A Framework for Health State Evaluation of the Complex Mechanical System With Its Occurrence Probability of Failure Mode

YANG TANG1,2,3, XIN YANG1,3, AND GUORONG WANG1,2,3

1School of Mechatronic Engineering, Southwest Petroleum University, Chengdu 610500, China
2Southern Marine Science and Engineering Guangdong Laboratory, Zhuhai 524000, China
3Key Laboratory of Oil and Gas Equipment, Ministry of Education, Southwest Petroleum University, Chengdu 610500, China

Corresponding author: Yang Tang (tangyanggreat@126.com)

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ABSTRACT Safety and overall productivity of the complex mechanical system (CMS) are affected by their health state directly. In order to achieving accurate and effective health state evaluation (HSE) of the CMS, dependency and correlation among system, subsystem, component, failure mode and characteristic variable are revealed. Based on their dependency and correlation between failure mode and characteristic variable, two novel concepts, including occurrence probability of failure mode (OPFM) and degradation probability of characteristic quantity (DPCQ), are defined and their calculation function relation is established for the HSE of the CMS. A framework for HSE of the CMS based on the OPEM is proposed. This HSE method can deal with the CMS with characteristics such as the small number of characteristic quantity corresponding to a single failure mode, health state, the correlation between failure mode and characteristic quantity and so on. For quantitative HSE of the CMS, “failure mode—component—subsystem—system” can be realized by step-by-layer solution. Finally, this method has been verified by a case study, which can effectively avoid problems of redundancy of characteristic quantity, wrong selection of characteristic quantity, complex calculation relation and large amount of calculation data in the HSE of the CMS.

INDEX TERMS Asset integrity management, complex mechanical system, health state evaluation, occurrence probability of failure mode, prognostic and health management.

I. INTRODUCTION

Prognostic and Health Management (PHM) and Asset Integrity Management (AIM) are two important concepts and technologies adopted equipment and facilities asset management in the enterprise [1], [2]. They are also hot research topics in the aerospace, manufacturing, and energy industries. For the PHM and AIM, scientific HSE is one of their core technologies and contents. And the HSE results can be used as an important index and basis for their health management, integrity evaluation and maintenance decision-making of the CMS. But the existing HSE was mainly studied by using various mathematical evaluation algorithms, including Support Vector Machines, Neural Networks, based on the characteristics of data samples. Moreover, the data they put to use were mainly these kinds of data, including instrument measured data, manual measurement data, historical operation and failure data [3]. Some scholars have carried out a series of research on the theory and technology of equipment health assessment in the fields of electricity, aviation and nuclear power. Dussault et al. [4], applied intelligent reasoning model to evaluate the health state of critical airborne equipment by carrying out the airborne sensor data and maintenance test data. A three level health assessment mode, including, engine layer, aircraft layer and base layer, was summed up by Simon [5], for aircraft engines based on engine vibration data.
Based on the wavelet transform theory and the forward neural network, a set of health indexes for evaluating the failure severity of bearings is proposed and the purpose of automatic health assessment of bearings is realized by Gao et al. [6]. Du et al. [7], proposed a method for evaluating the health state of hydraulic piston pumps considering hierarchical clustering.

However, the HSE of the CMS is still in the stage of exploration and development at present, and its many basic theories and techniques is not yet mature. It is mainly manifested in the following aspects. Firstly, there is a problem in the research of parameter collection and analysis for HSE. More attention is paid to the research of new acquisition technology or means, but little attention has been paid to the deep analysis of the text data of historical events, such as inspection records, failure records, maintenance records, maintenance records, spare parts records, switch machine records. Secondly, in the research of equipment condition evaluation theory, there are some problems that pay more attention to equipment test information and less attention to real-time operation information, which leads to the lack of timeliness and feasibility of state evaluation. Thirdly, when the characteristic quantity space of the health state was constructed, it was not possible to determine whether sufficient characteristic quantity information is contained. Therefore, the number of characteristic quantities will be increased as much as possible. So the redundant characteristic quantities might be generated for complex structured mechanical system and the amount of computation will be increased, which is not conducive to fast and accurate HSE. Moreover, there are a lot of special mechanical systems with fine management, non-intelligent integrated, non-large high-end in the energy and construction industry. For the special mechanical system, there are some universal characteristics as follow, mutable and adverse operating conditions, sudden failure and high-risk consequences, as well as the lack of health state parameters and their acquisition technologies. At present, few studies have been carried out on the HSE of for such CMS. Therefore, a method for evaluating the health state of CMS was put forward by digging the historical events of equipment and considering the characteristics of their failures in this paper.

This paper is organized as follows. In Section 2, a new concept about the OPFM is defined, and its quantitative evaluation method is proposed. A membership function of the health state of CMS is established in Section 3. The Section 4 presents a method for fuzzy comprehensive evaluation of health state based on the OPFM. In Section 5, a case study is carried on. Conclusions and further work are discussed in Section 6.

II. DEFINITION AND QUANTIFICATION ON THE OPFM

A. CORRELATION ANALYSIS ON FAILURE MODE AND CHARACTERISTIC QUANTITY

Based on the Reliability Centered Maintenance (RCM) theory, the health state of the mechanical system is the ability to realize its specific performance under certain operating conditions. Failure modes are the diversified forms or phenomenon in the deterioration of health state of the mechanical system. Generally speaking, most of the failure modes in mechanical system do not occur instantaneously. In other words, the occurrence of failures usually has a potential process from potential defect to functional failure, namely P-F development stage, as shown in Fig. 1 [8].

When the mechanical system has been operating for some time stage, an initial defect will occur at some point $T_S$ on one or more parts or components. But the defect will not directly result in functional failure of the mechanical system. As time goes on, the defect will gradually grow so that its characteristics that can be detected appear. At this point $T_P$, if characteristics of the defect are identified, some measures may be taken to eliminate it. If the defect has not been detected and not eliminated or updated, it will continue to grow so that occurrence probability of its function failure will increase gradually. Defects of parts or components grow to a certain extent and form their failure modes. And health state of the parts or components affect health state of the whole mechanical system. So it may be gradually deteriorated with the defect growing. The deterioration degree of health state is reflected directly by deterioration degree of characteristics quantity of the defect on parts or components. In order to quantify the deterioration degree between them, the following hypotheses were defined in this study. When the defects of one part or component has grown into its functional failure, the occurrence probability of its failure modes is defined as 1 (namely, 100%). And characteristic quantity related the failure modes also reaches an outage threshold. At the same
time, deterioration degree value of the characteristic quantity is 1 (namely, 100%).

As we all known, the space vector composed of characteristic quantity can express the health state of a mechanical system. The failure development process of mechanical system corresponds to development degree of its failure modes, which can be regarded as occurrence probability of the failure mode. With the failure development, namely defect growing, the change of characteristic quantity is to be brought about. Therefore, there is a close relationship among the three types of failure modes, characteristics quantity and health state. In other words, the OPFM is internal representation as the change of health state of mechanical system. Suppose that a mechanical system has $m$ failure modes, namely $F_1, F_2, \ldots, F_m$, and a failure mode corresponding to the $n$ characteristic quantities, namely $x_1(t), x_2(t), \ldots, x_n(t)$. Health state of the mechanical system is represented as $S(t)$. Then, a mapping relation among failure modes, characteristic quantities and health state can be expressed as follows,

$$S(t) \leftarrow \{x_1(t), x_2(t), \ldots, x_n(t)\} \leftarrow \{F_1, F_2, \ldots, F_m\} \quad (1)$$

According to performing FMEA for a mechanical system, there are one or more failure modes for a part or component as well as a failure model usually has one or more failure causes and failure consequences.

Through analysis, it is found that a characteristic quantity can partly reflect development degree of failure modes related a part or components. And the development process of a failure mode will lead to a change of the number of characteristic quantities. In the other words, a value changing of characteristic quantity corresponding to the failure mode can reverse an OPFM.

Based on the above analysis, the development state of the failure model is related to the deterioration degree (value changing) of characteristic quantity, and the deterioration degree of characteristic quantity is related to the deterioration degree of health state. Therefore, the internal relations between development state of failure mode and deterioration degree of health state in mechanical system can be established based on the deterioration degree of characteristic quantity.

The development state of the failure mode at time $t$ is represented by the occurrence probability $P(t)$ of the failure mode at time $t$, and the influence value of the state characteristic quantity on the OPFM at $t$ is the total DPCQ $P(t)$. The state characteristic quantity corresponding to the failure mode is $x_1(t), x_2(t), \ldots, x_n(t)$. To ensure that each state characteristic quantity corresponds to one characteristic quantity total degradation probability $p_i(t)$, the correspondence between the state characteristic quantity $x_i(t)$ and the total degradation probability $p_i(t)$ is represented by a function $F$, that is $p_i(t) = F[x_i(t)]$. Finally, the OPFM can be obtained according to the $x_1(t), x_2(t), \ldots, x_n(t)$ total degradation probability of all state characteristic quantities corresponding to the failure mode at time $t$.

**B. COMPREHENSIVE ASSESSMENT OF THE OPFM**

In order to reasonably utilize the information of each state characteristic quantity, the weighted average of the total DPCQ is used as the OPFM. The influence degree of the characteristic quantity on the OPFM is reflected by the weight
of the characteristic quantity, and the calculation result of the OPFM is more scientific and reasonable.

Assuming that the state characteristic quantity set corresponding to the failure mode \( F_i \) in a CMS is \( Y_j = \{ Y_1, Y_2, \ldots, Y_n \} \), and the total deterioration probability value of each state characteristic quantity \( Y_j \) is \( p(Y_j) \), the failure probability \( P(F_i) \) corresponding to the failure mode is expressed as [9],

\[
P(F_i) = \left[ P(Y_1), P(Y_2), \ldots P(Y_n) \right] \tag{2}
\]

In Eq. (2), where \( n \) is the number of characteristic quantity corresponding to the failure mode \( F_i \), determined by the correspondence between the failure mode and the characteristic quantity in the previous section; \( \omega = [\omega_1, \omega_2, \ldots, \omega_n]^T \) is the weight vector corresponding to the state characteristic quantity set, wherein \( \omega_i \in [0, 1] \) and satisfy \( \sum_{i=1}^{n} \omega_i = 1 \).

There is a one-to-one correspondence between the characteristic quantity and the weight. If a certain characteristic quantity is missing in the calculation process, the weight of the missing characteristic quantity is taken as zero, and the weight of the corresponding remaining characteristic quantity is recalculated.

1) DETERMINING TOTAL DEGRADATION PROBABILITY \( p(Y_j) \)

According to the variation law and feature of the state characteristic quantity, the case where the relative deterioration degree reaches “1” is defined as the total degradation state, and the relative deterioration degree \( b_i(t) \) of the state determination quantity at the time \( t \) is taken as the occurrence probability \( p(Y_j) \) of total degradation, that is, the relative deterioration degree function of the characteristic quantity is the total degradation probability calculation function, and the greater the relative deterioration degree calculated, the greater the probability that the characteristic quantity total degradation occurs. Therefore, the total deterioration probability value \( p(Y_j) \) of the \( j^{th} \) state characteristic quantity can be expressed as

\[
p(Y_j) = b_i = F[Y_i(t), Y_{i0}, Y_i^f] \tag{3}
\]

where \( j = i = 1, 2, \ldots, n \), \( F[\bullet] \) is the relative deterioration degree function of the \( i^{th} \) characteristic quantity; \( Y_i(t) \) is the state value of the \( i^{th} \) characteristic quantity at time \( t \); \( Y_{i0} \) is the normal value of the \( i^{th} \) characteristic quantity; \( Y_i^f \) is the threshold for failure or shutdown due to the \( i^{th} \) characteristic quantity.

2) CHARACTERISTIC WEIGHT BASED ON VARIABLE WEIGHT SYNTHESIS THEORY \( \omega_i \) CALCULATION

By analyzing the actual situation of the equipment health state change, the characteristic quantity is dynamically changed during the failure development process, so the influence degree on the failure probability is also constantly changing, and the sensitivity and accuracy they reflect are constantly changing. The change, therefore, the characteristic quantity weight \( \omega_i \) should also change. According to the variable weight synthesis theory, the comprehensive.

Evaluation of the OPFM belongs to the variable weight synthesis mode, and the variable weight vector calculation method can be used to determine the \( \omega_i \) weight of the characteristic quantity.

From the Eq. (2), the calculation equation of the OPFM can be transformed into,

\[
P(F_i) = \sum_{j=1}^{m} \omega_j P(Y_j) \tag{4}
\]

The normal weight comprehensive mode equation under normal conditions [10], [11],

\[
V_0 = \sum_{i=1}^{m} \omega_i x_i \tag{5}
\]

The variable weight vector calculation equation [10], [11],

\[
\omega_j(x_1, x_2, \ldots, x_m) = \omega_j(0)x_i^{a-1}/\sum_{j=1}^{m} \omega_j(0)x_j^{a-1} \tag{6}
\]

The above equation is consistent with the structure type of Eq. (5), that is the comprehensive evaluation is carried out by means of factor summation. Thus, the variable weight vector of the characteristic quantity can be calculated using the Eq. (6). At the same time, according to the influence law of the variable weight factor \( a \) on the evaluation result, taking into account the influence of the state characteristic quantity of the CMS on the probability of failure, take \( a = 0.5 \), so the calculation equation of the OPFM is,

\[
P(F_i) = \sum_{j=1}^{n} \omega_j(0) P(Y_j)^{0.5} / \sum_{k=1}^{n} \omega_k(0) P(Y_k)^{-0.5} \tag{7}
\]

III. MEMBERSHIP FUNCTIONS OF HEALTHY STATE

A. MEMBERSHIP FUNCTIONS

A paper entitled “Fuzzy Sets” first published by Zadeh in 1965 [12], which defined a fuzzy set: a given subset \( A \) on \( U \), a fuzzy subset \( A \) on \( U \). Any element \( x \in U \) has a number \( \mu_A(x) \in [0, 1] \) corresponding to it. This number \( x \) is used to indicate the degree of belonging to \( A \), and its existence is as follows:

\[
\mu_A : U \rightarrow [0, 1] \tag{8}
\]

\[
x \rightarrow (x) \in [0, 1] \tag{9}
\]

The constant \( \mu_A(x) \) is called the membership degree of the element in \( U \) to the fuzzy subset \( A \). When \( x \) changes in \( U \), \( \mu_A(x) \) is a function called the membership function of \( A \). The membership degree \( \mu_A(x) \) indicates the degree to which \( x \) belongs to \( A \). The closer the membership degree \( \mu_A(x) \) is to 1, the higher the degree to which \( x \) belongs to \( A \). The closer \( \mu_A(x) \) is to 0, the lower the degree to which \( x \) belongs to \( A \). The closer \( \mu_A(x) \) is to 0.5, the more the \( x \) belongs to the
more blurred the degree of fuzzy set \( A \). Using the membership function \( \mu_A(x) \) that takes the value \([0,1]\) to characterize the degree to which \( x \) belongs to \( A \), it is more reasonable to describe the ambiguity problem than the classical set theory.

Determining the membership function is the basis of fuzzy set application. Correctly constructing the membership function is one of the keys to whether fuzzy evaluation can be realized. The process of determining the membership function should be objective in nature, but each person has different understanding and understanding of the same fuzzy concept. Therefore, the process of determining the membership function is subjective. There is not a set of mature and effective methods to determine membership function. Most of the methods are still based on experience and experiment. For the same fuzzy concept, different people will establish a membership function that is not exactly the same. Although the forms are not identical, or can only reflect the same fuzzy concept, they still have the same goal in solving and dealing with the actual fuzzy information. The determination of the membership function needs to be done manually. Generally, the following principles should be followed:

1. The fuzzy set represented by the membership function is a convex fuzzy set, that is, the shape of the membership function is required to have a unimodal shape.
2. The membership function is symmetrically balanced, that is, the nominal value of the description variable is usually odd, and the number is moderate, generally 3 to 9.
3. The membership function conforms to the linguistic order of people, that is, the distribution of linguistic values conforms to common sense and practical experience.
4. Each point in the universe belongs to at least one membership function region.
5. When two membership functions overlap, the maximum membership degree cannot occur simultaneously for the same variable value.

At present, the methods of determining the membership function mainly include statistical survey method, fuzzy statistical test, expert evaluation method, the historical experience method, reservation-modification-complete method, analytical reasoning method, fuzzy operation, binary comparison sorting method and so on. Among them, the binary comparison sorting method first determines the general shape of the membership function, according to which an appropriate membership function model can be selected. Commonly used membership functions are rectangular distribution, semi-trapezoidal and trapezoidal distribution, parabolic distribution, normal distribution, ridge distribution, etc. These distributions include functions suitable for describing fuzzy concepts such as small, large and intermediate.

**B. METHOD ON HEALTH STATE PARTITION OF THE CMS**

Generally, the CMS goes through two phases during the operating process, namely the normal operation phase and the defective operation phase, as showed in Fig. 3 [13]. Therefore, the process which may be combined and the deterioration degree of the relative development, to be described in more detail and in accordance with the division of the health state of the CMS performance capability for mechanical system specific properties, namely the good state, the better state, the general state, the proposed failure the status of the four health states, as shown in TABLE 1. In the actual situation, there is no clear boundary between the four states in which the mechanical system operates, and there is an intermediate transition in the adjacent state. Therefore, in order to scientifically evaluate the health state, the fuzzy set theory is used to treat the four health states as four fuzzy subsets, and the membership functions of various health states are determined, so that the health state of the items is calculated to belong to the four types. The membership degree of the
TABLE 1. Health state division of the CMS.

| State description | Health state division | State consistency |
|-------------------|-----------------------|-------------------|
| The CMS can achieve the specific functions well and can be continuously used for a long time | Good state | $s_1$ |
| Abnormal sign occurs in the system, the CMS can operate, but performances degrade | Better state | $s_2$ |
| More serious abnormal sign occurs in the system, the CMS can operate, but performances greatly degrade | General state | $s_3$ |
| Serious sign occurs in the system, the CMS can hardly achieve the specific performances thereof | Quasi-failure state | $s_4$ |

TABLE 2. The main technical parameters of the mud pump.

| Item          | Model | Bore (mm) | Rated Pressure (MPa) | Rated Power (KW) | Impulse (spm) | Stroke Length (mm) | Displacement (L/s) |
|---------------|-------|-----------|----------------------|------------------|--------------|------------------|-------------------|
|               | F1300 | 180       | 18.7                 | 960              | 120          | 305              | 46.54             |

C. ESTABLISHED ON MEMBERSHIP FUNCTIONS OF HEALTHY STATE

In TABLE 1, the health state division mode of the equipment, the health state space of the CMS of the offshore platform can be expressed as $S = \{s_1, s_2, s_3, s_4\}$. According to the OPFM of the CMS, the membership degree corresponding to various states in the health state can be obtained. Through analysis, it is found that the common membership functions collected by Prof. A. Kaufmann of France are 28 kinds, which can be divided into four types: small, large, intermediate symmetric and small [14]. Among them, the ridge-shaped distribution has the characteristics of wide main value interval and gentle transition zone, which can better reflect the fuzzy relationship between the OPFM and the health state of CMS. Therefore, different types of ridge-shaped distribution functions are used as the membership function of the health state of CMS. According to the definition of the health state of CMS, the domain is $[0,1]$, namely the range of values for the fuzzy subsets of the four health states is also $[0,1]$, combined with the expert opinion and the OPFM. The fuzzy relationship between size and health state determines the fuzzy subset is further judged according to the degree of membership.

FIGURE 4. Flowchart of state fuzzy evaluation method based on the OPFM.
| Serial number | Parts                  | Importance | Failure mode | Risk equivalent | Direct cause of failure     | Indirect cause of failure | Direct failure consequences | Indirect failure consequences | Detection method | Measurable characteristic parameter |
|--------------|------------------------|------------|--------------|----------------|----------------------------|---------------------------|---------------------------|-------------------------------|------------------|-------------------------------------|
| 1            | Hollow Crankshaft      | 0.815      | Stock        | 44             | Fatigue fracture becomes larger, the raceway surface is not smooth | Asymmetrical stress       | Downtime                  | Major economic loss           | Visual inspection | Vibration amplitude, temperature, pump pressure, oil temperature, oil level, etc. |
| 2            | Main Bearing           | 0.922      | Abnormal sound | 34             | Bearing clearance becomes larger, the raceway surface is not smooth, the cage is loose or broken | Subject to alternating stress, impurities are mixed into the bearing, excessive fatigue wear | Increased noise and temperature rise at the main bearing | Reduced impulse, reduced displacement, reduced pump pressure | Noise detection, lubricant detection, temperature detection | No                                                                 |
| 3            | Eccentric Bearing     | 0.945      | Vibration    | 33             | Bearing clearance becomes larger, the raceway surface is not smooth | Insufficient lubricating oil, excessive fatigue and wear, poor lubrication | Vibration and temperature rise at eccentric bearing | Reduced impulse, reduced displacement, reduced pump pressure | Vibration detection, lubricant detection, temperature detection | Vibration amplitude, temperature, pump pressure, oil temperature, oil level, etc. |
|                | Large Ring Gear            | Connecting Rod             | Eccentric Bearing           |
|----------------|----------------------------|----------------------------|-----------------------------|
| Noise          | 0.661                      | 0.513                      | 0.945                       |
| Stuck          | 37                         | 43                         | 34                           |
| Edge of the connecting rod starts or wears | Affected by alternating stress; impact collision | Impurities in the bearing; excessive fatigue and wear; poor lubrication |
| Noise          | 34                         | 41                         | 34                           |
| Stuck          |                            |                            | Abnormal sound              |
| Bearing clearance becomes larger; the raceway surface is not smooth; the cage is loose or broken |
| Wear and gluing | Broken teeth, deformation  |                            | Subject to alternating stress; impurities are mixed into the bearing; excessive fatigue wear |
| Relative sliding on the tooth surface; contact with the two tooth surfaces to form local high temperature, poor lubrication |
| Increased temperature and noise increase at the large ring gear | Downtime                   | Increased noise at the connecting rod | Downtime |
| Reduced impulse, reduced displacement, reduced pump pressure | Major economic loss         | Reduced impulse, reduced displacement, reduced pump pressure | Major economic loss |
| Temperature detection, noise detection, lubricant detection | Visual inspection          | Unable to detect            | Visual inspection |
| Noise, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | No                         | No                         | No |
| Noise, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | No                         | No                         | No |
| 7 | 6 |
|---|---|
| **Bearing** | **Pinion Shaft** |
| 0.875 | 0.661 |
| **Stuck** | **Noise** | **Vibration** | **Noise** | **Stuck** |
| 39 | 34 | 31 | 30 | 43 |
| Roller is broken or worn; the cage is loose or broken; the bearing burns out | Bearing clearance becomes larger; the raceway surface is not smooth; the cage is loose or broken | Bearing clearance becomes larger; the raceway surface is not smooth | Wear and gluing | Broken teeth, deformation |
| Impurities in the bearing; excessive fatigue and wear; poor lubrication | Subject to alternating stress; impurities are mixed into the bearing; excessive fatigue wear | Insufficient lubricating oil; impurities in the bearing; excessive fatigue wear | Relative sliding on the tooth surface; contact with the two tooth surfaces to form local high temperature, poor lubrication | Subject to alternating stress, fatigue fracture; overload |
| **Downtime** | Increased noise at the bearing and increased temperature | Vibration at the bearing, temperature rise | Increased temperature at the pinion and increased noise | Downtime |
| **Major economic loss** | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Major economic loss |
| **Visual inspection** | Noise detection, lubricant detection, temperature detection | Vibration detection, lubricant detection, temperature detection | Temperature detection, noise detection, lubricant detection | Visual inspection |
| **No** | Noise, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | Vibration amplitude, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | Noise, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | No |
|     | Cross Head Bearing | Upper and Lower Guide Plates | Cross Head |
|-----|--------------------|------------------------------|------------|
|     | 0.663              | 0.462                        | 0.462      |
| Stuck | Noise | Vibration | Heat | Noise | Heat | Noise |
| 34   | 23    | 29       | 17   | 21    | 17   | 22    |
| Roller is broken or worn; the cage is loose or broken | Bearing clearance becomes larger; the raceway surface is not smooth; the cage is loose or broken | Poor heat dissipation, wear and tear | Wear and tear | Poor heat dissipation, wear and tear | Wear and tear |
| Impurities in the bearing; excessive fatigue and wear; poor lubrication | Subject to alternating stress; impurities are mixed into the bearing; excessive fatigue wear | Insufficient lubricating oil; impurities in the bearing; excessive fatigue wear | Insufficient cooling water, severe wear | Mud or impurities enter the cross head and the guide; impact by impact | Insufficient cooling water, severe wear | Mud or impurities enter the cross head and the guide; impact by impact |
| Downtime | Increased noise at the bearing and increased temperature | Vibration at the bearing, temperature rise | Increased temperature at the cross head and the guide | Increased temperature at the cross head and the guide | Increased temperature at the cross head and the guide | Increased temperature and local vibration at the cross head and guide |
| Major economic loss | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure | Reduced impulse, reduced displacement, reduced pump pressure |
| Visual inspection | Noise detection, lubricant detection, temperature detection | Vibration detection, lubricant detection, temperature detection | Coolant inspection, noise detection, temperature detection | Cooling water inspection, temperature detection | Vibration detection, noise detection, temperature detection |
| No | Noise, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | Vibration amplitude, temperature, impulse, displacement, pump pressure, oil pressure, oil temperature, oil level, etc. | Temperature, coolant contamination, tank water level, etc. | Vibration amplitude, noise, temperature, impulse, displacement, pump pressure, etc. | Temperature, cooling water quality, cooling water height, etc. | Vibration amplitude, noise, temperature, impulse, displacement, pump pressure, etc. |
TABLE 4. Data acquisition of characteristic quantities corresponding to the failure modes.

| Part or component | Failure mode | Measurable characteristic quantity | Rated value | Normal value | Allowed band | Weight | Measured value | Unit symbol | Degradation factor | Relative deterioration |
|-------------------|--------------|------------------------------------|-------------|--------------|--------------|--------|----------------|-------------|-------------------|----------------------|
| Vibration         | Vibration Amplitude (Left) | 20 | 0-65 | 0.4 | 63 | μm | 2 | 0.846 |
|                   | Temperature (Left) | 25 | ≤60 | 0.3 | 55 | °C | 1 | 0.457 |
|                   | Vibration Amplitude (Right) | 20 | 0-65 | 0.4 | 50 | μm | 2 | 0.445 |
|                   | Temperature (Right) | 25 | ≤60 | 0.3 | 40 | °C | 1 | 0.307 |
|                   | Stroke rate | 120 | >110 | 0.1 | 116 | Spm | 1 | 0.400 |
|                   | Displacement | 36.77 | >32.32 | 0.1 | 35.50 | L/s | 1 | 0.285 |
|                   | Export pumping pressure | 23.7 | >21 | 0.1 | 22.3 | MPa | 1 | 0.519 |
| Main Bearing      | Level of noise (Left) | 90 | ≤120 | 0.2 | 114.0 | dB(A) | 2 | 0.640 |
|                   | Level of noise (Right) | 90 | ≤120 | 0.2 | 105 | dB(A) | 2 | 0.250 |
|                   | Temperature (Left) | 25 | ≤60 | 0.2 | 55 | °C | 1 | 0.333 |
|                   | Temperature (Right) | 25 | ≤60 | 0.2 | 40 | °C | 1 | 0.307 |
|                   | Stroke rate | 120 | >110 | 0.1 | 116 | spm | 1 | 0.400 |
|                   | Displacement | 36.77 | >32.32 | 0.1 | 35.50 | L/s | 1 | 0.285 |
|                   | Export pumping pressure | 23.7 | >21 | 0.1 | 22.3 | MPa | 1 | 0.519 |
| Abnormal Sound    | Lubrication pressure | 0.3 | 0.1-0.4 | 0.1 | 0.36 | MPa | 1 | 0.600 |
|                   | Return oil temperature | 35 | -40—50 | 0.05 | 45 | °C | 1 | 0.667 |
|                   | Lubrication oil cleanliness | 18/12 | ≥18/16 | 0.1 | 18/15 | 2 | 0.563 |
|                   | Allowance ratio of lubricating oil | 1 | ≥2/3 | 0.05 | 3/4 | 2 | 0.563 |
| Eccentric Wheel Bearing | Level of noise (Left) | 90 | ≤120 | 0.4 | 105 | dB(A) | 2 | 0.250 |
| Abnormal Sound    | Level of noise (Middle) | 90 | ≤120 | 0.4 | 102 | dB(A) | 2 | 0.160 |
|                   | Level of noise (Right) | 90 | ≤120 | 0.4 | 100 | dB(A) | 2 | 0.111 |
|                   | Stroke rate | 120 | >110 | 0.1 | 116 | spm | 1 | 0.400 |
|                   | Displacement | 36.77 | >32.32 | 0.1 | 35.50 | L/s | 1 | 0.285 |
|                   | Export pumping pressure | 23.7 | >21 | 0.1 | 22.3 | MPa | 1 | 0.519 |
TABLE 4. (Continued.) Data acquisition of characteristic quantities corresponding to the failure modes.

| Pinion Shaft Abnormal Sound | Lubrication pressure | 0.3 | 0.1-0.4 | 0.1 | 0.36 | MPa | 1 | 0.600 |
|-----------------------------|----------------------|-----|---------|-----|------|-----|---|-------|
| Return oil temperature      | 35                   | -40—50 | 0.05 | 45 | °C | 1 | 0.667 |
| Lubrication oil cleanliness | 18/12                | ≥18/16 | 0.1 | 18/15 | 2 | 0.563 |
| Allowance ratio of lubricating oil | 1 | ≥2/3 | 0.05 | 3/4 | 2 | 0.563 |
| Level of noise              | 90                   | ≤120 | 0.4 | 95 | dB(A) | 2 | 0.028 |
| Stroke rate                 | 120                  | >110 | 0.1 | 116 | spm | 1 | 0.400 |
| Displacement                | 36.77                | >32.32 | 0.1 | 35.50 | L/s | 1 | 0.285 |
| Export pumping pressure     | 23.7                 | >21 | 0.1 | 22.3 | MPa | 1 | 0.519 |
| Lubrication pressure        | 0.3                  | 0.1-0.4 | 0.1 | 0.36 | MPa | 1 | 0.600 |
| Return oil temperature      | 35                   | -40—50 | 0.05 | 45 | °C | 1 | 0.667 |
| Lubrication oil cleanliness | 18/12                | ≥18/16 | 0.1 | 18/15 | 2 | 0.563 |
| Allowance ratio of lubricating oil | 1 | ≥2/3 | 0.05 | 3/4 | 2 | 0.563 |

| Pinion Bearing Abnormal Sound | Vibration Amplitude (Right) | 20 | 0-65 | 0.4 | 35 | μm | 2 | 0.111 |
| Temperature (Right)          | 25                   | ≤60 | 0.3 | 32 | °C | 1 | 0.200 |
| Stroke rate                  | 120                 | >110 | 0.1 | 116 | spm | 1 | 0.400 |
| Displacement                 | 36.77              | >32.32 | 0.1 | 35.50 | L/s | 1 | 0.285 |
| Export pumping pressure      | 23.7                | >21 | 0.1 | 22.3 | MPa | 1 | 0.519 |
| Level of noise (Right)       | 90                  | ≤120 | 0.3 | 95 | dB(A) | 2 | 0.028 |
| Temperature (Right)          | 25                   | ≤60 | 0.2 | 30 | °C | 1 | 0.143 |
| Stroke rate                  | 120                 | >110 | 0.1 | 116 | spm | 1 | 0.400 |
| Displacement                 | 36.77              | >32.32 | 0.05 | 35.50 | L/s | 1 | 0.285 |
| Export pumping pressure      | 23.7                | >21 | 0.05 | 22.3 | MPa | 1 | 0.519 |
| Lubrication pressure         | 0.3                  | 0.1-0.4 | 0.1 | 0.36 | MPa | 1 | 0.600 |
| Return oil temperature       | 35                   | -40—50 | 0.05 | 45 | °C | 1 | 0.667 |
| Lubrication oil cleanliness  | 18/12                | ≥18/16 | 0.1 | 18/15 | 2 | 0.563 |
| Allowance ratio of lubricating oil | 1 | ≥2/3 | 0.05 | 3/4 | 2 | 0.563 |
TABLE 4. (Continued.) Data acquisition of characteristic quantities corresponding to the failure modes.

| Cross Head and Guide Plate Assembly | Abnormal Sound | Vibration Amplitude | 25 | 0-70 | 0.4 | 65 | μm | 2 | 0.790 |
|-------------------------------------|----------------|-------------------|----|------|----|----|----|---|------|
| Level of noise                      | 100            | <130              | 0.3| 127  | dB(A) | 2  | 0.810|
| Stroke rate                         | 120            | >110              | 0.1| 116  | spm  | 1  | 0.400|
| Displacement                        | 36.77          | >32.32            | 0.1| 35.50| L/s   | 1  | 0.285|
| Export pumping pressure             | 23.7           | >21               | 0.1| 22.3  | MPa  | 1  | 0.519|
| Temperature                         | 25             | <45               | 0.4| 43   | °C    | 1  | 0.900|
| Coolant temperature                 | 25             | 0—40              | 0.3| 38   | °C    | 1  | 0.867|
| Coolant cleanliness                 | 19/13          | ≥19/16            | 0.2| 19/15 |       | 2  | 0.445|
| Allowance ratio of water tank       | 1              | ≥2/3              | 0.1| 4/5  |       | 2  | 0.360|

The calculation equation of the membership degree of each health state corresponding to the different failure probability of CMS [15]–[17]:

(1) Fuzzy subset \( s_1 = \text{Good state} \)

The part is in a good state when the value of the OPFM \( P_i \) is within [0, 0.2], is in a good state or better state when it is within [0.2, 0.4], and is out of a good state when it is within [0.4, 1], and then a computational equation for a health state membership degree function of the part is as follows:

\[
r_{s_1}(P_i) = \begin{cases} 
1, & P_i \leq 0.2 \\
1 - \frac{1}{2} \cdot \sin\left(\frac{\pi}{0.2}(P_i - 0.3)\right), & 0.2 < P_i \leq 0.4 \\
0, & P_i > 0.4 
\end{cases} \quad (10)
\]

(2) Fuzzy subset \( s_2 = \text{Better state} \)

The part is out of a better state when the value of the OPFM \( P_i \) is within [0, 0.2], is in a good state or better state when it is within [0.2, 0.4], is in a better state or general state when it is within [0.4, 0.7] and is out of a better state when it is within [0.7, 1], and then a computational equation of the health state membership degree function of the part is as follows:

\[
r_{s_2}(P_i) = \begin{cases} 
0, & P_i \leq 0.2 \\
\frac{1}{2} + \frac{1}{2} \cdot \sin\left(\frac{\pi}{0.2}(P_i - 0.3)\right), & 0.2 < P_i \leq 0.4 \\
\frac{1}{2} - \frac{1}{2} \cdot \sin\left(\frac{\pi}{0.3}(P_i - 0.55)\right), & 0.4 < P_i \leq 0.7 \\
0, & P_i > 0.7 
\end{cases} \quad (11)
\]

(3) Fuzzy subset \( s_3 = \text{General state} \)

The part is out of a general state when the value of the OPFM \( P_i \) is within [0, 0.4], is in a good state or better state when it is within [0.4, 0.7], is in a quasi-failure state or general state when it is within [0.7, 0.9] and is out of a general state when it is within [0.9, 1], and then a computational equation of the health state membership degree function of the part is as follows:

\[
r_{s_3}(P_i) = \frac{1}{2} + \frac{1}{2} \cdot \sin\left(\frac{\pi}{0.3}(P_i - 0.55)\right), \quad 0.4 < P_i \leq 0.7
\]

(4) Fuzzy subset \( s_4 = \text{Quasi-failure state} \)

The part is out of a quasi-failure state when the value of the OPFM \( P_i \) is within [0, 0.7], is in a quasi-failure state or general state when it is within [0.7, 0.9], and is in a quasi-failure state when it is within [0.9, 1], and then the computational equation of the health state membership degree function of the part is as follows:

\[
r_{s_4}(P_i) = \begin{cases} 
0, & P_i \leq 0.7 \\
\frac{1}{2} + \frac{1}{2} \cdot \sin\left(\frac{\pi}{0.2}(P_i - 0.8)\right), & 0.7 < P_i \leq 0.9 \\
1, & P_i > 0.9 
\end{cases} \quad (13)
\]

Therefore, the fuzzy relation matrix with the occurrence probability of failure as the evaluation criterion can be obtained, that is, the probability matrix (subordinate degree matrix) belonging to the health state space \( \{s_1, s_1, s_1, s_4\} \) when the occurrence probability of the failure is certain.

\[
R_i = \begin{bmatrix}
0 & r_{s_1}(P_1) & r_{s_2}(P_1) & r_{s_3}(P_1) & r_{s_4}(P_1) \\
0 & r_{s_1}(P_2) & r_{s_2}(P_2) & r_{s_3}(P_2) & r_{s_4}(P_2) \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & r_{s_1}(P_{im}) & r_{s_2}(P_{im}) & r_{s_3}(P_{im}) & r_{s_4}(P_{im})
\end{bmatrix} \quad (14)
\]

The probability matrix \( R_i \) represents the membership degree matrix of the \( n^{th} \) OPFM of the \( i^{th} \) item belonging to the state space \( \{s_1, s_1, s_1, s_4\} \).
IV. FUZZY COMPREHENSIVE EVALUATION ON HEALTHY STATE BASED ON THE OPFM

A mechanical, electrical and hydraulic system consists of multiple subsystems, each with numerous components, each component having one or more failure modes, and the failure mode can correspond to one or more characteristic quantity.

In the evaluation of the health state of the equipment or system, if the characteristic quantity extraction is performed for all failure modes, a large amount of characteristic quantity space will be formed, which makes the state evaluation extremely difficult. Based on the importance analysis method and failure mode risk assessment method in the previous chapters, the importance ordering and failure mode risk levels of items in the system or equipment can be obtained, so that the characteristic quantity extraction of key items and key failure modes can be performed to form the original equipment. The state characteristic quantity space achieves the purpose of reducing the spatial dimension of the characteristic quantity. Since it is impossible to determine whether sufficient state category information is included when constructing the state characteristic quantity space, in order to ensure the accuracy and scientifically of the state evaluation, the number of characteristic quantities is increased as much as possible, which is appropriate for the mechanical system that are not complex structure. But for a mechanical system with a complicated structure, it will cause redundancy of characteristic quantity. The introduction of a large number of redundant characteristic quantities will lead to complicating data calculation, which is not conducive to state evaluation and prediction. Due to the existence of subordination and association between equipment, subsystems, components, failure modes and characteristic quantities, for equipment or systems with complex structures, failure modes - components - subsystems - equipment or the system gradually solves the problem of the number of characteristic quantities in the calculation, so as to avoid the wrong choice of the original characteristic quantity, which effectively guarantees the feasibility and accuracy of the state evaluation. In this paper, a fuzzy evaluation method for item operation status is shown in Fig. 4. The specific analysis process is as follows [18]–[20]:

**Step 1**: Determining the collection of important functional items and their key failure mode sets

Dividing CMS into l parts, the l parts constituting a part set \( Z = \{z_1, z_2, \ldots, z_l\} \); carrying out failure risk identification on each part, and acquiring all the failure modes of each part to constitute a failure mode set \( F = \{F_1, F_2, \ldots, F_m\} \) of each part.

**Step 2**: Determining a characteristic quantity set corresponding to each key failure mode

Carrying out failure risk identification on the parts to obtain failure modes, failure causes and failure effects; calculating state characteristic quantities respectively corresponding to m failure modes of the \( k^{th} \) part, thereby obtaining a state characteristic quantity space \( Y^m \) of \( m \) failure modes.

**Step 3**: Calculating the degradation degree of each characteristic quantity

Calculating the relative degradation degree \( b_i(t) \) of the \( i^{th} \) characteristic quantity in the state characteristic quantity space \( Y^m \) at a moment \( t \), i.e., an occurrence probability \( p(Y) \) of the state characteristic quantity, and calculating a state characteristic quantity full-degradation probability space \( p^m \) corresponding to \( m \) failure modes.

**Step 4**: Calculating the occurrence probability of each failure mode

Calculating a comprehensive occurrence probability \( P(F_j) \) of the \( j^{th} \) failure mode in the failure mode set \( F \) to obtain an occurrence probability set \( P_j = \{P(F_1), P(F_2), \ldots, P(F_m)\} \) of \( m \) failure modes of the \( k^{th} \) part.

**Step 5**: Calculating the membership degree of the occurrence probability of each failure mode

Substituting the occurrence probabilities of \( m \) failure modes in the OPFM set \( P_j \) into a part health state membership degree function respectively to calculate a membership degree matrix \( R_k \) of \( m \) failure mode included in the \( k^{th} \) part.

\[
R_k = \begin{bmatrix}
    r_{11}(P_{k1}) & r_{12}(P_{k1}) & r_{13}(P_{k1}) & r_{14}(P_{k1}) \\
    r_{21}(P_{k2}) & r_{22}(P_{k2}) & r_{23}(P_{k2}) & r_{24}(P_{k2}) \\
    \vdots & \vdots & \vdots & \vdots \\
    r_{m1}(P_{km}) & r_{m2}(P_{km}) & r_{m3}(P_{km}) & r_{m4}(P_{km})
\end{bmatrix}
\]  

**Step 6**: Fuzzy evaluation of the operating status of components

In the fuzzy evaluation, the weight distribution of each factor has a great influence on the evaluation result. Therefore, how to determine the reasonable weight set becomes one of the key points and difficulties in the fuzzy evaluation. The determined weights should be as close as possible to the actual situation and usually given empirically based on the importance of the factors and the actual situation. Since the failure mode affects the health state of the components differently, the evaluation of the health state of the \( k^{th} \) component requires determining the relative importance of the \( m \) failure modes, namely the weight. Since the respective gray correlation degrees are obtained in the failure mode risk analysis, the gray correlation degree of the failure modes included therein can be normalized, that is, their respective weight values; In the chapter, the AHP-based weight assignment method is used to calculate and obtain. Therefore, the weight matrix \( B_k \) of the \( m \) failure modes included in the \( k^{th} \) component can be constructed.

\[
B_k = [\beta_{k1}, \beta_{k2}, \ldots, \beta_{km}]  
\]  

Therefore, after determining the weight matrix \( B_k \) of the failure mode on the health state of the item and the failure mode membership probability matrix \( R_k \), the fuzzy relationship calculation can obtain the membership degree of the \( k^{th} \)
According to the principle of maximum membership degree, it is possible to determine the status of the \( k \)th item operating status, that is, the state in which it is located.

Repeat Step 2 to Step 5 to calculate the health state membership space of the \( l \) components included in the system, namely,

\[
C_l = \begin{bmatrix}
d_1(s_1) & d_1(s_2) & d_1(s_3) & d_1(s_4) \\
d_2(s_1) & d_2(s_2) & d_2(s_3) & d_2(s_4) \\
\vdots & \vdots & \vdots & \vdots \\
d_l(s_1) & d_l(s_2) & d_l(s_3) & d_l(s_4)
\end{bmatrix}
\]  

(18)

**Step 7**: Fuzzy comprehensive evaluation of system operation status

In general, a system consists of multiple subsystems, which contain multiple components, namely the system contains multiple items. The operating status of each item has different effects on the overall operating status of the system, namely the impact of each item on the system has different weights. If the weight of the \( k \)th item is \( \omega_k \), the weight vector of the \( l \) items included in the system can be expressed as \( W_l = (\omega_1, \omega_2, \ldots, \omega_l) \), which indicates the degree of influence of the operating status of \( l \) components in the system on the overall health state of the system. For the weight of each item, according to the item importance evaluation method, the importance of \( l \) items can be obtained, and then normalized, which is the weight of the item in the system state evaluation. Similarly, it can also be calculated by expert scoring and using the AHP-based weight assignment method [21]. Combined with the membership space of the item operating status, the state evaluation of the system can be calculated by

\[
S = W_l \circ C_l = (C(s_1), C(s_2), C(s_3), C(s_4))
\]  

(19)

Based on the principle of maximum membership degree, the state of the system can be determined.
TABLE 5. OPFM of each part for the power end of mud pump.

| Names of Parts                      | Failure mode | OPFM |
|-------------------------------------|--------------|------|
| Spindle bearing (Left)              | Vibration    | 0.692|
|                                     | Noise        | 0.517|
| Spindle bearing (Right)             | Vibration    | 0.397|
|                                     | Noise        | 0.331|
| Eccentric gear bearing (Left)       | Noise        | 0.429|
| Eccentric gear bearing (Middle)     | Noise        | 0.405|
| Eccentric gear bearing (Right)      | Noise        | 0.393|
| Pinion and large gear               | Vibration    | 0.244|
|                                     | Noise        | 0.374|
| Pinion bearing                      | Vibration    | 0.244|
|                                     | Noise        | 0.358|
| Cross head and upper and lower guide plates | Vibration | 0.734|
|                                     | Noise        | 0.829|

V. CASE STUDY
Taking an F1300 mud pump used in a SZ36-1J workover rig platform as an example, the main technical parameters of the mud pump as follows:

In order to analyze the health state of the mud pump at the power end, the importance degrees and a sequence thereof of parts of the mud pump are determined based on the previously described importance degree evaluation method [22]. The important functional items at the power end are selected: Crankshaft, Bearing, Eccentric Gear Bearing, Connecting Rod, Large Ring Gear, Pinion Shaft, Transmission Bearing, Cross Head, Upper and Lower Guide Plates, and Cross Head Bearing. The important functional items are subject to FMECA analysis to determine the risk level of the failure mode [23]. The features corresponding to all the failure modes of each important functional item are determined according to the characteristics of the items per se, existing inspection means for platform maintenance, failure modes of the item, failure causes, results and other information, as shown in TABLE 3.

According to the analysis results of failure modes and characteristic quantities of the important functional parts at the power end in TABLE 3, various means, including vibration detection, noise test, temperature detection and qualitative evaluation, are selected to carry out real-time characteristic quantity monitoring on the spindle bearing, the eccentric gear bearing, the cross head assembly and the like at the power end. In the process of arranging test points, points are arranged as much as possible in combination with the overall structural characteristics of the mud pump, as well as the vibration, noise and temperature coupling relationship between adjacent parts, so as to acquire sufficient and accurate characteristic quantity measured data. The layout of the field data acquisition device is shown in Fig. 5.

After a period of continuous data acquisition and evaluation of each failure mode characteristic quantity, a set of data of a time node is selected for statistics and processing, and the measured data of each characteristic quantity data are obtained. At the same time, through the field research, related data query and expert evaluation, etc., the rated value, failure-free state value and the allowable range of each characteristic quantity and the weights having impacts on parts or equipment state are determined, thus calculating the relative degradation degree $b_i$ of the characteristic quantity. As shown in TABLE 4.

The OPFM of each part is evaluated by means of the OPFM evaluation method based on the variable weight synthesis theory. The calculation results are shown in TABLE 5.

The sensitivity of the above-mentioned characteristic parameters to the health state response is considered in the calculation process in combination with the OPFM of each part in TABLE 5 by adopting a fuzzy comprehensive evaluation model based on the OPFM. The variable weight vector is taken as $\alpha = 0.3$, thereby calculating a state evaluation result of the following parts at the power end, as illustrated in TABLE 6.

The importance degree values of the above-mentioned parts are normalized as weight values in a process of evaluating overall health state of the power end of the mud pump on the basis of the health states of the parts. The health state of the power end of the mud pump can be then evaluated in combination with the state evaluation results of important
TABLE 6. State evaluation result of parts or assemblies for the power end of mud pump.

| Names of assemblies and parts | State evaluation result | Semantic description of state evaluation results                          |
|------------------------------|-------------------------|-------------------------------------------------------------------------|
| Spindle bearing(Left)        | (0.0, 0.370, 0.620, 0)  | General state, it is necessary to find failures in time                 |
| Spindle bearing(Left)        | (0.0, 0.854, 0.146, 0)  | Better state, it is necessary to intensify monitoring                   |
| Eccentric gear bearing (Left)| (0.0, 0.977, 0.023, 0)  | Better state, it is necessary to intensify monitoring                   |
| Eccentric gear bearing (Middle)| (0.0, 0.993, 0.007, 0)  | Better state, it is necessary to intensify monitoring                   |
| Eccentric gear bearing (Right)| (0.0, 0.003, 0.997, 0)  | Better state, it can proceed to run                                    |
| Pinion and large gear sets assemblies | (0.0, 0.041, 0.959, 0)  | Better state, it can proceed to run                                    |
| Pinion bearing               | (0.0, 0.529, 0.471, 0)  | Good state, it can proceed to run                                      |

Functional parts or assemblies at the power end in TABLE 6. The evaluation result is as follows

\[ S = W_1 \circ C_1 = (C(s_1), C(s_2), C(s_3), C(s_4)) = (0.072, 0.723, 0.171, 0.033) \]  

According to the principle of maximum membership degree, the health state of the power end of the mud pump is better, and the monitoring to the power end should be intensified during the operating process. At the same time, the health state within the short time can be predicted, and then a reasonable, economical and scientific power-end failure inspection and maintenance program is formulated in combination with the maintenance outline and the item task requirements.

VI. CONCLUSION
Safety item management of the enterprise will be helped by the research on PHM and AIM technology to carry out HSE of CMS to change from experience to science, and the means of safe item and enhancing competitiveness of enterprises are based on theoretical foundations and science and technology. In this study, by analyzing the correlation between health state, failure mode and characteristic quantity, the OPFM and the total DPCQ are defined, and combined with fuzzy theory, a fuzzy comprehensive evaluation method for CMS that are based on OPFM is proposed. At the same time, in order to avoid the problem of deviation of evaluation results caused by sudden changes in factors, in this method, the variable weight synthesis theory is applied innovatively, which makes the balance of various factors and the weight of factors in the above comprehensive evaluation process be characterized by the variation law of quantity. Finally, the method is applied to the HSE of the mud pump. The evaluation results are consistent with the actual situation, which effectively verifies the feasibility and accuracy of the method. The application of the HSE technology for the CMS in the equipment asset management process will help the company to develop a more scientific and effective maintenance strategy, which will reduce the total workload of the CMS maintenance, reduce maintenance costs, and increase operating life. Item efficiency is improved to ensure the safety, environmental protection, energy saving, consumption reduction and efficient operation of the CMS in item, thus effectively controlling major accidents of item enterprises and reducing general accidents. At the same time, the related ideas, models and methods formed by this research can also be used as reference for the maintenance management of the CMS in other high-risk industries, and can also be used as reference for other types of equipment related technology research. The research will also actively promote the research and application of AIM and PHM technology for enterprises with the high-risk CMS, strengthen item safety management, improve asset operation efficiency, and gradually realize the integrity management of equipment and facilities assets.

VII. CONFLICT OF INTERESTS
The authors declare that there is no conflict of interests regarding the publication of this paper.

VIII. DATA AVAILABILITY STATEMENT
The data of used to support the findings of this study are available from the corresponding author upon request.
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YANG TANG received the B.E. degree in process equipment and control engineering, the M.E. degree in fluid machinery and engineering, and the Ph.D. degree in Mechanical Engineering from Southwest Petroleum University, China, in 2010, 2013, and 2016, respectively. He was a Visiting Scholar with the IMS Center, University of Cincinnati, USA, from 2017 to 2018. He is currently an Associate Research Fellow with Southwest Petroleum University. He has published nearly 30 articles and awarded 22 patents. His research interests include quantitative risk assessment, fault prediction and health management, asset integrity management, FMECA, natural gas hydrate development, oil and gas equipment modern design and simulation, reliability, and maintainability engineering.

Dr. Yang Tang was awarded the Chinese postdoctoral innovative talents Program in 2019.

XIN YANG received the B.E. degree, in 2015. He is currently pursuing the M.E. degree in power engineering from Southwest Petroleum University.

GUORONG WANG received the B.E., M.E., and Ph.D. degrees in mechanical engineering from Southwest Petroleum University, China, in 1998, 2001, and 2004, respectively.

He is currently a Professor in mechanical engineering. He is also mainly involved in equipment research in the field of oil and gas drilling and hydrate development. His research direction mainly includes drill string/riser string dynamics, bionic texture and tribology of oil and gas equipment, modern design theory and method of oil and gas equipment, new equipment for hydrate extraction, and supporting new technologies.

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