a military aircraft engine are used to verify the method. Seven commonly used important elements are selected for fault diagnosis, including Fe, Al, Cu, Cr, Ag, Ti, and Mg, so the characteristic dimension of the data is 7.

*4.1. Feature Fusion.* Firstly, the original spectral data are normalized to avoid the influence of magnitude difference on the fusion results. Then, SOM training is carried out on the normalized original data. Then, by comparing the distance distribution between neurons, the number of samples gathered on each neuron, and the value size, 401 samples on the third neuron are selected as normal samples and trained and fused to obtain the fusion value of the samples. Finally, the characteristic data of the sample and the fusion features are formed into a new vector matrix, which is adjusted in ascending order according to the value of the fusion value based on the fusion value. The concentration value of each element is compared with the fusion value one by one, and it is concluded that the wear element and the fusion value show the same change trend. It can be seen that the fusion eigenvalue can reflect the change trend and law of engine wear state [19].

*4.2. Formulation of Limit Value.* It can be seen from Figure 4 that the fitting effect of probability density function curve of statistics and estimation is good. Therefore, the limit value of the fusion value is formulated, and the data samples are divided into normal, warning, and abnormal.

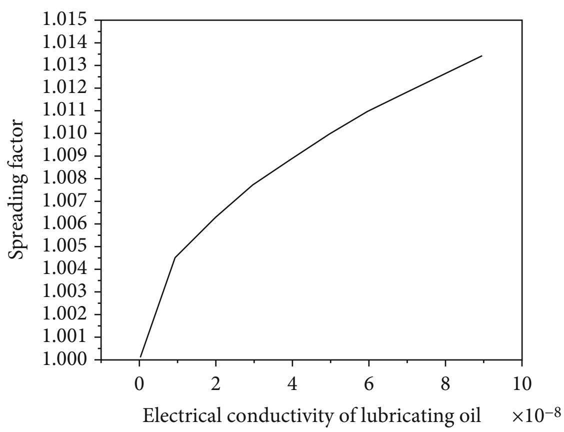


Figure 8: Relationship between propagation factor and change of lubricating oil conductivity (frequency 1 GHz).

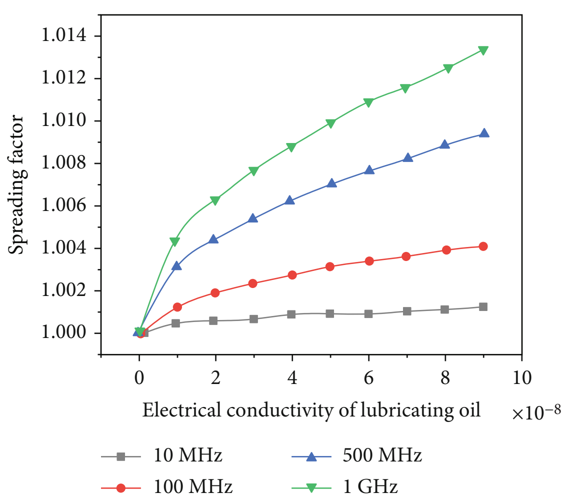


Figure 9: Relationship between electromagnetic wave propagation factors of different frequencies and changes of lubricating oil conductivity.

Figure 5 shows the propagation of electromagnetic wave with frequency of $F = 10\,\mathrm{MHz}$ in lubricating oil. The relationship between electromagnetic wave propagation factor and lubricating oil conductivity is simulated by MATLAB. The abscissa represents the electrical conductivity of lubricating oil, the ordinate represents the propagation factor of electromagnetic wave, and the black curve in the figure represents the changing relationship between these two physical quantities.

It can be seen from Figure 5 that when the conductivity of lubricating oil $\sigma = 10^{-15}$S/m, the propagation factor of electromagnetic wave is about equal to 1. When the conductivity increases to $\sigma = 10^{-8}$S/m, the propagation factor of the corresponding electromagnetic wave is about 1.0004. When the conductivity continues to increase to $\sigma = 5 \times 10^{-8}$S/m, the propagation factor of the corresponding electromagnetic wave is 1.0010. Finally, when the conductivity $\sigma = 9 \times 10^{-8}$ S/m, the propagation factor of electromagnetic wave is about 1.0013. The increasing trend of conductivity can be roughly divided into two stages. The first stage: $\sigma = (10^{-15} \sim 10^{-8})$S/m ($\Delta\gamma$ represents the change rate of propagation factor) and the corresponding electromagnetic wave propagation factor changes to $1 \sim 1.0004$ ($\Delta\gamma = 0.0004$). At this stage, the electromagnetic wave propagation factor changes slowly with conductivity. The second stage: $\sigma = (10^{-8} \sim 9 \times 10^{-8})$S/m, the corresponding electromagnetic wave propagation factor changes from 1.0004 to 1.0013 ($\Delta\gamma = 0.0009$) [20]. At this stage, the electromagnetic wave propagation factor changes rapidly with the conductivity. Through comparative analysis of these data changes, it is easy to conclude that with the increase of lubricating oil conductivity, the propagation factor of electromagnetic wave also increases, and their change relationship is nearly linear in these two stages.

Figure 6 shows the propagation of electromagnetic wave with frequency of $F = 100\,\mathrm{MHz}$ in lubricating oil. The black curve in the figure shows the relationship between the transmission coefficient of lubricating oil and the change of electrical conductivity of lubricating oil. It can be seen from Figure 6 that when the conductivity of lubricating oil $\sigma = 10^{-15}$S/m, the propagation factor of electromagnetic wave is about equal to 1. When the conductivity increases to $\sigma = 10^{-8}$S/m, the corresponding propagation factor of electromagnetic wave is about 1.0014. When the conductivity continues to increase to $\sigma = 5 \times 10^{-8}$S/m, the corresponding propagation factor of electromagnetic wave is 1.0031. Finally, when the conductivity $\sigma = 9 \times 10^{-8}$S/m, the propagation factor of electromagnetic wave is about 1.0042. Similarly, the increase of conductivity is roughly divided into two stages. The first stage: $\sigma = (10^{-15} \sim 10^{-8})$S/m, the change value of corresponding electromagnetic wave propagation factor is $1 \sim 1.0014$ ($\Delta\gamma = 0.0014$). It can be seen from the figure that the change of electromagnetic wave propagation factor with conductivity is relatively slow at this stage; The second stage: $\sigma = (10^{-8} \sim 9 \times 10^{-8})$S/m, the change value of electromagnetic wave propagation factor is 1.0014~1.0042 ($\Delta\gamma = 0.0028$). At this stage, the electromagnetic wave propagation factor increases rapidly with the increase of conductivity. It is easy to conclude from the data change that as the conductivity of lubricating oil increases, the propagation factor of electromagnetic wave in the whole process also increases: especially from Figure 6, it can be intuitively found that the relationship between the propagation factor and the change of conductivity is a star near linear relationship [21].

Figure 7 shows the propagation of electromagnetic wave with frequency of $F = 500\,\mathrm{MHz}$ in lubricating oil. The black curve in the figure shows the relationship between the propagation coefficient and the conductivity. It can be clearly seen from Figure 7 that when the conductivity of lubricating oil is $\sigma = 10^{-15}$S/m, the propagation factor of electromagnetic wave is about equal to 1. When the conductivity increases to $\sigma = 10^{-8}$S/m, the corresponding propagation factor of electromagnetic wave is about 1.0031. If the conductivity continues to increase to $\sigma = 5 \times 10^{-8}$S/m, the propagation factor value of electromagnetic wave is 1.0071; finally, when the conductivity increases to $\sigma = 9 \times 10^{-8}$S/m, the propagation factor value of electromagnetic wave is about 1.0095. Similarly, the increase of conductivity is

Table 1: Summary of rules.

| | | |
|---|---|---|
| Rule 1 | Condition | $c(\mathrm{AI}) \leq 0.4$ |
| | Conclusion | Normal |
| Rule 2 | Condition | $0.4 < c(\mathrm{AI}) \leq 0.8$ and $c(\mathrm{Ag}) \leq 0.1$ |
| | Conclusion | Normal |
| Rule 3 | Condition | $c(\mathrm{Fe}) \leq 0.2$ and $0.4 < c(\mathrm{AI}) \leq 0.8$ and $c(\mathrm{Ag}) > 0.1$ |
| | Conclusion | Normal |
| Rule 4 | Condition | $c(\mathrm{Fe}) > 0.2$ and $0.4 < c(\mathrm{AI}) \leq 0.8$ and $c(\mathrm{Ag}) > 0.1$ |
| | Conclusion | Warning |
| Rule 5 | Condition | $c(\mathrm{AI}) > 0.8$ |
| | Conclusion | Warning |

roughly divided into two stages for comparative analysis. The first stage: $\sigma = (10^{-15} \sim 10^{-8})$S/m, the variation range of corresponding electromagnetic wave propagation factor is $1 \sim 1.0031$ ($\Delta\gamma = 0.0031$). At this stage, the electromagnetic wave propagation factor increases slowly with the increase of conductivity. However, in the second stage: $\sigma = (10^{-8} \sim 9 \times 10^{-8})$S/m, the corresponding electromagnetic wave propagation factor changes from 1.0031 to 1.0095 ($\Delta\gamma = 0.0064$). In this stage, the electromagnetic wave propagation factor increases with the increase of conductivity. It can be concluded from the figure and table that the change law of these data can be obtained. When the conductivity of lubricating oil increases, the propagation factor of electromagnetic wave also increases, and their change relationship is also nearly linear in the first and second stages [22].

Figure 8 shows the propagation of electromagnetic wave with frequency of $F = 1$ GHz in lubricating oil. The black curve in the figure shows the relationship between the transmission coefficient of lubricating oil and the electrical conductivity of lubricating oil. It can be seen from Figure 8 that when the conductivity of lubricating oil $\sigma = 10^{-15}$S/m, the propagation factor value of electromagnetic wave is about 1. As the conductivity increases to $\sigma = 10^{-8}$S/m, the propagation factor of electromagnetic wave is 1.0045. When the conductivity continues to increase to $\sigma = 5 \times 10^{-8}$S/m, the propagation factor of electromagnetic wave is 1.0100. Finally, when the conductivity $\sigma = 9 \times 10^{-8}$S/m, the corresponding propagation factor of electromagnetic wave is about 1.0134. The change of conductivity can be roughly divided into two stages. The first stage: $\sigma = (10^{-15} \sim 10^{-8})$S/m, the variation range of corresponding electromagnetic wave propagation factor is $1 \sim 1.0045$ ($\Delta\gamma = 0.0045$). At this stage, the electromagnetic wave propagation factor increases slowly with the change of conductivity. The second stage: $\sigma = (10^{-8} \sim 9 \times 10^{-8})$S/m, the change value of the corresponding electromagnetic wave propagation factor is $1.0045 \sim 1.0134$ ($\Delta\gamma = 0.0089$). At this stage, the electromagnetic wave propagation factor changes rapidly with the conductivity. It can be seen from the figure that the change relationship between these two change stages is also nearly linear. From the relationship between the propagation factors of the above electromagnetic waves with different frequencies in the lubricating oil and the conductivity, the graphics drawn by MATLAB show that they all have a common feature: in the two different stages of conductivity change, they all have a nearly linear relationship [23].

In Figure 9, the abscissa is the variation range of electrical conductivity of lubricating oil, ordinate is the size of propagation factor, black is the electromagnetic wave with a frequency of 10 MHz, red is the electromagnetic wave with a frequency of 100 MHz, blue is the electromagnetic wave with a frequency of 500 MHz, and green is the electromagnetic wave with a frequency of 1 GHz. It can be concluded that the change of the conductivity factor is very linear, but it is not completely linear at several turning points in the curve of the propagation factor $\sigma = 10^{-8}$S/m. From the variation law of several curves, it can be concluded that with the increase of the frequency of electromagnetic wave, under the same change of conductivity, the change of propagation factor also increases, that is, it can be understood that the higher the frequency, the higher the sensitivity of electromagnetic wave to the change of conductivity [24, 25]. Through the simulation of the relationship between the electromagnetic wave propagation factor and the conductivity of lubricating oil by MATLAB software, it is verified that the change between propagation factor and conductivity is nearly linear.

*4.3. Rule Extraction.* In order to verify the effectiveness of the method, 1/2 samples in the divided state are randomly selected for rule extraction and the other 1/2 samples for rule verification. Based on the fusion of important elements, the rules of samples are extracted with the help of Weka software to build the knowledge base of fault diagnosis. The mined rules are shown in Table 1.

The extracted knowledge rules are used to verify the state of samples, and the recognition rate is 97.47%. In order to more fully explain the difference between important element fusion and all feature fusion, all features are extracted. At the same time, the fault diagnosis and recognition rate of all features is not high, only 62.39%. This means that not all features play a positive role in the fault diagnosis of the automobile engine wear state.

## 5. Conclusion

An automobile engine wear fault diagnosis algorithm based on SOM feature fusion based on Internet of Things technology is proposed. Through the feature fusion of multifeature data, the fusion value is obtained, and then, the boundary value of the fusion value is formulated to divide the sample state. Finally, Weka software is used to extract the knowledge rules of oil data. The relationship between the propagation factor of the excitation signal in the sensor in the lubricating oil and the change of the conductivity of the lubricating oil is simulated, and the curve between the output signal of the sensor and the conductivity of the lubricating oil is simulated. It can be seen at a glance that the lubricating oil sensor designed in this paper is feasible and practical. The automation and intellectualization of fault diagnosis of automotive engine lubricating oil spectral wear data are realized. According to the actual wear data of automobile engine, the proposed method is used for wear fault diagnosis, and the recognition rate is 97.47%, which shows that this method has a high recognition rate for fault state.

## Data Availability

The data underlying the results presented in the study are available within the manuscript.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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