Application Research on Ship Diesel Engine Condition Assessment System

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Abstract. In order to promote the development of intelligent ships, accelerate the application research of intelligent technology engineering, and build an intelligent information platform for big data fusion environment based on ship safety, economy and intelligence, it has become an important development direction in the industry. In the process of research and study on the existing methods of ship dynamic system state assessment, this paper applies the rough set theory and DS evidence theory to the application of ship dynamic system state assessment, and builds a ship dynamic system based on rough set theory and DS evidence theory. The state assessment model, and a detailed description of the assessment method, is used to verify the feasibility of the ship instance. Finally, the article uses Visual C# language and MATLAB mathematics tools to carry out systematic experiments on ship power system state assessment.

1. Introduction

After years of development, the ship power system state assessment technology has been continuously developed, and domestic research institutes have strengthened research work in this field. At present, the method of obtaining the technical parameters of the power system through monitoring technology, applying the data analysis or intelligent diagnosis method to evaluate the state of the ship's power system, and determining the state of the ship's power system has been widely used. However, many problems in the power system are gradually exposed, such as large data volume, redundant information affecting analysis results, inability to visually interpret the inherent relationship between data and device state, imperfect reasoning, and insufficient expert knowledge. In addition, the data information still has the characteristics of incompleteness and inaccuracy, and even there is ambiguity and contradiction to some extent. Therefore, the rough set theory with precise computational efficiency, optimization and reduction function [1] and D-S evidence theory for processing uncertainty problems and enhancing reliability [2] important reasoning methods have been gradually introduced into the field of state evaluation.

The ship power system is the guarantee of ship navigation. Among them, the diesel engine is one of the important power sources. Its monitoring involves various parameter indicators and data information such as speed, pressure and temperature. There are many sensors in the monitoring system of the diesel engine to monitor the working state and stability of the diesel engine. The personnel on board record and analyze the sensor information to comprehensively evaluate the operation of the host. This is also a common method for assessing the state of a ship's powertrain, and is mostly suitable for normal operation of equipment or obvious failure conditions.
However, between the normal operation and the fault condition of the equipment, there is often a critical state, that is, the potential risk of the equipment. If this potential risk is not detected early, it will become a malfunction of the equipment and even cause casualties. With the advancement of science and technology and the continuous development of intelligent ships, the conventional methods of ship equipment monitoring and management have been gradually replaced, followed by the integrated processing and analysis of the massive data of the engine room. How to optimize the mass data of the power system and transform it into the analysis and treatment of the potential uncertainty of the equipment, has gradually become an important research direction of the state assessment of the ship's power system.

Among the commonly used algorithms for state evaluation, rough set and D-S evidence theory have important scientific research value for solving the problem of complex data and strong unknowns. In view of the insufficiency of the two algorithms, in order to ensure the rationality of the power system state assessment method and the accuracy of the evaluation results, try to combine the two algorithms to optimize the algorithm and make up for the shortcomings. On the one hand, rough set theory can analyze the reliability and correlation between evaluation parameters through the original data information table, and use it as evidence information to promote the use of synthetic information. On the other hand, according to the analysis of the original data information table, the classification reduction of the evaluation parameters is transformed into the credibility of the evidence information in the D-S evidence theory, the synthesis effect is improved, and the accuracy of the decision result is enhanced. The effective fusion of rough sets and D-S evidence theory and its application in practical problems has far-reaching significance for solving complex and uncertain research on data information.

2. Rough set theory and D-S evidence theory

Rough set theory is a mathematical tool that processes data mathematically and accurately describes an uncertain and incomplete event. It has a strong ability to classify objects. DS evidence theory is a tool to effectively distinguish between uncertainties and unknowns. It is an important means of uncertainty reasoning to describe the credibility and uncertainty of events through the upper and lower limits of the interval and to use the interval estimates to identify uncertain and unknown information.

2.1. Rough set theory

Rough set theory is based on the premise of classification mechanism, which defines the classification as the indistinguishable relationship on the domain, and forms the division of the domain. Rough set theory uses known information base to divide inaccurate or indefinite information, and does not need prior knowledge to obtain information directly from the narrative of a given problem. By reducing the redundant components of interference factor in the information, the problem is eliminated.

(Information System, Approximate Space) The domain $U$ represents a non-empty finite set, $A$ representing a set of attributes about $U$, $V = \bigcup_{a \in A} V_a$, $V_a$ represents a set of values of attribute $a \in A$, and map $f : U \times A \rightarrow V$ represents pairs $\forall x \in U, a \in A, \exists F(x,a) \in V$, and each attribute object is given a corresponding attribute value. Therefore the information system can be represented by a quadrant $I = \langle U, A, V, f \rangle$. The information system can also be represented by a two-dimensional table.

When describing the proposition, each row of the two-dimensional table is the research object $x_i$ in the domain, and each column of the two-dimensional table is each attribute.

For an approximate space, it can be seen as an information system.

(Unresolvable relationship) Any subset $B$ of attribute set $A$, indistinguishable relationship $INB(B)$ has:

$$INB(B) = \left\{ (x, y) \bigg| (x, y) \in U^2, \forall b \in B \left( b(x) = b(y) \right) \right\}$$

(1)
(Upper approximation, Lower approximation) If \( X \subseteq U \) is any subset and \( R \) is an equivalence relation on \( U \), then there is a lower approximation \( \overline{RX} \) and an approximation \( \underline{RX} : \)

\[
\overline{RX} = \bigcup \{ x \in U : [x]_R \subseteq X \} \\
\underline{RX} = \bigcup \{ x \in U : [x]_R \cap X \neq \emptyset \}
\]

(2)

The \( R \) positive domain of set \( X \) is expressed as:

\[
POS_R(X) = \overline{RX}
\]

(3)

The \( R \) negative domain of set \( X \) is expressed as:

\[
NEG_R(X) = U - \overline{RX}
\]

(4)

The boundary field of set \( X \) is expressed as:

\[
BN_R = \overline{RX} - \underline{RX}
\]

(5)

(Approximate accuracy, Approximate quality) For \( I = (U, R) \), \( X \subseteq U \), there is an approximate accuracy:

\[
\alpha_R(X) = \frac{|RX|}{|\overline{RX}|} (X \neq \emptyset)
\]

(6)

The approximate quality \( \gamma_R(X) \) of \( X \) for knowledge \( R \) is defined as:

\[
\gamma_R(X) = \frac{|RX|}{|U|}
\]

(7)

(Attribute importance) In the attribute set, if \( A = C \cup D \), \( D \neq \emptyset \), and \( I = \langle U, A, V, f \rangle \) is a decision table, then \( c \in C \) exists. The importance \( SIG(c) \) of \( c \) relative to \( D \):

\[
SIG(c) = \gamma_C(D) - \gamma_{C-\{c\}}(D)
\]

(8)

(Relative redundancy attribute) Suppose \( P \) and \( Q \) are equivalent relationship classes in \( U \), \( R \in P \), if:

\[
POS_{(P-\{R\})}(Q) = POS_P(Q)
\]

(9)

Then \( R \) is called \( Q \) redundant in \( P \); otherwise, \( R \) is necessary for \( Q \) in \( P \). The set consisting of all \( P \)'s reductions is denoted as the \( Q \) core of \( R \), is \( \text{core}_Q(P) \).
(Differential matrix, Difference function) Let there be a decision information table \( I = \{ U, A, V, f \} \), where \( A = C \cup D \), \( C \cap D \neq \emptyset \). \( a(x) \) represents the value of \( x \) on attribute \( a \), \( D(x) \) represents the value of \( x \) on decision attribute \( D \), and the difference matrix is defined as:

\[
C_y = \begin{cases} 
(a \in C, a(x_i) \neq a(x_j)) & \text{if } D(x_i) \neq D(x_j), \\
0 & \text{if } D(x_i) = D(x_j)
\end{cases} \quad i, j = 1, 2, \ldots, n
\]  

(10)

2.2. D-S Evidence Theory

In D-S evidence theory, for any problem to be solved, \( \Theta \) describes a set of all possible outcomes. The elements in \( \Theta \) are mutually exclusive, and the result can only take one element. Such \( \Theta \) is called identification frame. Prior knowledge and our understanding are the ways to obtain the identification framework.

\( \Theta \) is a non-empty finite set, and a subset of \( \Theta \) is called a proposition \( A \), one of the possible cognitive results. The power set \( 2^\Theta \) of \( \Theta \) represents the set of all subsets, that is, the set of all possible propositions \( A \). \( R \) represents a set class on \( \Theta \), that is, any set of propositions that may exist, and \( (\Theta, R) \) represents a proposition space.

(Basic credibility allocation) On the identification framework \( \Theta \), define \( m : 2^\Theta \rightarrow [0,1] \). For any proposition \( A \) on \( \Theta \), the following conditions are met:

\[
m(\emptyset) = 0 \quad \sum_{A \subseteq \Theta} m(A) = 1
\]  

(11)

(Reliability function) On the identification framework \( \Theta \), the reliability function \( \text{Bel} : 2^\Theta \rightarrow [0,1] \) is derived from the basic credibility assignment function, defined as:

\[
\text{Bel}(A) = \sum_{B \subseteq A} m(B)
\]  

(12)

(Likelihood function, Credibility) Identifies any subset \( A \) in the framework \( \Theta \), \( \overline{A} = \Theta - A \), and the likelihood function \( \text{Pls} : 2^\Theta \rightarrow [0,1] \) of the proposition is:

\[
\text{Pls}(A) = 1 - \text{Bel}(\overline{A})
\]  

(13)

When \( A_k \cap B_L = A \), the total reliability assigned to \( A \) on the reliability \( m_1(A_k)m_2(B_L) \) can be expressed as \( \sum_{A_k \cap B_L = A} m_1(A_k)m_2(B_L) \). When \( A_k \cap B_L = \emptyset \), there is a part of the reliability falling on the empty set, and by definition 2.9 we know: \( m(\emptyset) = 0 \), the total reliability is 1. So when \( A_k \cap B_L = \emptyset \), we need to remove \( m_1(A_k)m_2(B_L) \) and multiply by the normalization factor to match the total confidence value of 1.

\[
K = \sum_{A_k \cap B_L = \emptyset} m_1(A_k)m_2(B_L)
\]  

(14)
The normalization factor is \((1-K)^{-1}\), and after synthesis, for \(m: 2^\Theta \rightarrow [0,1]\):

\[
m(A) = \left\{ \begin{array}{ll}
0 & A = \emptyset \\
\frac{\sum_{A_c \cap B_c = A} m_c(A_c)m_s(B_c)}{1-K} & A \neq \emptyset
\end{array} \right.
\] (15)

3. State evaluation of D-S evidence theory based on rough sets

3.1. Common methods for status assessment

The application of fuzzy set theory and rough set theory are all aimed at the problem of incomplete knowledge incompleteness. The fuzzy set describes the unclearness of the set, and the rough set describes the equivalence relation between the objects. In addition, the fuzzy function of the membership function of the concept of ambiguity is derived from expert experience. It describes the affiliation between multiple research objects under the same premise, and the degree of membership is the key. The rough set objectively obtains the equivalence class relationship between the objects from the data, and describes the relationship among the research objects in different equivalence classes. The classification is the key. In the state evaluation, the state has many influencing factors, and the object description state of the different classes is more accurate and comprehensive.

As a machine learning algorithm, the support vector machine has more ability to solve regression problems and pattern recognition ability, and is used more in research directions such as prediction and evaluation. However, it also has some shortcomings, such as the difficulty of processing large-scale sample models and weak classification ability. Therefore, in the application of fusion algorithms, more applications use the combination of support vector machine and rough set theory. On the one hand, rough set theory has a good advantage in attribute reduction, enabling it to play the role of small sample learning problems. And simplify the use of the algorithm; on the other hand, the advantages of the rough set in the classification also greatly compensate for the shortcomings of the support vector machine. The fused optimization algorithm reduces training time, speeds up, and reduces complexity.

The neural network, by constructing a simple nonlinear network, simplifies the model with its self-learning, self-organization and self-adaptation, and is widely used in the fields of fault diagnosis and state evaluation. Because the model is divided into multiple simple sub-networks, the processing speed is faster. However, the aspects of its analysis and processing are relatively simple, and it is not possible to fully integrate multiple sub-networks to obtain a comprehensive analysis of information. Therefore, the fusion algorithm of neural network and D-S evidence theory came into being. Moreover, because the basic credibility distribution of the evidence information of D-S evidence theory mainly comes from expert experience, not only subjective but also difficult to obtain, the self-learning of neural network just makes up for this deficiency.

3.2. Fusion algorithm state evaluation

Rough set theory has a good effect on the classification and reduction of data. After processing, the extracted data rules represent the attribute set and decision set of the information system. However, it has certain shortcomings, that is, the relationship between the rules cannot be seen from the extraction rules. D-S evidence theory has strong probability estimation ability, and can combine independent evidence of data sources through synthesis rules to obtain quantitative results [1]. However, the amount of calculation is large, and the research work becomes difficult as the complexity of the data information becomes deeper.

The DS evidence theory based on rough set [2] can comprehensively analyze massive data source information, reduce effective information, convert it into basic credibility distribution of evidence information, and then obtain decision results through evidence synthesis, and optimize the accuracy of state evaluation conclusions degree.
The D-S evidence theory based on rough set theory also has the function of making up for the deficiency of many single algorithms:

First of all, the rough set theory is very different from other theories dealing with uncertainty problems, that is, without obtaining any prior knowledge, it can objectively deal with the uncertainty problem, and because it does not contain the original information to solve the uncertainty problem. Therefore, it has a greater complementarity to the theory of evidence.

In addition, the decision information table is reduced by rough set theory, which is simplified under the premise that the decision classification ability does not change, and is applied as evidence to the D-S synthesis rule, which simplifies operation and reduces errors.

The identification framework and the approximate spatial description are all sets of all the possibilities of the problem to be processed or the research object; the likelihood function and the upper approximation describe the probability or degree of the event that may exist or occur; the reliability function, the lower approximation description The probability or degree of an event that is definitely present or occurring; the credibility and boundary fields describe the problem to be dealt with or the uncertainty factor in the research object.

Therefore, we can clearly establish the relationship between the two. When using the fusion algorithm, we analyze the attribute of the reduction in the rough set theory, and convert the evidence information under the corresponding identification framework to obtain the basic credibility distribution. Comply with DS synthesis rules and synthesize final conclusions.

4. State evaluation model research

4.1. State evaluation model

In the decision system, \( S = \{U, C \cup D, V = V_c \cup V_d\} \), let \( R \) be the equivalence relation on \( U \), then there is an equivalence class \( U / R = \{Y_1, Y_2, \ldots, Y_n\} \). Therefore, the following function on \( 2^U \) is a quality function:

\[
m(Y_j) = \frac{|Y_j|}{|U|} \quad (j = 1, 2, \ldots, n)
\]  

(16)

According to the upper approximation and the lower approximation concept, the reliability function and the likelihood function concept, it is also possible to derive:

Upper approximation mass function:

\[
Pls(X) = \frac{|R(X)|}{|U|} = \frac{\bigcup_{Y_i \in U/R, Y_i \cap X \neq \emptyset} Y_i}{|U|}
\]  

(17)

Lower approximation mass function:

\[
Bel(X) = \frac{|R(X)|}{|U|} = \frac{\bigcup_{Y_i \in U/R, Y_i \cap X} Y_i}{|U|}
\]  

(18)

In the decision system, decision information table \( S = \{U, C \cup D, V = V_c \cup V_d\} \), mapping \( \alpha : U \to P(V) \), \( \alpha(x) = \{d(x) \mid x \in U, x \in [x_{\alpha(x)}] \} \) is called generalized decision of \( S \).

For information system \( S = \{U, C \cup D, V = V_c \cup V_d\} \), the decision-making value partition space is \( V_p = \{d_1, d_2, \ldots, d_l\} \), and the decision is divided into \( U/D = \{Y_1, Y_2, \ldots, Y_n\} \), \( Y_i = \{x \in U \mid \alpha(x) = d_i \in V_D\} \).

For any given \( \beta \in V_D \) and \( IND(A) = A \), the indistinguishable relationship exists:
\[
m_I(\beta) = \left\lceil x \in [x]_{IND(A)} : \alpha_I \left( [x]_{IND(A)} \right) = \beta \right\rceil / |U|
\]  

(19)

D-S evidence theory has a good effect in solving the uncertainty problem, but because its basic credibility distribution mainly comes from expert experience, it will cause certain errors [3]. In this case, the rough set theory is used to discretize and reduce the attributes, and according to the function correspondence between the two, the decision table data is transformed into generalized decision attributes, making it the evidence condition in evidence theory. After the calculation of the basic credibility distribution, the application of DS evidence theory is improved.

4.2. Model building
S =< U, C ∪ D, V = V_c ∪ V_d > in the decision information table, including 12 research objects, 16 condition attributes, and 1 decision attribute D. Set the state evaluation decision attribute code set D = \{d_1, d_2, d_3\}, set the fault state code to 1, the hazard state code to 2, and the good state code to 3. As shown in the following table:

| Serial number (D) | State name        | Decision attribute coded value |
|-------------------|-------------------|-------------------------------|
| d_1               | Fault status      | 1                             |
| d_2               | Hidden state      | 2                             |
| d_3               | Good condition    | 3                             |

Figure 1. Evaluation model of D-S evidence theory based on Rough Set Theory
Table 2. The condition attribute code (C)

| Serial number | Parameter name          |
|---------------|-------------------------|
| c1            | Fuel consumption        |
| c2            | Highest burst pressure  |
| c3            | Exhaust gas temperature |
| c4            | Supercharger speed      |
| c5            | Oil inlet temperature   |
| c6            | Oil outlet temperature  |
| c7            | Fresh water inlet temp. |
| c8            | Fresh water outlet temp.|
| c9            | Oil cooler oil inlet pres.|
| c10           | Oil cooler oil outlet pres.|
| c11           | Supply pump suction pres.|
| c12           | Supply pump discharge pres.|
| c13           | Double filter front and back pres. difference|
| c14           | Circulating pump suction pres.|
| c15           | Circulating pump discharge pres.|
| c16           | Fuel viscosity          |

Table 3. The raw data table (1)

| U   | c1  | c2  | c3  | c4  | c5  | c6  | c7  | c8  |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| x1  | 289.1 | 6.71 | 562 | 38050 | 45  | 62  | 87  | 82  |
| x2  | 270.3 | 8.06 | 557 | 39990 | 48  | 66 | 84  | 76  |
| x3  | 232.4 | 6.92 | 481 | 44760 | 46  | 67 | 82  | 83  |
| x4  | 261.2 | 7.75 | 470 | 44810 | 50  | 63 | 81  | 80  |
| x5  | 267.5 | 7.90 | 500 | 41550 | 51  | 63 | 83  | 75  |
| x6  | 310.1 | 6.97 | 558 | 43830 | 54  | 62 | 85  | 82  |
| x7  | 262.3 | 7.95 | 491 | 40190 | 45  | 63 | 85  | 73  |
| x8  | 300.6 | 6.82 | 562 | 43940 | 42  | 67 | 84  | 81  |
| x9  | 244.5 | 7.86 | 492 | 40420 | 46  | 63 | 82  | 77  |
| x10 | 242.6 | 7.69 | 493 | 41020 | 48  | 65 | 82  | 81  |
| x11 | 239.2 | 6.95 | 481 | 44210 | 41  | 66 | 80  | 74  |
| x12 | 238.1 | 5.98 | 486 | 44100 | 43  | 64 | 85  | 71  |

Table 4. The raw data table (2)

| U   | c9  | c10 | c11 | c12 | c13 | c14 | c15 | c16 |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| x1  | 0.35 | 0.30 | 0.01 | 0.04 | 0.05 | 0.30 | 0.80 | 14 |
| x2  | 0.35 | 0.32 | 0.03 | 0.30 | 0.06 | 0.26 | 0.78 | 15 |
| x3  | 0.35 | 0.33 | 0.02 | 0.11 | 0.31 | 0.79 | 12 |
| x4  | 0.35 | 0.31 | 0.02 | 0.10 | 0.32 | 0.80 | 14 |
| x5  | 0.35 | 0.29 | 0.03 | 0.09 | 0.30 | 0.83 | 11 |
| x6  | 0.35 | 0.31 | 0.01 | 0.08 | 0.29 | 0.80 | 9 |
| x7  | 0.35 | 0.29 | 0.01 | 0.11 | 0.30 | 0.78 | 15 |
| x8  | 0.35 | 0.32 | 0.01 | 0.06 | 0.28 | 0.80 | 12 |
| x9  | 0.35 | 0.30 | 0.02 | 0.09 | 0.32 | 0.80 | 13 |
| x10 | 0.35 | 0.33 | 0.03 | 0.06 | 0.26 | 0.82 | 12 |
| x11 | 0.35 | 0.30 | 0.03 | 0.06 | 0.28 | 0.83 | 11 |
| x12 | 0.35 | 0.29 | 0.02 | 0.10 | 0.29 | 0.81 | 10 |
Set the research object $U = \{x_1, \ldots, x_{12}\}$, the raw data table is shown in Table 3 and Table 4.

As shown in Table 3 and Table 4, for the 12 groups to be studied, there are 16 attributes respectively, and the research object in the data table $x_1, x_2, x_3, x_4$ is the data under the fault state (\(d_1\)), $x_5, x_6, x_7, x_8, x_9, x_{10}, x_{12}$ is the data under the hidden danger state (\(d_2\)), $x_{11}, x_{13}, \ldots, x_{19}$ is the data under a good state (\(d_3\)).

4.3. Evaluation calculation

After the above steps are calculated and analyzed, each evidence information has met the conditions for applying the D-S synthesis rule. First, we synthesize the evidence $m_{c_1}(\beta)$ and synthesize $m_{c_2}(b)$ according to the D-S synthesis rule, which is calculated by the formula (4):

$$K_{12} = \sum_{A_K \cap B_L = \emptyset} m_1(A_K)m_2(B_L) = 0.6528$$

And calculated by the formula (5):

$$m_{c_1}m_{c_2}(F_1) = 0.3200, m_{c_1}m_{c_2}(F_2) = 0.5000, m_{c_1}m_{c_2}(F_3) = 0.1800.$$  

Combine $m_{c_1}m_{c_2}(F)$ and $m_{c_5}(\beta)$ in the same way:

$$K_{123} = \sum_{A_K \cap B_L = \emptyset} m_{12}(A_K)m_3(B_L) = 0.7500$$

By calculating the conflict degree of the three kinds of evidence meta-information, it can be concluded that none of them is close to 1, so there is no conflict evidence. It can be solved according to the general evidence synthesis rules.

According to formula (5), the final composite result is:

$$m_{c_1}m_{c_2}m_{c_3}(F_1) = 0.2133, m_{c_1}m_{c_2}m_{c_3}(F_2) = 0.6667, m_{c_1}m_{c_2}m_{c_3}(F_3) = 0.1200.$$  

In the previous section, the results obtained by applying the composition rule can be used as decision information for inferential evaluation. In this paper, the decision support method based on basic reliability assignment is used to make inferential judgment on the state assessment of ship power system.

According to the calculation results and formula in the previous section, let $\varepsilon_1 = 0.1000$, $\varepsilon_2 = 0.1000$, and then:

$m(\Theta) = 1 - 0.2133 - 0.6667 - 0.1200 = 0$  

In applying the d-s rule, we take four significant digits, $m_{c_1}m_{c_2}m_{c_3}(F_2)$ approximately 0.6667, and the uncertainty $m(\Theta)$ is infinitely close to zero, the default value here is zero.

$$m(A_1) = 0.6667, m(A_2) = 0.2133,$$  

the formula can be obtained (4.9):

$$\begin{align*}
    m(A_1) - m(A_2) > \varepsilon_1 \\
    m(\Theta) < \varepsilon_2 \\
    m(A_1) > m(\Theta)
\end{align*}$$

Therefore, the state evaluation results show that the probability of no obvious fault in the operation of diesel engine equipment is 66.67%. The diesel engine is in a hidden danger state, and maintenance inspection should be carried out to avoid failure. In this case, the algorithm is accurate, reasonable and efficient, which proves that the method proposed in this paper is feasible and reliable.
5. Application and implementation

The ship power system status assessment software introduced in this paper is developed with Visual C# language [4]. Visual C#, its object-oriented, strong operational ability, innovative language features and modular design ideas not only meet the needs of software system development, but also ensure the perfection of the function. In the algorithm part of the software system, MATLAB mathematical tool [5] is used to write the algorithm program. Select MATLAB and Visual C# for complementary advantages, on the one hand with the help of MATLAB powerful numerical analysis function, on the other hand with Visual C# efficient design and development of friendly human-machine interface.

In the software system design, this method can not only make MATLAB powerful numerical calculation and analysis function to play, but also can provide data type conversion for M function, so that it can run independently of the MATLAB environment, maintain the flexibility of MATLAB, simplify the Visual C# system development.

The main function of the interface in Fig.2 is to monitor the diesel engine parameter information from the data acquisition system. While preparing for the state assessment, the integrated monitoring and alarming function is also realized.

![Comprehensive monitoring and control interface](image)

**Figure 2.** Comprehensive monitoring and control interface

Fig.3 shows the state evaluation interface. The main function is to select the parameters involved in the status assessment from the "parameter summary bar" on the left side of the interface, and the selected parameters are displayed in the "parameter box" on the right side of the parameter summary box. Relevant data information in the database can be extracted through the "data import" button. Click "status assessment", and the result information of this status assessment will be displayed in the text box below.
Figure 3. Interface of evaluation state

Figure 4 shows the state management interface. The main function of the interface is to list solutions to abnormal conditions of related parameters according to common problems of the power system. By clicking the corresponding fault information on the left side of the interface, the corresponding auxiliary suggestion information will be displayed in the "decision suggestion" column on the right side, for the ship management personnel to quickly troubleshooting problems and enrich the "personnel experience" in the status assessment of the power system.

6. Conclusion
In the future, further research is needed in the following parts, so as to improve the research and establish a rich and comprehensive theoretical research and application design and development of ship status assessment system.
(1) The algorithm selected in the state assessment needs to be further deepened and improved. In the future, the state assessment can be developed from a single system to the whole ship to ensure the reliability of the ship and promote the intelligent development of the ship [6].

(2) The processing of conflict evidence in d-s evidence theory. For the evidence with big conflict or completely opposite, the method of discarding conflict evidence [7] [8] will lead to the violation of the actual situation. The algorithm theory should be studied deeply to find a widely applicable solution.

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