Advances in Reliability, Safety and Security, Part 9 – Kołowrocki, Dąbrowska (eds.)
© 2024 Polish Safety and Reliability Association, Gdynia, ISBN 978-83-68136-21-0 (printed), ISBN 978-83-68136-08-1 (electronic)

Advances in Reliability, Safety and Security

ESREL 2024
Monograph Book Series

General Indicators Of Equipment Health State Perception Ability

Yong Zhang, Peng Yang, Kehong Lv, Wenxiang Yang, Qiang Guo, Guanjun Liu, Jing Qiu

College of Intelligence Science and Technology, National University of Defense Technology ,Changsha, China
Science and Technology on Integrated Logistics Support Laboratory, National University of Defense Technology, Changsha, China

Abstract

The future logistics support mode will be based on Prognostic and Health Management (PHM) as the premise and foundation. This mode emphasizes the importance of perceiving health status, which requires evaluable indicators for verifying the health status of equipment. The paper proposes verifiable statistical indicators to assess equipment health status perception capability, with a focus on fault detection, diagnosis, prediction, and health status evaluation. These indicators mainly include state parameter coverage rate, fault coverage rate, fault detection rate, fault isolation rate, false alarm rate, fault prognostic rate, relative accuracy of fault occurrence time prediction, health degree, health status level, and health status evaluation accuracy. Mathematical definitions and physical interpretations are provided to establish a basis for the test and evaluation of equipment health status perception ability. It provides technical support for the engineering application of PHM systems.

Keywords: health status perception, fault prognostic, health management, indicator evaluation

1. Introduction

The extensive integration of high and new technologies in complex equipment has notably enhanced performance, leading to advanced functionalities, improved task response times, and enhanced continuous workability. However, the structure of such equipment and the interdependent relationships among various levels of testing have become more intricate. Therefore, maintenance and comprehensive support must adapt to meet evolving performance and development needs, necessitating characteristics that are fast, accurate, efficient, independent, multi-level, all-encompassing and systematic. This has led to the emergence of new support concepts and modes such as condition-based maintenance, predictive maintenance, CBM+, and autonomous maintenance. These new support modes are all predicated on the comprehensive, accurate, and timely perception of equipment technology, emphasizing the importance of technology and health status awareness for proactive issue prevention. Only through a comprehensive understanding and accurate prediction of the product, as well as the health status of its components, can proactive measures be taken to prevent future issues. Such technological advancements have garnered attention and research interest from scientific institutions and military establishments both domestically and internationally (Peng et al., 2010; Wang et al., 2020; Fedele et al.,2011; Luna et al.,2009; Hess et al.,2005).

Given the diverse monitoring objects, complex monitoring types, and changeable service environments of new equipment, traditional condition monitoring platforms fall short of meeting the comprehensive equipment status perception requirements. It is imperative to build upon existing concepts and technical expertise in PHM both domestically and internationally to develop an equipment health status perception platform. This platform aims to comprehensively monitor key equipment operating parameters, accurately perceive and evaluate equipment health status, and integrate equipment condition monitoring, fault diagnosis, fault prognostic, and health status evaluation into a unified approach.

2. Current status of general indicators of equipment health status perception ability

The health status of equipment refers to the ability of the equipment and its constituent units at each level to perform the designed functions, which reflects whether the equipment can meet the needs of the task and its satisfaction degree. The health status of the components at each level is the ability of the components at the corresponding level to perform their designed functions.

Equipment health status perception is the process of testing and evaluating the running status and health status of equipment. This process involves the development of organic testing, automatic testing, condition monitoring, and fault diagnosis. Leveraging information and intelligent means, equipment health status perception can sense and evaluate the health status in real time, enabling effective monitoring and tracking of the fault evolution process.

The ability to perceive the health status of equipment in PHM system encompasses the following aspects:

- From a system functionality standpoint, it involves monitoring status, detecting faults, diagnosing issues, forecasting potential faults, predicting the remaining useful life of critical components, evaluating overall system health, providing real-time intelligent reasoning and information fusion, offering maintenance decision recommendations, initiating efficient regulation and maintenance activities, preventing accidents, and optimizing the operational performance of the product.
- From a technological perspective, this capability is achieved through state monitoring, fault diagnosis, fault prognostics, health assessment, decision-making, and regulation technologies
- From an engineering design angle, these requirements are deemed essential elements of equipment system design and should be integrated into the initial stages of system design rather than treated as an add-on feature.

Health status awareness system plays an important role in monitoring the working status of large equipment, predicting the trend of change, calculating the life consumption, evaluating the remaining life, and ensuring the safe and reliable operation of equipment. It is an important part of equipment comprehensive support, and is also the premise and foundation of condition-based maintenance. Therefore, it is necessary to carry out research on related key technologies, and it is particularly urgent to develop a health status awareness system for large equipment.

The research hotspots of health status awareness mainly focus on the establishment of fault diagnosis models and fault prognostic models, the design and development of fault diagnosis algorithms and prediction algorithms, and the realization of fault diagnosis and prediction prototype systems. How to verify the proposed models, algorithms and prototype systems is a challenging problem. Research has been conducted domestically and internationally on capability verification in this field. Bertolino proposed simulation degradation model for assessing the execution time of PHM algorithms can also be applied to evaluate fault detection metrics, fault classification rates, convergence, and the accuracy of long-term predictions (Bertolino et al., 2023). Federici proposed a scalable deployment strategy for PHM technology for airborne systems, referencing a generic CBM framework, which uses the RMS error indicator to evaluate the model's accuracy when validated offline (Federici et al., 2022). Shen developed a new data-driven fault diagnosis framework, focusing on fault diagnosis under the coexistence of multimodal and concurrent faults, and evaluated the performance of the model based on accuracy and false alarm rate indicators (Shen et al., 2020).

Zhang expounded the performance evaluation indicators of prediction model, such as accuracy, precision, timely prediction failure time, false alarm rate and false negative rate, and put forward the evaluation method (Zhang et al., 2013). Yang qualitatively summarized the performance evaluation method of PHM for the fault prognostic and health management technology of airborne system, and evaluated the performance based on timeliness, functionality and end users (Yang et al., 2012). Qin used the combined weighting method to determine the indicators weight coefficient for the PHM system of armored vehicle, and evaluated the performance of PHM system of different armored vehicles by fuzzy comprehensive evaluation method (Qin et al., 2022). Long summarized the diagnostic indicators, prediction indicators and decision evaluation indicators of electromechanical systems (Long et al., 2021). Li summarized the PHM system verification and validation indicators, and defined and interpreted (Li et al., 2013). Dai pointed out that there are many problems to be solved in the verification and evaluation technology of PHM system. One is the difficulty of obtaining data and ensuring data quality of the object system, the other is the lack of a general health management test environment, and the third is the verification and evaluation indicator system has not been improved (Dai et al., 2012).

Some new research products are also gradually improving and carrying PHM systems. The manufacturers are vigorously developing and promoting the functional performance of PHM systems. However, owing to the absence of robust verification methodologies, the scientific evaluation of its performance metrics becomes challenging, leaving both the service provider and the end-user in a quandary. When the outcomes of PHM research lack systematic and effective testing and assessment, it raises skepticism among equipment users regarding the PHM system's efficacy. This skepticism may lead to reduced utilization or outright rejection of the PHM system, posing a significant impediment to the advancement and widespread implementation of PHM technology. Consequently, the practical application of PHM in engineering may fall substantially behind the growing demand.

With the promotion of product development engineering, many models of products are facing the finalization, how to test and measure the ability of product health state perception system? What indicator is used to measure the ability level of health status perception system? How to give a scientific evaluation recognized by both the contractor and the ordering party? To answer the above questions, it is necessary to have scientific and reasonable indicators to test and evaluate the health status perception ability of products.

It is very important to evaluate the health status of equipment, measure the ability of equipment to perform the designed function and meet the task needs, and monitor the performance and condition of equipment. Without proper condition monitoring systems and well-developed failure detection devices in place, there is a high chance of missing signs that indicate that a major catastrophic accident is about to occur. Therefore, the development of reasonable condition monitoring and fault detection indicators is the basis of equipment health condition measurement indicator system.

When the fault is detected in the process of the equipment performing the task, the significance of fault diagnosis technology is to determine the position where the fault state occurs and preliminarily determine the cause of the fault without disassembling the equipment. On this basis, fault prognostic technology focuses on predicting the future degradation or deterioration of components before they actually fail. By forecasting the development trend of the degradation state, this technology provides a basis for "condition-based maintenance," aiming to enhance the efficiency and reliability of equipment. In addition to prognostication, it is crucial to establish appropriate indicators to evaluate equipment diagnosis and prediction capabilities, as this forms a vital component of the equipment health state measurement indicator system.

The health status evaluation indicator of equipment is closely related to the structure and main functions of the equipment. In order to establish a comprehensive evaluation indicator for the health status of equipment, a consideration of its various subsystems and components is imperative. The equipment's health status is influenced by a multitude of factors due to its complex structure, emphasizing the need to identify characteristic parameters and interdependencies within each subsystem. A systematic analysis of the hierarchical influencing factors of the equipment is thus essential to construct a scientifically sound evaluation indicator system. Consequently, a step-by-step examination of the corresponding evaluation indicators ensures clarity and precision in defining the content of each indicator.

This paper proposes that the indicators that can be used to describe the health state perception ability mainly include four categories: detection indicators, diagnostic indicators, predictive indicators, and health measurement indicators. Detection indicators include the coverage ability of the test system for critical faults, serious faults, common faults, and state parameters, and detection ability. The diagnostic indicator includes the isolation and location ability of the test system for the causes of critical faults, serious faults, ordinary faults and abnormal phenomena. The predictive indicator includes the prediction ability of the two dimensions of the fault occurrence time and the size of the degradation. The above indicators can be classified into two types of indicators in statistics: quantitative indicators and counting indicators.

3. General indicators of detection and diagnosis

3.1. Status monitoring indicators

This indicator primarily evaluates the accuracy of monitoring state parameters, including the monitoring coverage rate of state parameters and the monitoring coverage rate of key state parameters.

State parameter coverage refers to "the ratio of the number of state parameter types that can be covered by test equipment and means to the total number of state parameter types that need to be monitored, expressed as a percentage".

$$r_{\mathrm{CC}} = \frac{N_{\mathrm{CC}}}{N_{\mathrm{C0}}} \times 100\%, \tag{1}$$

where N_{CC} is the number of state parameter types that can be covered by test equipment and means, and N_{C0} is the total number of state parameter types that need to be monitored.

After the key state parameters are specified, the coverage rate of key state parameters can be defined similarly. Generally, the coverage rate of key state parameters is required to be 100%. According to the actual situation, it can also be subdivided into online monitoring, offline monitoring and other requirements.

3.2. Fault detection and diagnosis indicators

"Accurate" and "timely" are two key characteristics and requirements in fault detection and isolation (location). "Accurate" is mainly reflected in high fault coverage rate, detection rate and isolation rate, and small false alarm rate. "Timely" is mainly reflected in the short time of fault detection and isolation.

Fault Coverage Rate (FCR) refers to the ratio of the number of fault mode types that can be covered by test equipment and means to the total number of fault mode types, expressed as a percentage.

$$r_{\mathrm{FC}} = \frac{N_{\mathrm{C}}}{N_0} \times 100\% \tag{2}$$

N_{C} is the number of fault mode types that can be covered by test equipment and means, and N_0 is the total number of fault mode types.

Fault coverage is a commonly used indicator in the field of testability, highlighting the coverage of fault patterns and the observability of a test to a fault. The higher the fault coverage, the more types of fault modes can be observed and detected accurately if the test is precise and dependable. After defining the critical fault according to practical requirements, the detection ability of test equipment can be limited by critical fault mode coverage and other indicators. This process ensures a holistic assessment of the system's effectiveness in detecting faults.

Fault detection rate, fault isolation rate, false alarm rate, mean fault detection time, mean fault isolation time and other indicators can refer to the monograph "Equipment Testability Test and Evaluation".

It should be pointed out that the fault coverage rate does not need to be used in the assessment, and there is no error caused by sample size allocation and other sampling schemes. As long as the fault mode set is comprehensive and accurate, the indicator can be objectively assessed and evaluated, and it is recommended to be included in the health status perception ability evaluation of PHM system. In addition, the user is very concerned about whether the fault mode with high severity can be detected. The critical fault mode coverage is an indicator that is in line with engineering practice and easy to assess.

4. General indicators of fault prognostic

4.1. Problem analysis

The key to minimizing damage, according to Weng Wenbo, lies in the accurate prediction and comprehensive assessment (Xu et al., 2007). The precondition for the smooth realization of PHM system functions is that there must be accurate and credible fault detection, diagnosis and prediction results.

Fault prognostic is a crucial aspect of PHM technology that aims to predict when a system will fail and estimate its remaining service life. Its fundamental goal is to maximize the use of equipment under the premise of ensuring the safety of equipment.

Fault prognostic methods can be roughly divided into three types: model-based methods, data-driven methods and hybrid prediction methods. Accurate fault/life prediction has always been an international problem. There are challenges in fault prognostics research both domestically and internationally. These challenges include non-targeted prediction algorithms, limited prediction confidence, and a scarcity of combined prediction methods that offer high confidence levels.

At present, the main research focus lies on the research, design, and verification of specific objects (faults) or specific prediction models/algorithms in the field. From the perspective of experimental verification, this research primarily addresses two key issues: firstly, the establishment of an evaluation system for fault prognostic models/algorithms and their validation; and secondly, the partial resolution of the challenge of selecting prediction samples during the degradation process of specific faults. However, for systems composed of multiple failure modes/multiple products, there are still two problems to be solved. Firstly, there are many failure prediction ability evaluation indicators for a single failure prediction algorithm or a single product and the relationship between each indicator is unknown, so how to construct or select failure prediction ability evaluation indicators needs to be studied. Secondly, within the constraints of statistical testing principles, how to design the test scheme of PHM system fault prognostic capability verification at the product system level needs to be studied. The core of the test scheme lies in determining the fault prognostic sample size and the selection of samples within the product system.

4.2. Random characteristics of fault prognostic

In addition to describing the detectability and diagnosability of faults in general, the health status awareness indicator of PHM system should also describe the predictability of slow faults and the health status assess ability.

Product degradation results from a confluence of internal and external factors such as workload and environmental load. An accurate fault prognostic model is challenging to establish due to insufficient understanding of the degradation process. Therefore, the unpredictability in predicting the degradation process leads to randomness in fault occurrence timing.

The factors that affect the randomness of failure time prediction can be summarized into three categories:

- The randomness of the future degradation process. It is inevitable that the environmental load changes and the uncertainty of the future load profile cause the randomness of the degradation process.
- Failure prediction models are inaccurate. It is impossible to obtain a completely correct fault prognostic model, and the nonlinearity of the model or the simplifying assumptions of the model will lead to the randomness of the fault prognostic.
- Uncertainty in degraded data. Current and past degradation data of equipment are obtained by sensors or test devices, and test errors or noise can cause uncertainty in the collected degradation data.

Due to the random factors in the degradation process, the prediction of the failure time also includes randomness, in other words, the probability distribution of the failure time is obtained.

PHM system emphasizes the predictability of failure from the design and overall consideration, focusing on whether there are tests and how many tests are needed to effectively detect and isolate faults, track the fault evolution process and predict the failure occurrence time.

4.3. Fault prognostic indicators

For single failure prediction, there are some quantitative evaluation indicators, such as accuracy, precision and confidence level, etc. These indicators mainly investigate the prediction model and algorithm of specific object failure mode. They can be used for the verification and evaluation of key fault prognostic methods, which are not discussed in this paper.

Similar to the testability indicator to evaluate the capability of the test system, the capability of the PHM system should be measured by the system-level indicator. In this paper, two general indicators are proposed: relative accuracy of failure time prediction and failure prediction rate.

Predicting the failure time is the core purpose of fault prognostic. For a prediction result of the failure time, the predicted value is denoted by $T_P(\cdot)$, and the true value of the failure time is denoted by $T_T(\cdot)$.

When only one fault mode is assumed to exist in the system, denoted $T_P^{(j,k)}$ is the predicted value of the k^{th} fault occurrence time in the degradation process of the j^{th} sample of the fault mode, and denoted $T_T^{(j,k)}$ is the true value of the k^{th} fault occurrence time in the degradation process of the j^{th} sample of the fault mode.

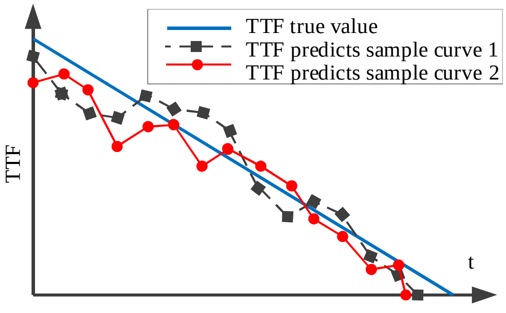

Fig. 1. Example of sample generation process for fault occurrence prediction in single fault mode.

For the case of multiple fault modes, denoted $T_P^{(i,j,k)}$ is the predicted value of the k^{th} fault occurrence time in the degradation process of the j^{th} sample of the i^{th} fault mode, and denoted $T_T^{(i,j,k)}$ is the true value of the k^{th} fault occurrence time in the degradation process of the j^{th} sample of the i^{th} fault mode. It can be seen that single fault is only a special case of multiple faults, and fault prognostic is also aimed at multiple faults in engineering practice.

Based on the above analysis, the relative accuracy of fault occurrence time prediction $r^{(i,j,k)}$ (referred to as relative accuracy) is defined as follows:

$$r^{(i,j,k)} = \frac{T_T^{(i,j,k)} - T_P^{(i,j,k)}}{T_T^{(i,j,k)}}, \tag{3}$$

where i is the fault mode mark, j is the fault mode sample mark, and k is the degradation process prediction sample mark.

It can be seen that the relative accuracy directly reflects the relative error of the single fault occurrence time prediction, and is dimensionless. When multiple relative accuracy samples of the PHM system are obtained, the fault prognostic ability of the PHM system can be evaluated. Since the relative accuracy is dimensionless, the relative accuracy of different PHM systems can be compared to measure the level of fault prognostic ability of different PHM systems.

Mathematically, the relative accuracy ranges from $r^{(i,j,k)} \in (-\infty, 1]$, when $r^{(i,j,k)} = 0$ the prediction is accurate, when $r^{(i,j,k)} > 0$ the prediction is early, and when $r^{(i,j,k)} < 0$ the prediction is late. Therefore, the relative accuracy requirements for any prediction result, that is, represented as $r^{(i,j,k)}$, are as follows:

- $r^{(i,j,k)}$ is as close to 0 as possible;
- predicting early ($r^{(i,j,k)} > 0$) is better than predicting late ($r^{(i,j,k)} < 0$);

The relative accuracy range is given by the formula $r^{(i,j,k)} \in (-\infty, 1]$, and the relative accuracy sample sequence $r^{(i,j,\bullet)}$ obtained by the j^{th} sample degradation process of the i^{th} failure mode is independent of each other. It can be considered that the random variable composed by the relative accuracy sample sequence $r^{(i,j,\bullet)}$ obtained by multiple fault occurrence prediction is independent of each other, and its joint probability density can be regarded as obeying normal distribution.

Based on the above analysis, the relative accuracy values $r^{(i,j,\bullet)}$ obtained in the j^{th} sample of the i^{th} failure mode are assumed to obey the normal distribution with mean $\mu_{(i,j)}$ and variance $\sigma^2_{(i,j)}$, i.e. $r^{(i,j,\bullet)} \sim N(\mu_{(i,j)}, \sigma^2_{(i,j)})$, then

$$\mu_{(i,j)} = E[\bar{r}^{(i,j)}] \tag{4}$$

In the above equation $\bar{r}^{(i,j)} = \frac{1}{N_{ij}} \sum_{k=1}^{N_{ij}} r^{(i,j,k)}$ denotes the N_{ij} mean value of the relative accuracy values $r^{(i,j,k)} | k = 1,2,\cdots,N_{ij}$ obtained in the j^{th} sample of the i^{th} fault mode, then $\bar{r}^{(i,j)}$ can be used as an estimate of the parameter $\mu_{(i,j)}$.

If it is assumed that N_i estimated values of the relative accuracy sample $\bar{r}^{(i,j)} | j = 1,2,\cdots,N_i$ of the fault occurrence time of the i^{th} fault mode has been calculated and obtained by the equation(4), the relative accuracy of the i^{th} fault mode can be estimated by the following equation:

$$\mu_i = E[\bar{r}^i],\ \bar{r}^i = \frac{1}{N_i} \sum_{j=1}^{N_i} \bar{r}^{(i,j)} \tag{5}$$

For a system with multiple fault modes to be predicted, and assuming that the occurrence process and prediction process of each fault mode are independent of each other, the predictive ability of the fault prognostic system can be estimated by the following equation:

$$\begin{aligned} \mu_r &= \frac{1}{n} \sum_{i=1}^{n} N_i \times \bar{r}^i \\ &= \frac{1}{N} \sum_{i=1}^{n} N_i \times \frac{1}{N_{ij}} \sum_{j=1}^{N_{ij}} \bar{r}^{(i,j)} \\ &= \frac{1}{\sum_{i=1}^{n} N_i} \sum_{i=1}^{n} \sum_{i=1}^{N_i} \frac{1}{N_{ij}} \sum_{k=1}^{N_{ij}} r^{(i,j,k)} \end{aligned} \tag{6}$$

In the above equation, N is the sum of the number of samples of all fault modes in the system, N_i denotes the number of samples of the first fault mode and satisfies $N = \sum_{i=1}^{n} N_i$ (n is the number of fault modes in the system), and N_{ij} is the number of fault occurrence time (relative accuracy) prediction samples obtained in the degradation process of the i^{th} fault mode and the j^{th} fault sample.

Further, the analysis shows that in order to obtain the relative accuracy parameter estimation μ_r of the whole fault prognostic system, the sample generation is divided into two steps: first, the number of samples N_i is determined for each fault mode in the system; Second, for each fault sample, the number of fault occurrence time prediction samples N_{ij} is determined in the degradation process of the fault sample.

The relative accuracy indicator of fault occurrence time prediction is defined as follows.

Define the relative accuracy of fault occurrence time prediction μ_r

In the whole life cycle of the equipment, the sample mean of the relative accuracy of the failure time prediction of all the failure modes to be predicted in the equipment is the relative accuracy of the failure time prediction of the equipment, referred to as the relative accuracy. The mathematical expression of the relative accuracy is as follows:

$$\mu_r = \frac{1}{N}\sum_{i=1}^{n}\sum_{i=1}^{N_i}\frac{1}{N_{ij}}\sum_{k=1}^{N_{ij}} r^{(i,j,k)} \tag{7}$$

Relative accuracy μ_r has the following properties:

- the value of μ_r follows normal distribution with a range of $\mu_r \in (-\infty, 1)$;
- μ_r should be as close to 0 as possible, and early prediction ($\mu_r > 0$) is better than late prediction ($\mu_r < 0$);
- from the designer's point of view, the value of μ_r should be constrained in the interval (μ_r^L, μ_r^U), where μ_r^L and μ_r^U are the upper and lower limits of the mean, respectively, such as desirable (-3,0.75).

Define the Fault Predictable Rate (FPR)

The ratio of the number of correctly predicted failure mode samples N_P in the equipment to the total number of fault samples N_{RP} occurring in the equipment that need to be predicted during the whole life cycle of the equipment from complete health to complete failure.

$$FPR = \frac{N_{\mathrm{P}}}{N_{\mathrm{RP}}} \times 100\% \tag{8}$$

In (8) above, N_P represents the number of correctly predicted failure mode samples, while N_{RP} represents the total number of failure mode samples to be predicted. These values do not indicate the number of failure modes, but rather serve as counting indicators. For instance, if a fault occurs twice in the whole cycle, it will have 1 failure mode and 2 failure mode samples. The fault prognostic rate definition adopts the constraint of "need" and agrees on the total number of fault modes due to the actual system having numerous fault modes. Only a subset of these fault modes is necessary or feasible for fault prognostic purposes.

The fault predictable rate uses the definition "the number of correctly predicted fault mode samples", and the correctness of fault prognostic needs a set of judgment procedures. For a single fault mode, the relative accuracy is estimated $\bar{r}^i$, assuming that the relative accuracy interval of a single fault mode is $[\bar{r}_L^i, \bar{r}_U^i]$, when $\bar{r}^i \in [\bar{r}_L^i, \bar{r}_U^i]$,the fault prognostic system is judged to be "correct". Otherwise, the fault prognostic system is judged to be "wrong" prediction. Due to the different predictive ability of different fault modes, the interval $[\bar{r}_L^i, \bar{r}_U^i]$ may be different for different fault modes. Of course, there are many ways to say whether the fault prognostic is correct or not. Obviously, the fault prognostic rate indicator is not a direct explicit result at the beginning, and the corresponding rules and discrimination need to be converted into correct or not (0/1). This discrimination often needs to give subjective rules, standards, criteria, etc., and the realization is complex. However, the physical meaning of the fault prognostic rate is simple and easy to understand. Similar to the fault detection rate, the testability indicator can completely describe the fault prognostic ability level of the system from the statistical count.

Different from fault detection and isolation, fault prognostic focuses on the change of fault degradation amount with time and the prediction of fault occurrence time during the fault degradation process. The single counting indicator "fault prognostic rate" is not enough to fully describe the measurement of such change and prediction accuracy of specific values, so the quantitative indicator must be added. Relative accuracy μ_r is proposed as one of the quantitative indicator metrics. After analysis, relative accuracy μ_r is sufficient to quantify the fault prognostic capability of PHM system, and other quantitative indicators such as accuracy, prediction level, $\alpha - \lambda$ accuracy, precision, error and so on can be characterized by relative accuracy μ_r or equivalent.

5. General indicators for health status evaluation

Traditional reliability indicators typically measure the average reliability of a category of products rather than the reliability of a single specific product. In this paper, the health status can be used to measure the technical status of a single specific product, which indirectly reflects the degree of its grasp to complete the task. The decline of equipment health status and operating reliability "occurs from inside but forms outside", which is the external manifestation of equipment health degradation. Dynamic signals can effectively reflect the internal characteristics of equipment dynamic operation, and provide important information for equipment health status and reliability evaluation. More and more scholars begin to integrate dynamic signal monitoring and processing into equipment health status and reliability evaluation.

The health status evaluation indicators mainly include discrete rating of health status and quantitative evaluation of health indicator. The method of discretization rating typically categorizes equipment health status into five distinct levels. However, there is a lack of consensus regarding the specific definition and principles guiding the division of these levels. The method of quantitative evaluation quantifies equipment health status by assigning a health degree within the range of [0-1]. When the health degree is 1, the system is in a completely healthy state. When the health degree is 0, the system is in a completely ill state.

In fact, it is almost impossible for equipment to be in a completely healthy state and a completely sick state. The two evaluation methods can be combined to construct the mapping relationship between the qualitative evaluation grade of system health status and the quantitative indicator of health degree. An example of five grades is shown in Table 1.

Table 1. Examples of health degree grades.

Serial number	Health range	Health status level	Health Status Description
1	0 -x_1	severely ill	the system is not operational and should be stopped immediately and overhauled for a long time
2	x_1-x_2	morbid	if the system shows signs of serious abnormality, it should be stopped immediately and repaired for a short time
3	x_2-x_3	unhealthy	abnormal symptoms of the system should not be operated continuously for a long time and measures should be taken
4	x_4-x_4	sub-health	the system works well and can run for a long time
5	x_4-1	health	the system works very well and is able to operate for a long time

A feasible evaluation indicator system is constructed based on the construction principle and characteristics of the equipment system, as well as considering the advantages and disadvantages of various evaluation methods and application contexts. Subsequently, the health degree of the equipment system is determined through a comprehensive evaluation of the hierarchical indicator system, which allows for an assessment of the equipment system's health status from both qualitative and quantitative perspectives.

The health degree is a dimensionless parameter to measure the health status of equipment and its constituent units at each level.

The current methods to construct equipment can be divided into two types, one is physics HIs (PHIs), and the other is virtual HIs (VHIs). Physical health indicators are related to the physical characteristics and quantities of equipment degradation. Statistical methods and signal processing methods are usually used to extract equipment health indicators, such as the root mean square (RMS) value of vibration signals. Virtual health indicators are usually constructed by fusing multiple sensor signals and using relevant data mining algorithms to describe the degradation trend of equipment, so they do not have clear physical meaning.

Scholars both domestically and internationally have conducted extensive research on health status metrics, resulting in fruitful outcomes. The health status of equipment is typically identified by specific physical health indicators or coefficients lacking tangible significance.

The health degree is generally a function of the functional representation parameters of the tested object, that is, $H(t) = f\big(X(t)\big)$,where $H(t)$ denotes the health degree at time *t*, $X(t) = \{x_1(t), x_2(t), \cdots, x_n(t)\}$ is the set of functional representation parameters, and whether the function is normal reflects its health status. Therefore, the functional representation parameters (or technical state parameters) are referred to as the health representation parameters, and $x_n(t)$ denotes the observed value of the n^{th} health representation parameter at time *t*. It can be assumed that the value of H is a dimensionless indicator ranging from 0 to 1 (it can also be 0 to 100, etc.). A value of H=0 indicates that the device is extremely unhealthy; When H = 1, it means the device is perfectly healthy. The healthier a device is, the better its ability to continuously perform its intended function.

In order to measure the accuracy of health status evaluation, the indicator of health status evaluation accuracy is proposed, which is defined as the ratio of the accurate number of health status evaluation to the total number of health status evaluation.

$$r_{\mathrm{HE}} = \frac{N_{\mathrm{HEC}}}{N_{\mathrm{HE}}} \times 100\%, \tag{9}$$

where, r_{HE} is the accuracy of health status evaluation, N_{HE} is the number of health status evaluation, and N_{HEC} is the number of correct health status evaluation.

6. General indicator system of health status perception ability

In order to accurately describe the health status of complex equipment and analyze its influencing factors, it is necessary to establish a perfect indicator system to effectively measure the health status of the system.

The ability of health status perception covers multiple ability dimensions such as condition monitoring, fault detection, diagnosis, prediction, health status representation and evaluation. Starting from multiple levels such as device level, subsystem level and system level, the ability of condition monitoring, fault detection, diagnosis and prediction are integrated into the indicator system of health status measurement and health status perception ability, as shown in Table 2.

Specifically, in terms of condition monitoring, there are technical status parameters or critical technical status parameters at the device level, subsystem level and system level, and their sensing ability can be measured by the coverage of (critical) status parameters. In terms of fault detection, the indicators to measure the ability level include critical fault detection rate, fault detection rate, false alarm rate, and average fault detection time. The parameters used in the calculation include failure rate and fault detection time, which are applicable to equipment level, subsystem level and system level, and the three levels of objects are applicable. In terms of fault isolation, the indicators to measure its ability level include fault isolation rate, mean fault isolation time, etc., and the parameters used include failure rate, fault isolation time, etc., which are generally applied to subsystem level and system level. In terms of fault prognostic, the indicators to measure its ability level include fault prognostic accuracy and relative accuracy of fault occurrence time prediction, and the parameters used include degradation degree and degradation level. It is suitable for critical equipment, and some subsystems and systems that can carry out fault prognostic can be selected. In terms of health status evaluation, the indicators to measure its ability level include health status evaluation accuracy, and the parameters used include health degree and health status level, which are applicable to equipment level, subsystem level and system level.

Table 2. General indicator system of equipment health status perception ability.

Multi-level / Perception	Related parameters // health status perception ability indicator used for evaluation e	Equipment level	Subsystem level	System level
Condition monitoring	(critical) state parameters // (critical) state parameter coverage	√	√	√
Fault detection	Fault rate, etc. // critical fault detection rate, fault detection rate, false alarm rate, mean time to fault detection	√	√	√
Fault isolation	Failure rate, etc. // failure isolation rate, mean time to failure isolation	△	√	√
Fault prediction	Degradation degree, degradation level // fault prognostic accuracy, relative accuracy of fault occurrence time prediction	√	△	△
Health status evaluation	Health degree, health status grade // accuracy of health status evaluation	√	√	√

Symbols description: √ means applicable, △ means optional

7. Conclusion

The ability to perceive the health status of equipment is decomposed into condition monitoring, fault detection, diagnosis, prediction and health status evaluation. In this study, we propose a set of general and assessable statistical indicators for evaluating the equipment's health status perception ability. These indicators include state parameter coverage rate, fault coverage rate, fault detection rate, critical fault detection rate, false alarm rate, mean fault detection time, fault isolation rate, mean fault isolation time, fault prognostic accuracy, relative accuracy of fault occurrence time prediction, health status level, health degree, and health status evaluation accuracy. The mathematical definition and physical interpretations are provided. Among these indicators, the state parameter coverage and fault coverage are two general measures that can be objectively and quantitatively assessed without being influenced by failure rates. we recommend including them in the indicator system for evaluating equipment's health status perception ability.

The indicators mentioned above are versatile and quantitatively assessable, providing a basis for evaluating equipment health status perception and supporting the implementation of PHM systems.

Acknowledgements

This work was partially supported by a ministry 's advance research project of China. The authors also thank Wang Zhan, Zhiao Zhao, Hongzheng Fang and Xinghong Hu for enlightening discussion and suggestions.

References

Allal, Z., Noura, H.N., Chahine, K. 2024. Efficient health indicators for the prediction of the remaining useful life of proton exchange membrane fuel cells.Energy Conversion and Management: X 21, 100503.

Bertolino, A.C., De Martin, A., Jacazio, G. et al. 2023. Design and preliminary performance assessment of a PHM System for electromechanical flight control actuators. Aerospace 10(4), 335.

Dai, J., Liu, H., Yu, J.S. 2012. Research on verification and evaluation technology of aircraft health management system . Electronic Measurement Technology 35(8), 1-10 (in Chinese)

Fedele, L. 2011. Methodologies and techniques for advanced maintenance. New York, Springer.

Federici, F., Tonelli, C., Le Cam, M. et al. 2022. Design and validation of scalable PHM solutions for aerospace onboard systems. PHM Society European Conference, 126-135.

Hess, A., Calvello, G., Frith, P. 2005.Challenges, issues, and lessons learned chasing the “Big P”: real predictive prognostics part 1. IEEE Aerospace Conference, Big Sky, MT, 5–12 March 2005. IEEE, 3610-3619.

Lamoureux, B., Mechbal, N., Masse, J.R. 2013. Numerical key performance indicators for the validation of phm health indicators with application to a hydraulic actuation system. Prognostics and Health Management Conference (PHM) 33, 43-48.

Li, F., Jiang, J.Y. 2013. Research on verification index of phm system . Aviation Standardization and Quality (2),36 - 40.

Long, J.B., Qu, C.Q., Jiang, J.Y. et al. 2021. Analysis of PHM evaluation indexes for typical electromechanical systems . Computer Measurement and Control 29(6), 255-259. (in Chinese)

Luna, J., Kolodziejski, P., Frankle, N., Conroy, D C., Shroder, R. 2009. Strategies for optimizing the application of prognostic health management to complex systems. Machine Failure Prevention Technology Conference, 1–14.

Peng, Y., Liu, D.T., Peng, Y. 2010. Review of fault prognostic and health management technology . Journal of Electronic Measurement and Instrument 24(1), 1-7. (in Chinese)

Qin, T., Lu, D. L., Zeng, Y. H. 2022. Performance evaluation of armored vehicle phm system based on combination weighting and improved extension cloud . Computer Measurement and Control 30(4), 237-243. (in Chinese)

Qiu, J., Liu, G.J., Zhang, Y. et al. 2017. Test and evaluation technology of equipment testability . Science Press, Beijing. (in Chinese)

Shen, Y., Khorasani, K. 2020. Multi-mode machine learning-based fault diagnosis strategies with application to aircraft gas turbine engines. Neural Networks 130, 126-142.

Wang, H.F., Wang, H.L., Yang, C.B. 2020. Understanding and discussion on intelligent development of aviation equipment support . Measurement and Control Technology 39(12), 1-9. (in Chinese)

Wang, P.J., Qin, J.H., Li, J.C. et al. 2023. Device status evaluation method based on deep learning for phm scenarios.Electronics 12(779), 779.

Xu, D.Y., Wang, M.T., Geng, Q.G. 2007.The creativity of informative forecasting theory and it's significance . Progress in Geophysics 4, 1375-1379, (in Chinese)

Yan, J.H., He, Z., He, S.G. 2022. A deep learning framework for sensor-equipped machine health indicator construction and remaining useful life prediction.Computers & Industrial Engineering 172, 108559.

Yang, Z., Jing, B.,2012. Validation method of fault prediction and health management for airborne system . Measurement and Control Technology 31(3), 101-104. (in Chinese)

Zhang, H.M., Song, D., Guo, Y. et al. 2013. Research on evaluation method of fault prediction model. Measurement and Control Technology, 32(5), 121-124. (in Chinese)