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Condition-Based Dynamic Supportability Mechanism for the Performance Quality of Large-Scale Electromechanical Systems

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ABSTRACT Scientific and effective supportability mechanisms have a profound impact on large-scale electromechanical systems and improve their performance quality, while decreasing costs. However, the contradiction between the static supportability strategy and time-varying performance quality conditions remains not sufficiently resolved. To solve this problem, this paper proposes a performance quality condition-based dynamic supportability mechanism. First, model-driven risk identification and control chart-based pattern recognition were used to trigger the dynamic allocation of the limit supportability resource. Second, the performance quality mode and effect analysis and the multiagent collaborative chain were defined to identify the resource lists of maintenance activities. Third, a general control framework was constructed to evaluate the compliance and applicability of maintenance activities. This study formulated a dynamic supportability mechanism for performance quality with a closed loop of activity triggering, resource guarantee, and maintenance effectiveness evaluation. As an expansion and improvement of condition-based maintenance, the dynamic supportability mechanism overcomes the several drawbacks of the existing supportability mechanisms of large-scale electromechanical systems. The proposed mechanism also advances the integration of management and technology in comprehensive supportability. Therefore, the proposed mechanism and methods can be flexibly and efficiently used for the dynamic supportability of electromechanical systems. Moreover, this study provides insights into risk identification, macro pattern recognition and process control and can be used for other engineering applications.

INDEX TERMS Condition-based dynamic supportability, limited resource allocation, collaboration of resource and condition, compliance and applicability control of maintenance, large-scale electromechanical system.

I. INTRODUCTION

Modern production systems, such as large-scale energy and power equipment, high-end compressor units and precision machine tools, can be considered typical large-scale electromechanical systems [1], [2]. A useful system should have the ability to perform missions at all times and maintain peak performance during missions. However, with increasing performance time, reliability degeneration and unexpected faults become inevitable. Hence, scientific and effective supportability mechanisms have profoundly impacted systems and improved performance quality at decreased costs.

For most systems and equipment, maintenance is the main task of supportability, which contains all the technical and managerial activities required for the maintenance, repair, and improvement of specified conditions with regard to storage and performance. With increasing equipment complexity, improvement of maintenance tools, development of condition inspection and fault diagnosis technologies, and innovation of maintenance theory, maintenance mechanisms can be classified into two categories: preventive maintenance and corrective maintenance [3]. Corrective maintenance is

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performed after the breakdown of a system [4], [5]. Although this mechanism increases the lifetime of components and systems, the downtime and resulting loss are high because of its unpredictability, which limits its application. Preventive maintenance uses the form of system overhaul or unit replacement based on elapsed time and is often referred to as time-based maintenance [6], [7]. The maintenance type, workload and time are predetermined based on the system degradation rule. This mechanism can prevent and decrease the severity of the expected potential fault, but it falls into the strict relationship between fault and time. Moreover, the absence of maintenance and excessive maintenance problems have not been fully investigated.

In recent literature, increasing attention has been focused on condition-based maintenance (CBM) [8]–[11]. Unlike previous maintenance mechanisms, CBM is a maintenance approach that emphasizes the combination of data-driven reliability models with sensor data collected from monitored operating systems and develops strategies to condition both monitoring and maintenance. The advantages of CBM lie in mastering the performance condition of systems, detecting exceptions, and performing timely initiation of the corresponding measures to prevent the occurrence of more faults by strengthening and perfecting the monitoring means. This process greatly decreases the fault rate, maintenance cost, and workload while improving system reliability. Moreover, CBM solves the lack of maintenance and excessive maintenance problems with periodic maintenance. Various methods have been described to monitor the degradation process and use these monitored data for the design of maintenance policy. Panagiotidou and Tagaras [12] introduced the relationship between statistical process control and CBM through data sharing. Vafaei *et al.* [13] presented a fuzzy early warning approach, which improved proactive CBM and enabled more informed decisions on maintenance strategies. Poppe *et al.* [14] introduced a hybrid multicomponent opportunistic maintenance policy that combined CBM on one monitored component, with periodic preventive maintenance and corrective maintenance on the other components. Jamshidi *et al.* [15] proposed a decision support approach for CBM of rails that relies on expert-based systems. Reviews on CBM can be found in [16]–[20].

Currently, researchers have increasingly been focusing on models of maintenance optimization. Truong-Ba *et al.* [21] combined partial opportunities and condition-based maintenance (CBM) strategies and proposed an innovative maintenance optimization method considering time-varying economic conditions. Ma *et al.* [22] investigated reliability analytical and maintenance optimization approaches for two-unit warm standby cooling equipment, and they developed a condition-based maintenance policy that incorporated multifactors. Kumar *et al.* [23] developed a big data analytics framework that optimized the maintenance schedule via CBM optimization and also improved the prediction accuracy to quantify the remaining life prediction uncertainty. Due to the availability of better alternatives to predict and optimize manufacturing processes, soft computing techniques such as artificial neural systems and fuzzy logic were utilized and reviewed by Goyal *et al.* [16]. Other studies on condition-based maintenance optimization are summarized by Alaswad and Xiang [3] and Ferrero Bermejo *et al.* [19].

In fact, maintenance represents an integration of management and technologies, and three main issues should be solved in CBM: (1) When to trigger maintenance activities; (2) how to guarantee resource collaboration in activities; and (3) how to evaluate the compliance and applicability of maintenance activities. However, prior studies have generally focused on maintenance models and technologies of equipment and focused less on investigating the mechanism, resource scheduling or quality evaluation of system maintenance. Furthermore, little information has been published about the dynamic mechanism based on collaborations of performance quality conditions, resource utilization and quality control.

Therefore, the conventional investigation must be extended and deepened to overcome these drawbacks of the existing maintenance mechanism of large-scale electromechanical systems and advance the integration of management and technology in comprehensive maintenance. This study explored a performance quality condition-based dynamic supportability mechanism. First, the limited supportability resources were dynamically reallocated and associated with the performance quality conditions via both model-driven risk identification and control chart-based pattern recognition. Second, performance quality mode and effect analysis (PQMEA) and the multiagent collaborative chain were defined to identify the resource lists in maintenance activities. Third, a general control framework was constructed to evaluate the compliance and applicability of maintenance activities. The proposed work formulated a dynamic supportability mechanism for performance quality with a closed loop integrating dynamic allocation, resource guarantee, and effectiveness evaluation of maintenance.

The main contributions of this work are: (1) the supportability resource and performance quality conditions are dynamically integrated, which implements condition-based resource allocation; (2) the maintenance activities and resource guarantee are dynamically integrated, which formulates the resource foundation for actual maintenance work; and (3) the maintenance activities and effectiveness control are dynamically integrated, which constructs a closed loop of dynamic events.

The overall structure of this paper is as follows: Section II introduces the framework of the proposed mechanism and briefly introduces the relationships between this framework and other related work. Section III explores the risk and condition-based resource reallocation, and implements model-driven risk identification and control chart-based pattern recognition. PQMEA and multiagent maintenance chain based-resource collaboration are investigated in Section IV. Section V establishes the general flowchart for process control and compliance and for applicability evaluation of

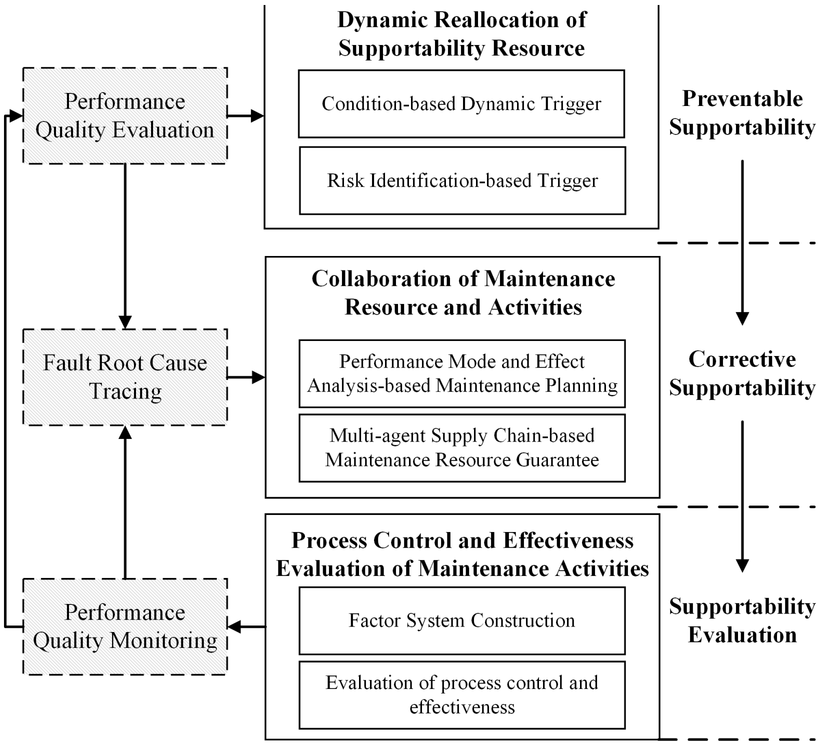

FIGURE 1. Content structure of the proposed supportability mechanism.

maintenance activities. Finally, conclusions are drawn in Section VI.

II. CONTENTS OF THE DYNAMIC SUPPORTABILITY MECHANISM OF PERFORMANCE QUALITY

Investigating and exploring supportability methods and theories for large-scale electromechanical systems help to recognize the failure mechanism and predict, control, and eliminate failures. There are common scientific problems that ensure operation reliability and improve performance quality at decreased costs, which provide insight into other equipment and systems. The drawbacks of conventional mechanisms, such as the contradiction between a static strategy and time-varying performance quality conditions, experience-based resource allocation, and lack of maintenance quality evaluation, are clearly based on the above review. To overcome these drawbacks, a new mechanism composed of supportability resource dynamic reallocation, maintenance resource collaboration, and quality evaluation is proposed. FIGURE 1 shows the structure of the mechanism.

Notably, performance quality control of large-scale electromechanical systems contains four parts: monitoring, evaluation, fault root cause tracing, and supportability. Detailed information on and the technologies that use the first three parts can be found in the literature [2], [24]–[30]. As shown in FIGURE 1, monitoring forms the foundation of supportability, and both evaluation and fault root cause tracing trigger dynamic supportability activities. The proposed mechanism integrates preventable supportability and corrective supportability, and it was evaluated to verify the compliance and applicability of supportability. The condition-based dynamic supportability mechanism was constructed accordingly. To avoid confusion, both supportability resources and maintenance resources are first defined and declared before introducing the proposed mechanism.

Definition 1: Supportability Resources: Supportability resources represent the sensing and monitoring facilities used to perceive of the performance quality in real time, the specific detection and analytic systems used to master the conditions of key components, the storage, the computation resources, the regulatory framework, and the operation specification. In general, supportability resources are nonparticipation maintenance actions defined and declared to prevent fault and maintain performance.

Definition 2: Maintenance Resources: Maintenance resources refer to both materials and services that are not directly composed of products or involved in the production process, but are only used for system maintenance, repair, and operation. Maintenance resources can generally be referred to as spare parts, materials, humans, and tools required for maintenance actions and also include auxiliary software, such as interactive electronic technical manuals and virtual factories, which improve the activity effectiveness and guarantee maintenance quality.

III. DYNAMIC REALLOCATION OF LIMITED SUPPORTABILITY RESOURCE

A large-scale electromechanical system is a typical complex electromechanical system that includes many large-scale power mechanical devices, high-temperature and

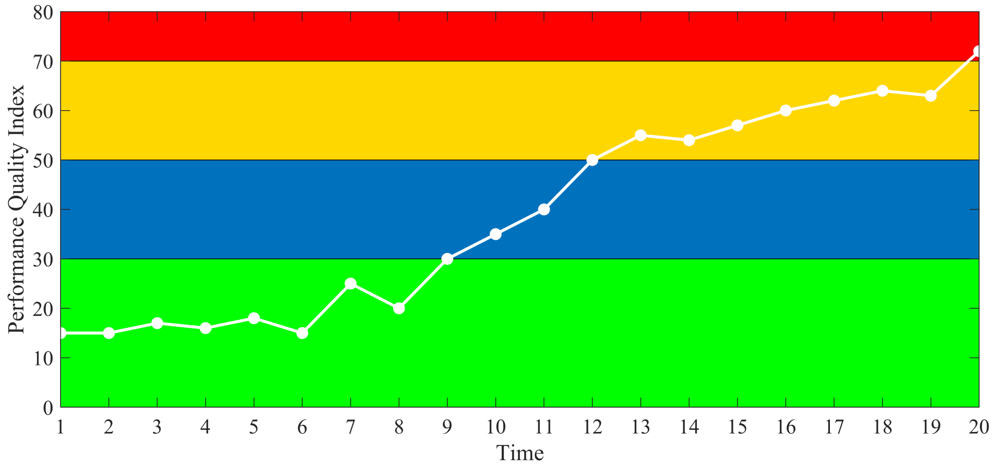

FIGURE 2. PQI spectrum of a large-scale electromechanical system.

high-pressure devices and automation equipment. This type of system also requires auxiliary systems, such as power supply, water supply and cooling. The production process connects various controllers, pressure cylinders, tanks and pumps through pipes or circuits. Through the conversion of materials, energy, and information, the monitoring variables are coupled in a complex manner to form a production system with very complex processes and interactions. To monitor the performance quality condition of this type of equipment in real time, modern enterprises often employ a distributed control system (DCS) with thousands of sensors of various types and specific analysis systems for critical components. Examples are the turbine supervisory instrument system (TSI) and turbine diagnosis management (TDM), which constitute the performance quality supportability resource pool of large-scale electromechanical systems.

On one hand, the performance quality condition of a large-scale electromechanical system is a dynamic and complex result that is affected by the environment, load, and other internal and external conditions. On the other hand, with accumulating equipment performance time, the performance of the system will inevitably deteriorate, which will result in new performance risk points. Thus, a static performance quality resource allocation strategy cannot be adapted to the actual production and management requirements of enterprises, so the resource requirements will continuously increase. However, the supportability resources are limited, which is a central challenge to enterprises. Dynamic reallocation of the limited resources to achieve maximum efficiency is a powerful method to overcome this problem. This section solves two main issues that reallocation faces: (1) When should dynamic actions be triggered to reallocate the supportability resource? (2) Where should the limited resources be reallocated?

A. CONDITION-BASED DYNAMIC TRIGGER FOR THE REALLOCATION ACTIONS

Condition evaluation results provide the basis for the dynamic allocation of supportability resources of large-scale electromechanical systems. This study applies the results to trigger different plans of supportability resource allocation, but it does not investigate the processes required to obtain these evaluation results. Details of condition evaluation can be found in [31], which defines the performance quality index (PQI) to quantify different performance quality conditions. FIGURE 2 shows a PQI spectrum of a large-scale electromechanical system in which the conditions were divided into four categories by PQI according to the following criterion:

$$Condition = \begin{cases} Normal, & PQI \in (0, 30); \\ Attentive, & PQI \in [30, 50); \\ Warning, & PQI \in [50, 70); \\ Dangerous, & PQI \in [70, 80); \end{cases} \tag{1}$$

Clearly, when the performance quality condition of a large-scale electromechanical system is abnormal or degraded, to avoid spreading failure and stop the degradation, dynamic reallocation of supportability resources should be performed in time. This reallocation can be achieved by e.g., increasing the frequency of data collection monitoring, temporarily increasing the monitoring point, shortening the system condition evaluation interval, increasing the frequency of patrol inspection and condition analysis resources, and even implementing temporary shutdowns. For different performance quality conditions, supportability resource allocation should be applied correspondingly. Transfinite points, such as points (9, 30), (12, 50), and (20, 71) in FIGURE 2, are critical points where performance quality conditions change. When these points appear in a system, the supportability resource allocation plan and contingency plan should be initiated in time.

For a specific performance quality condition of a large-scale electromechanical system, equal to different index values in the Normal state, as shown in FIGURE 2, the performance quality index is undergoing a dynamically changing and complex process. How to identify the signs of state change from the seemingly stable and normal change of performance quality state and how to trigger dynamic

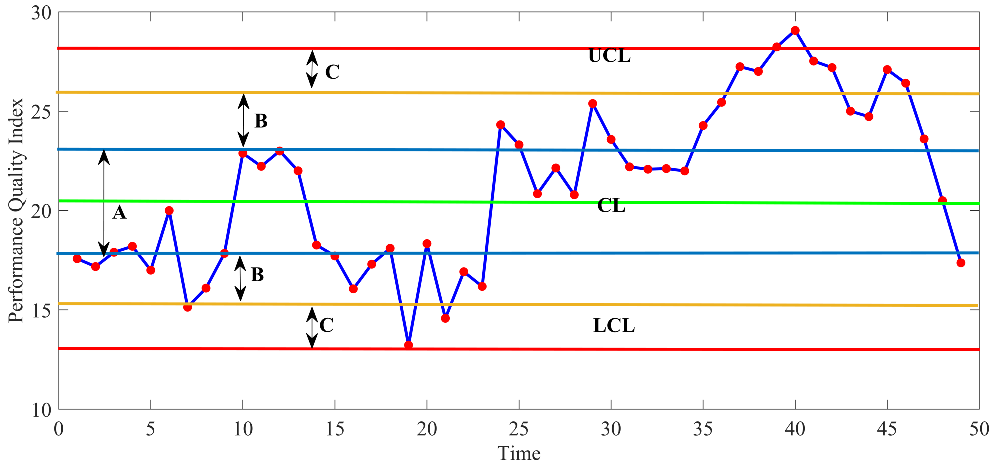

FIGURE 3. Schematic diagram of the *Normal* state.

allocation events of equipment performance quality maintenance resources are core problems to be solved. Doing so will enable the optimal allocation of supportability resources based on the results of the comprehensive quantitative assessment of performance quality. This process offers great practical significance for the system to conduct preventive operations based on the state, to cut off the abnormal propagation chain in time, and to avoid the occurrence of major faults. To identify variations of the performance quality state behind the fluctuation of the PQI, the PQI interval under the same performance quality state is subdivided in this paper. FIGURE 3 shows a schematic diagram for index subdivision of a large-scale electromechanical system in the normal performance state. The subdivision process is described as follows:

(1) Collect index data under normal performance quality, and mark them as D.

(2) Determine the probability p of the collected index, using the kernel density estimation method.

(3) Sort the indices according to their probability density in descending order.

(4) Calculate the cumulative sum of the probability density, P_{cum};

(5) Set the threshold value α to determine the domain of index values. When P_{cum} is no less than α, the minimum and the maximum values of the domain are determined as the lower control line and upper control line and are labeled LCL and UCL, respectively. Furthermore, the average values of LCL and UCL are defined as the value of the central line (CL). This step can be performed using the following rule:

$$\begin{cases} UCL = PQI_{max} \\ LCL = PQI_{min} \\ CL = (UCL + LCL)/2, \end{cases} \quad P_{cum} \geq \alpha \tag{2}$$

(6) Calculate the variance of the index values in the upper and lower control lines σ and divide the original area into areas A, B and C using Equation 3.

$$\begin{cases} A \sim CL \pm \sigma \\ B \sim CL \pm 2\sigma - A \\ C \sim CL \pm 3\sigma - A - B \end{cases} \tag{3}$$

In this study, from the perspective of performance quality fluctuation, the following trigger rules for the reallocation of supportability resources are proposed:

(1) the index exceeds the state limit. When the index exceeds the critical point of the performance state, the resource allocation scheme of the next performance quality state will be automatically triggered. As shown in FIGURE 2, point (20, 71) indicates that the performance quality of the system has entered a hazardous state. Intervention measures such as load reduction and temporary shutdown must be initiated to prevent the further deterioration of the performance quality and the occurrence of severe production accidents. For the assessment results under the same performance quality state, according to the subdivided control areas of A, B and C, when the PQI fluctuates in the subdivided area, corresponding dynamic resource allocation events should also be triggered.

(2) The indices are continuously increasing. As shown in FIGURE 3, during two periods of 7-10 and 35-38, the indices show a continuously increasing trend, which indicates that the performance quality state is continuously deteriorating; therefore, dynamic resource allocation events should be triggered.

(3) The indices are staggered. As shown in FIGURE 3, in the period 9-13, the performance quality state is staggered, which indicates that the system state is unstable. Therefore, resource allocation plans should be triggered in time and actions should be initiated to eliminate the instability and identify its causes.

(4) The indices continuously appear on the same side of the centerline. Although the indices are within the range of the control line, they continuously appear on the same side

of the central control line, which indicates that the performance state may be out of control and the state center is offset. Therefore, the supportability resource allocation scheme should be initiated in time to identify and correct the cause.

(5) The indices are continuously located outside of area B. As shown in FIGURE 3, indices at times 35-37 indicate that the center of the performance quality mode has changed; therefore, the supportability resource allocation scheme should be started in time to identify and correct the cause.

This paper proposes five principles for optimal allocation of maintenance resources based on the evaluation results of performance quality. The parameters in each principle can be specifically defined according to the specific situation of the application object. For example, there is a principle set for the large-scale electromechanical system "number of points outside control line: 1, on the same side of the control line: 7, increase continuously: 9, staggered continuously: 11, and outside area B: 3 in 5". This information indicates that in the results of the performance quality state assessment, if one point is outside the control line (the same performance quality state line or different performance quality state lines), 7 consecutive points are located on the same side of a performance quality state center control line, 9 performance quality state indices continuously increase, 11 consecutive results are staggered, or 3 in 5 consecutive results of a performance quality state are outside area B, the dynamic reallocation actions for the performance quality supportability resources will be triggered.

This section proposes the triggering rules for the supportability resources of a large-scale electromechanical system. The actual allocation scheme can be planned according to the enterprise situation and management process in response to different triggering actions. The specific contents of the allocation scheme are not studied in this paper.

In this section, four categories were taken as examples to explain and quantify the difference in conditions. The specific category number does not affect the proposed actions or processing procedures. Even if only one performance condition indicates that the performance conditions are undistinguishable or are very difficult to distinguish, the processes for the subdivision and determination of the control lines of performance condition based on formulas (2) and (3) are constant, and the proposed trigger rules to reallocate supportability resources in this section remain valid.

B. B RISK IDENTIFICATION-BASED RESOURCE REALLOCATION

After determining the time to reallocate the supportability resources, the next important task is to identify where the limited resources should be allocated. There is a complex coupling constraint relationship among the influencing factors of large-scale electromechanical systems. The system includes several parts or subsystems that are considered risk areas and key links, whose failure will expand the transmission of fault; therefore, more attention must be focused on these parts when performance quality maintenance resources are allocated. The system risk point is influenced and determined by the inherent characteristics and performance processes. For a complex industrial system, when the design is finalized, it must include potential fault-sensitive nodes, i.e., the risk points are determined by the inherent characteristics of the system itself. Simultaneously, in the process of equipment performance degradation, new risk points will inevitably and dynamically appear. Many accident investigations show that component failure often indicates the beginning of a serious accident. However, the expansion phase of the accident is closely related to the risk points or risk parts of the system. Based on the identification of the inherent and dynamic risk point of the equipment, conducting dynamic resource allocation is important to protect the equipment performance quality state and decrease the risk point from technology to management.

The concept of the risk point is broad and has different connotations in different fields, such as financial risk [32], [33], management risk and technical risk [34], [35]. In this article, the performance risk points of large-scale electromechanical systems refer to inherent structural risk points that form in the design and manufacturing process. The performance risk points also refer to the physical units that are influenced and determined by the production process and are vulnerable to the outside world. The physical units lack antijamming and recovering abilities, such as high-pressure valves, or sensitive process control parameters. With the development of complex network theory [36]–[39], risk point identification has gradually become a research hotspot with important content. Moreover, risk point identification has become an effective method to identificate the equipment risk points and vulnerable points of the physical structure and information structure of equipment because of the topological structure and properties of complex networks.

Coupling network construction builds the foundation for network-based risk identification. Here, information transfer relationships among variables are used to assess and characterize the extent of their coupling. In this paper, based on the improved calculation method for symbol transfer entropy, the information model of large-scale electromechanical systems is established. The essence of this model is a network expression of the internal connections of the complex system, which can be applied as the basis to identify equipment performance quality risk points. FIGURE 4 shows an information network model based on the information transfer relationship among the monitoring variables of a large-scale electromechanical system [2].

Many importance measures have been proposed, developed, and successfully applied for decision purposes; e.g., [40], [41]. However, in the literature, few papers have addressed the use of importance measures for maintenance decision-making [42]. Due to the complexity associated with the calculation of the used importance measures, these papers only apply to the maintenance of systems with few nodes and specific structures. The use of importance measures for maintenance decision-making remains challenging.

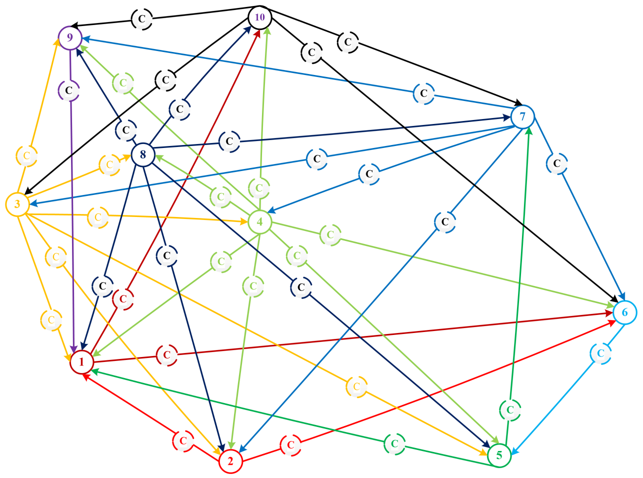

FIGURE 4. Sketch map of an information model for an electromechanical system.

Here, a novel criterion is proposed to estimate the risk of each node in the model. In graph theory, the node degree and number of edges associated with each node are used to quantify the relationship among nodes. The output of the information model node can be calculated as follows:

$$k_i = \sum_{j=1,j\neq i}^{n} r_{i\to j}, r_{i\to j} = 0 or r_{i\to j} = 1, \tag{4}$$

where k_i represents the output degree of node i, and $r_{i\to j}$ represents the directed connection relationship from node i to j. If there is a connection relationship, $r_{i\to j} = 1$; otherwise, $r_{i\to j} = 0$.

Since the information model established in this paper has edges among nodes, there is an information propagation relationship. In other words, a larger output of the node indicates that it affects more nodes and the propagation paths and ranges are wider and more numerous. An exception or failure that occurs at nodes with large outputs (e.g., nodes 7 and 8 in FIGURE 4) more likely causes exception propagation and amplification. Therefore, node outages can be used as a viable judgment index of risk nodes. However, it is not sufficient to only consider these outages. For example, a simple system is shown in FIGURE 5 that contains two parts and 10 nodes.

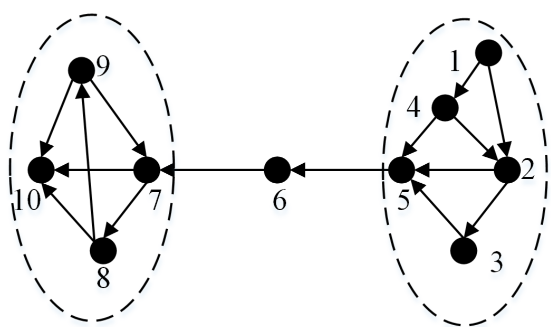

FIGURE 5. Relationship between system risk and structure character.

The edges of these nodes indicate that they are related to each other. Through these connections, the nodes form a complete system. Clearly, the locations of nodes 5, 6, and 7 in the system are very important because the nodes in the two subsystems are only connected through these three nodes. Thus, if nodes 5, 6, and 7 fail, other nodes will inevitably be affected.

Therefore, how to identify nodes such as nodes 5, 6, and 7 (FIGURE 5) in the information model of large-scale electromechanical system is particularly important. There are few adjacent nodes (although the degree is small), but they play a significant role. Both node 5 and node 7 have degree 4, which exceeds the degrees of other nodes in the system; therefore, these are important nodes with identical intuitive understanding. However, the degree of node 6 is 2; thus, its importance can intuitively be easily ignored. Consequently, the importance of a node cannot be measured only by the degree of the node. To fully quantify the importance and risk of each node in the information model, the following quantitative indicators are defined in this paper:

Definition 3 Correlation Strength of the Information Node Pe: Correlation strength Pe is the connection weights of nodes i, j. In the information model, the correlation strength of information nodes is the entropy of the information transfer between nodes calculated by the information model.

Definition 4 Optimal Path of the Information Node d_{ij}: d_{ij} is the optimal path between nodes i, j and can be calculated as follows:

$$d_{ij} = max(\sum (1/Pe_k)^{-1}), \tag{5}$$

where Pe_k is the correlation strength of k edges in the path.

Definition 5 Information Node Load l_{di}: Suppose that any two nodes are related to each other via the optimal efficiency path d_{ij}; then, the total number of optimal paths passing through the node is defined as the node load l_{di}. Similarly, the total number of the optimal paths passing through edge e_{ij} is defined as the edge load l_{eij}.

Since the connection between nodes is represented by the edge when information structure networks are constructed, the load reflects the role and influence of the corresponding nodes in the entire network. A larger load indicates a more important role of this node in establishing connections with other nodes. For nodes with long distance connections, although the node degree is small, the shortest path between other node pairs must go through these nodes, which leads to a high load of those nodes. Because there are long range connections, their failure affects the function of the subsystem and propagates to other subsystems. Therefore, the node load should also be used as an indicator for the sensitive nodes of the system.

By integrating these two factors, we obtain a large-scale node electromechanical system risk evaluation criterion, i.e., a greater information node degree and load imply higher performance quality sensitivity. Consequently, this type of node is easily affected by the performance of other related nodes with abnormal quality and also easily causes and promotes the occurrence of abnormal qualities of other nodes. Therefore, this type of node can be understood as risk and the sensitive part of the system. To quantitatively evaluate the performance quality risk of each information node, the risk coefficient RC_i is introduced to measure the node vulnerability:

$$RC_i = \frac{w_k k_i + w_l l_{di}}{max(w_k k_i + w_l l_{di})}, \tag{6}$$

where k_i, l_{di} are the node degree and load of node i, respectively; w_k, w_l are the node degree and node load weights, respectively. Compared with other measures for risk quantification, such as structural importance measures [43], the risk coefficient provides the structural importance of a node regarding the global structure of the system using the node load and considers its local structure in amplifying or reducing of risk using the correlation strength. Moreover, the risk coefficient coincides with the structural importance measure in physical meaning when $w_k = 0$ and $w_l = 1$.

According to the definition of the risk coefficient, the system risk point may not refer to the key equipment or device in the system. Devices or components that are not important or only connect to other nodes may also pose a risk to the system.

Since nodes with a higher degree and load play an important role in maintaining the structure and function of the system network, when the structural units represented by these nodes fail or show abnormal performance, failure diffusion likely occurs. Therefore, it can be considered that these nodes have high performance quality sensitivity and should be protected as system risk points. Under the condition of limited performance quality maintenance resources, protecting nodes with a higher risk coefficient first (e.g., by increasing the number of preventive maintenance or replacement) is better than the random protection of selected nodes. Enterprises should conduct personalized allocation of guarantee resources in advance, to prioritize and focus on guarantee according to the identification results of the system risk points.

IV. COLLABORATION BETWEEN MAINTENANCE RESOURCES AND ACTIVITIES

Through the dynamic reallocation of limited supportability resources based on the performance quality condition and risk identification, the contradiction between a static supportability strategy and time-varying performance quality conditions has been relieved. However, regardless of the optimization or reallocation strategy used as a preventive means to avoid (or slow) the degradation of performance quality, the abnormality or malfunctioning of the system is inevitable. Thus, moderate and scientific maintenance is still a necessary intervention to repair and improve the system performance quality. Therefore, collaboration between maintenance resources and performance quality states has become one of the key goals of supportability mechanism research for large-scale electromechanical systems.

A. PERFORMANCE MODE AND EFFECT ANALYSIS-BASED MAINTENANCE PLANNING

Because of the discrepancies of the working condition parameters and the influence of exception and failures, the performance quality always presents different modes. Furthermore, different modes are associated with different performance quality states and trigger different performance exceptions and influences. Collecting and analyzing the historic performance data of a system and recognizing the potential performance modes to plan the corresponding maintenance resources is an effective means to realize collaboration between resources and performance quality states.

Definition 6 Performance Quality Mode: The performance quality mode is a normative description of the state of the performance quality of the study object that can be observed, measured, or analyzed. The performance quality mode is generally described according to the investigated phenomenon under the performance quality state of the studied object. Because of the limitation caused by conditions, the observed or measured performance quality phenomenon may be systematic, e.g., the steam turbine cannot start. The reason may also be a specific component, e.g., when the spindle vibration exceeds the standard or a specific part fails, e.g., shaft seal failure.

Definition 7 Performance Quality Mode and Effect Analysis (PQMEA): is a performance quality mode-oriented analysis method that determines the causes of its mode, analyzes the subsequent impact of the mode, and conducts targeted maintenance resource allocation. The work flow of performance quality mode effect analysis is introduced as follows:

(1) Determine the known and potential performance quality modes;

(2) Analyze both the causes and effects of each performance quality mode;

(3) Quantize and evaluate the specific performance quality mode based on its detection (D), severity (S) and occurrence (O), using the following formula:

$$PQMPN = w_S \times S \times w_O \times O \times w_D \times D \tag{7}$$

where $PQMPN$ is the priority number of the performance quality mode considering the joint influences of the detection, severity, and occurrence of the performance quality. A larger number indicates a larger impact of the quality mode; w_S, w_O, and w_D are the weights of detection, severity, and occurrence of the performance quality mode, respectively;S, O, and D are the quantitative values of detection, severity and occurrence of the performance quality mode, respectively, which can be determined according to the experience of enterprise experts.

(4) Sort the performance quality modes according to the priority numbers;

(5) Generate maintenance resource plans for each performance quality mode based on the following format.

PQMPN defined in this work originates from the risk priority number (RPN) in the failure mode and effect analysis (FMEA). However, in the calculation of the RPN, risk

TABLE 1. A sample for maintenance resource plan based on PQMEA.

Equipment unit				Performance quality mode		Mode Effect	Maintenance resources		
Order	Name	Quantity	Unit	Order	Name		Maintenance plan (Overhaul / Daily)	Resource name	Quantity

factors O, S, and D are assigned the same weight for each factor. This assumption may not be true in practical applications involving FMEA. To overcome this problem, the weights of each factor were considered in the calculation of PQMPN. This operation expanded the practicability and feasibility of RPN, and will be changed into the traditional RPN when the factors have equal weights.

The determination of the weights of the factors can be carried out by a team of experts. Since it is carried out by a team of experts and because of their subjectivity and cognitive differences, linguistic variables are used and then aggregated by fuzzy arithmetic. The FN-OWA (Fuzzy Number Ordered Weighted Average) [44] operator can be used for averaging expert evaluations, which is an OWA operator, designed especially for fuzzy numbers and linguistic data. The main reason why FN-OWA was chosen is that it has the ability to aggregate not only quantitative data, but also can handle linguistic as well as crisp data.

Essentially, PQMEA is an analytical method that assesses all the possible performance quality modes and evaluates the effect of each mode for the entire electromechanical system. Then, a specific maintenance resource plan is developed to realize collaboration between maintenance resources and performance quality states.

B. MAINTENANCE BILL OF MATERIAL AND MULTIAGENT MAINTENANCE CHAIN-BASED RESOURCE GUARANTEE

PQMEA-based maintenance resource collaboration solves the problems of resource requirements for each performance quality state. However, another critical problem in maintenance is how to supply and guarantee resource requirements. In fact, large-scale electromechanical systems always consist of an electronic system, a mechanical system, and a power system (and possibly other relevant systems). These systems constitute typical technology-intensive and knowledge-intensive comprehensive systems. Moreover, using companies, main engine factories, auxiliary equipment factories, and other component suppliers a multi-agent maintenance chain is constructed that effectively guarantees the required resources at low cost. The maintenance activities demand that this chain should be an agile and effective system that integrates with technologies and knowledge as much as possible. Then, the construction of a maintenance bill of material (M-BOM), shares and schedules technologies and resources among members of the maintenance chain. The construction of the M-BOM is the key to solving the problem of maintenance resource guarantee.

M-BOM contains the assembly and quantity relationships of parts and contains the quantity, natural properties, and other additional information of spares obtained by using the fault rates of different parts. In general, the information in M-BOM can be divided into four categories: (1) Information of maintenance devices, e.g., structure, assembly and basic technical parameters; (2) maintenance activity information, which contains resource requirements; the maintenance plan, maintenance history and knowledge, (3) human information, which is related to the technical degree, skill and conditions of the personal; and (4) spare information, which contains basic information, order information, in-and-out-of-storage information, cost and other relevant information.

Over the entire performance lifetime, the performance quality will degenerate over time, and exceptions and faults will occur; thus, maintenance activities are unavoidable. Therefore, basic information such as the structure and parts of a system will be updated. Additionally, the information in M-BOM that corresponds to these maintenance activities is updated to guarantee up-to-date information in M-BOM. Therefore, M-BOM is dynamic and evolves with maintenance activities.

FIGURE 6 shows a diagram of maintenance guarantee based on M-BOM and the multiagent maintenance chain, in which the spare requirements for different quality modes are integrated and a multiagent chain combined with the usage factory, manufacturing factory, auxiliary engine factory, and part suppliers is constructed from the perspective of the source of maintenance resource. Furthermore, the sharing mechanism of the technical and material resources among the members of the chain is established, and the abilities for resource scheduling and process control are improved.

V. PROCESS CONTROL AND EFFECTIVENESS EVALUATION OF MAINTENANCE ACTIVITIES

As mentioned, the performance quality and conditions will deviate from the original design values, and the lifetime and technical parameters will gradually degenerate. Therefore, maintenance activities are necessary processes to adjust degenerated states and satisfy the requirements for a given set of working parameters and performances. However, because of the lack of effective quality control and evaluation for these activities, fault rates related to invalid or improper maintenance activities are high. With the maturity of manufacturing quality control technologies, the maintenance process and quality-like controlling in manufacturing must be controlled in the comprehensive supportability of large-scale electromechanical systems.

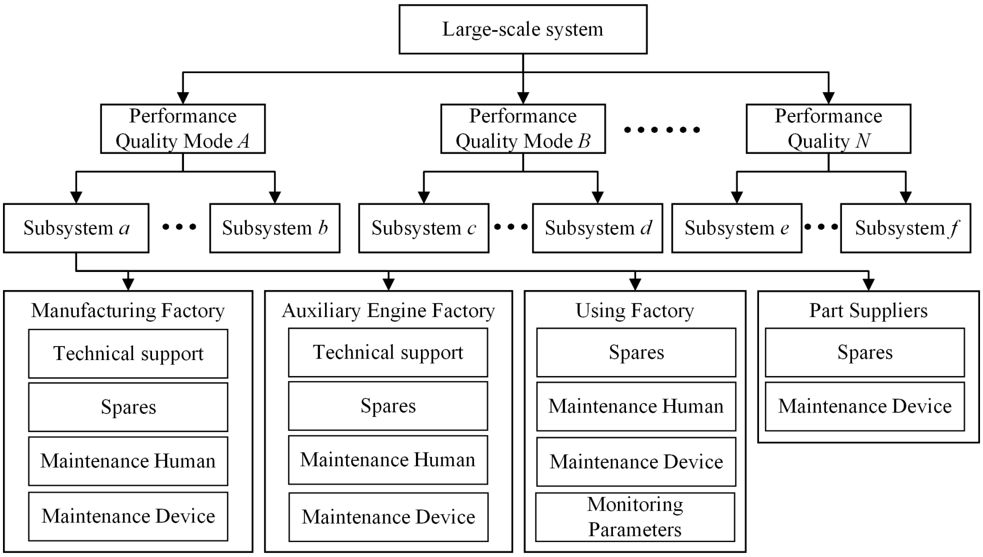

FIGURE 6. Diagram of maintenance guarantee based on the M-BOM and multiagent maintenance chain.

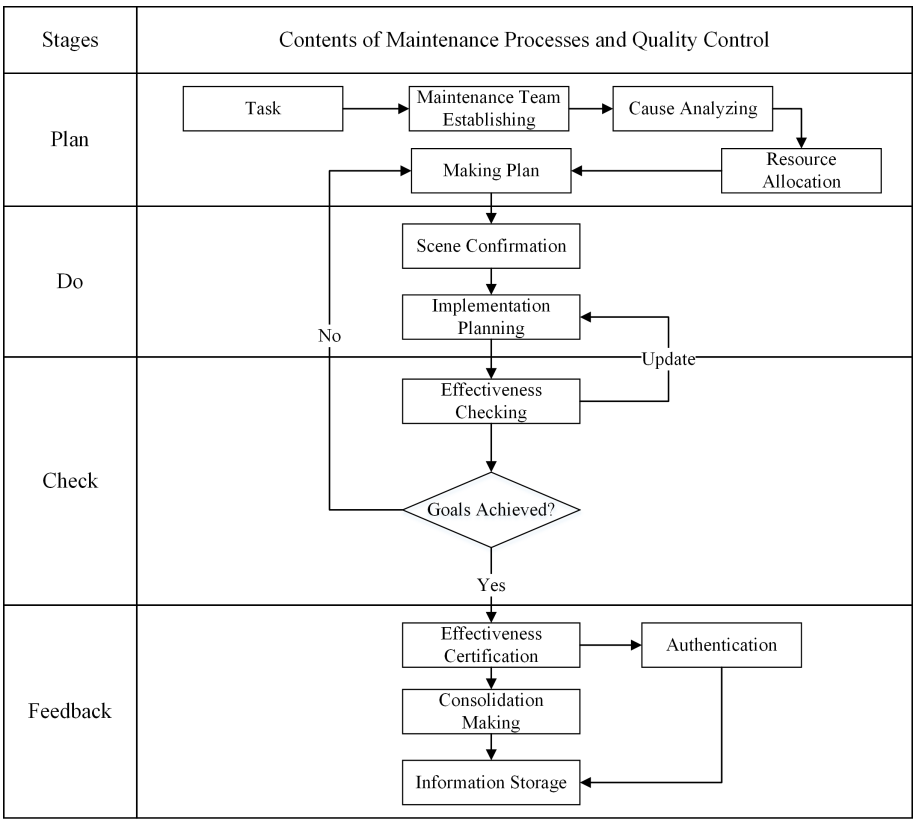

FIGURE 7. Diagram of the maintenance processes of large-scale electromechanical systems.

A. A CONSTRUCTION OF A FACTOR SYSTEM FOR PROCESS CONTROL AND EFFECTIVENESS EVALUATION

The maintenance processes for large-scale electromechanical systems is composed of a series of activities. FIGURE 7 shows a diagram for the maintenance processes and activities of a steam turbine in a power plant. As shown, plan, do, check, and feedback are the four main stages, and each stage has different activities and contents assigned to it. Thus, to control and evaluate the maintenance activities and quality, a scientific and rational maintenance quality evaluation index system must be established prior to performing further analysis.

1) PRINCIPLES FOR THE SELECTION OF MAINTENANCE PROCESS CONTROL AND QUALITY EVALUATION FACTORS

To ensure the accuracy and authority of process control and the feasibility evaluation of maintenance, a factor system must be established to scientifically, objectively, reasonably and comprehensively collect all the indicators associated with the maintenance activities. Therefore, several principles must be followed to analyze these potential indicators.

a: SCIENTIFICITY

The factor system is not a simple composition of relevant factors. This system should comprehensively, objectively, scientifically, and accurately reflect the essential characteristics of the maintenance activities, and the relevant relationships and should also reflect the internal relationships between various related indicators and maintenance quality. Each indicator should be objective and have a precise connotation and denotation.

b: SYSTEMATIZATION

A factor system must be established from an overall and comprehensive perspective that can reflect the reality of different elements and processes of the system in a comprehensive and multifaceted perspective. Therefore, oversimplification of the factor system must be avoided in which several important factors will be ignored, which will make it difficult to reflect the internal nature of the maintenance quality. One must also avoid overly complicating the factor system, which will make it difficult to implement quality control.

c: COMPARABILITY

Because various factors of the factor system involve various aspects, whose measurement units differ, in the process of comprehensive evaluation, different evaluation indicators must be quantified as the same unit for comparison and calculation. Stronger comparability corresponds to more credible results of the quality evaluation. Therefore, the factors of the factor system should be representative and universal, and the evaluation content should eliminate uncertain factors and effects under specific conditions as much as possible. All the incomparable factors should be transformed into comparable factors, and the measurement values of all the factors are converted into uniform equivalent and dimensionless values. Consequently, all the control factors are compatible in the same model, and the results of the entire quality evaluation are comparable.

d: PRACTICABILITY

The factor system must have clear levels and a clear meaning. The system must consider the current and long-term, local and overall, qualitative and quantitative relationships, and design a specific, measurable, easy to calculate and handle, simple and moderate factor system. There should be sufficient standard information for relevant factors of the factor system, among which qualitative factors can be quantified and quantitative factors can be directly measured.

e: INDEPENDENCE

The elements of the factor system should be independent of one another and not be subordinate to other factors or overlap with one another. Otherwise, the weight of the relevant factors will increase, and, the scientificity and accuracy of quality control will be affected. Because of the redundancy of components, the workload of quality control increases and the feasibility of the maintenance quality evaluation decreases.

2) DETERMINATION OF MAINTENANCE PROCESS CONTROL AND QUALITY EVALUATION FACTORS

This section determinates the factors that affect the maintenance process control and quality evaluation of large-scale electromechanical systems based on the aforementioned selection principles.

a: CONFORMITY FACTORS OF MAINTENANCE RESOURCES

One of the necessary prerequisites for maintenance activities is the acquisition of sufficient maintenance resources, such as adequate spare parts, a qualified and skilled construction team, the necessary maintenance tools and auxiliary equipment. Resource compliance is one of the important factors to evaluate the maintenance quality.

b: NORMATIVITY FACTORS OF THE MAINTENANCE PROCESS

Large-scale electromechanical systems often form the core production equipment of enterprises, which often consist of a collection of electronic systems, mechanical systems, and power systems. Any operation and maintenance activities for such equipment must satisfy the following normative requirements.

Normativity factors of maintenance planning: Planning is the first step for maintenance activities. Strict maintenance plans must be formulated before maintenance activities can be performed, and the process of formulating plans must conform to the review process.

Normativity factors of maintenance operation: The maintenance operation must conform to the operation specifications of the operation object, such as the removal of static electricity, or dust prevention, to avoid secondary faults and accidents caused by improper maintenance operation.

Normativity factors of maintenance feedback: After the maintenance activities have been completed, there must be detailed feedback of the maintenance activities (such as whether the operation expectations are satisfied), maintenance process records, improvement measures, and suggestions. On one hand, a control loop of maintenance activities is formed, on the other hand, the meta knowledge accumulation of the maintenance activity knowledge base is formed.

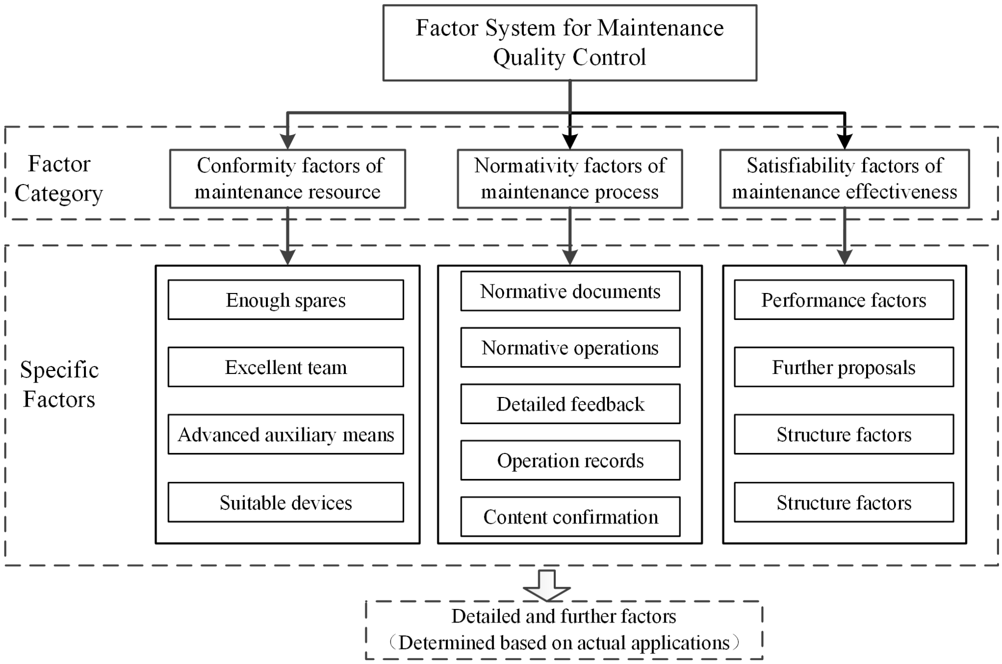

FIGURE 8. A simple instance of factor system for maintenance quality control.

c: SATISFIABILITY FACTORS OF MAINTENANCE EFFECTIVENESS

The main purpose of these factors is to evaluate whether the maintenance activities can ensure the maximum continuous operation of production, improve the operation conditions of the equipment, extend the service life of the equipment, and restore the performance of the system to ensure that the maintenance activities are implemented according to the maintenance plan procedure. Whether the effect of maintenance activities satisfies the established goal is key for the evaluation of the maintenance quality. Simultaneously, the evaluation of maintenance effect satisfaction improves the maintenance plan.

According to the former analysis, FIGURE 8 shows a simple instance of a factor system for maintenance quality control. Because of the limited space, the factor categories and some of the factors are represented, and detailed and sub-level factors can be determined based on actual applications.

At any level, the factors can be directly quantified to evaluate the performance quality states of the system and can be further subdivided according to the situation at hand. Therefore, the proposed maintenance quality evaluation factor system of large-scale electromechanical systems in this paper is a typical multilevel, multifactor hierarchical structure evaluation system.

B. B EVALUATION OF MAINTENANCE PROCESS AND QUALITY

Each factor reflects a specific content and only reflects a specific dimension of the maintenance process and quality, which is not sufficient to comprehensively reflect the overall maintenance quality. Therefore, a comprehensive dimensionless index, such as the maintenance quality index, must be defined to integrate different evaluation factors, which can abstract and generalize the maintenance quality. Because of the variety of evaluation objects and factors, the integrated measurement of maintenance quality and the unified quantification of evaluation factors must be solved prior to the evaluation and analysis of maintenance quality of large-scale electromechanical systems.

Notably, actual applications have many detailed factors with different characteristics and quantitative methods. Some of applications and factors are as high as possible, while others are as low as possible. To evaluate the maintenance process and quality based on the factor system, it is necessary to quantify these factors and describe them by a unified data structure.

Definition 8 Maintenance Quality Factor (MQF): Here, a seven-elements set named MQF is defined to represent a single factor for the maintenance quality evaluation. MQF is defined as follows:

$$MQF = (element, factor, value, weight, \\ proportion, character, calculation) \quad (8)$$

where *element* is the factor category, whose datatype is defined as a character string; *factor* is the name of a specific evaluation factor, the datatype of which is a character string; *value* is the value of the factor, whose datatype is a double number; *weight* is the weight of a factor, whose datatype is a double number; *proportion* is the proportion of the *element*, whose datatype is double number; *character* is the factor property, whose datatype is enumeration (the larger, the better or the smaller, the better); and *calculation* is the calculation approach of this factor, whose datatype of which is enumeration (e.g., multiplication, logarithm, or exponent). According to the physical significance of the proportion, all factors in a specific factor category have identical proportions, and the accumulation of all proportions for factor categories is 1:

$$\sum_{i=1}^{n} proportion_i = 1, 0 < proportion_i < 1 \tag{9}$$

where n is the number of factor categories and $proportion_i$ is the proportion of the i^{th} factor category.

Definition 9 Maintenance Quality Index (MQI): MQI is a special relative number to measure the comprehensive changes of multiple maintenance quality evaluation factors in different situations. This index represents the overall dynamics of different types of maintenance quality evaluation factors, and analyzes the influence degree of each factor change in the total change of maintenance quality. Here, MQI is calculated using Equation (10):

$$\begin{aligned} MQI &= \sum_{i=1}^{n} E_i \\ E_i &= \sum_{j=1}^{m_i} f_j(value, weight, proportion) \end{aligned} \tag{10}$$

where i is the order of factor categories; n is the number of factor categories; $E_i, 1 \leq i \leq n$ is the influence of the i^{th} factor category on the entire index; j is a specific factor; m_i is the number of factor in the i^{th} category; f_i is a mapping function that reflects the quantitative method of this factor.

For example, five factors are used to evaluate a maintenance activity: (conformity factors of maintenance resource, spares, 0.8, 10, 0.2, the larger, the better, exponent), (conformity factors of maintenance resource, auxiliary devices, 2, 8, 0.2, the larger, the better, multiplication), (normativity factors of maintenance process, normative operation, 2, 9, 0.3, the larger, the better, multiplication), (satisfiability factors of maintenance effectiveness, performance factor, 1, 9, 0.5, the larger, the better, multiplication), and (satisfiability factors of maintenance effectiveness, performance factor, 1, 3, 0.5, the larger, the better, multiplication). Then, the MQI for this activity is

$$\begin{aligned} MQI &= 10^{0.8} \times 0.2 + 2 \times 8 \times 0.3 + 2 \times 9 \times 0.3 \\ &\quad + 1 \times 9 \times 0.5 + 1 \times 3 \times 0.5 \\ &= 1.262 + 4.8 + 5.4 + 4.5 + 1.5 \\ &= 17.462. \end{aligned} \tag{11}$$

Thus, the influence degree of the first factor is $10^{0.8} \times 0.2/17.462 = 0.07$. Similarly, the influence degrees for the other four factors are 0.27, 0.31, 0.26 and 0.09.

After the construction of this factor system for maintenance process control and effectiveness evaluation based on the selection principles and factor categories proposed in this work, the value of each factor can be determined based on the task procedures, and the quality of each maintenance activity can be evaluated. Furthermore, the MQI and sensitivity for each factor are analyzed to control the maintenance processes and quality.

VI. CONCLUSION

There are supportability activities for performance quality over the entire operation lifetime of large-scale electromechanical systems, and a scientific and timely supportability mechanism plays a critical role to ensure performance quality and prevent serious faults or performance degenerations. Focusing on the contradiction between the static supportability mechanism and the dynamic performance quality conditions, this study posed a dynamic supportability mechanism to reallocate limited supportability resources, achieve collaboration among the multiple agents in resource guarantee, and control the process quality of maintenance activities. The proposed mechanism formulated a dynamic supportability mechanism for performance quality with a closed loop that consisted of an activity trigger, a resource guarantee, and an effectiveness evaluation of the maintenance action. As a supplement and extension of condition-based maintenance, this mechanism focuses on the trigger events of dynamic supportability and highlights the execution and processes of events, which integrates the management and technology. Moreover, the mechanism forms a closed-loop for performance quality control with quality monitoring, evaluation, and fault root cause tracing. Several ideas or methods, such as principles for factor selection, MQI, and factor sensitivity, provide a beneficial reference for other engineering problems.

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