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Remaining Useful Life Prediction Method for Multi-Component System Considering Maintenance: Subsea Christmas Tree System as A Case Study

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Abstract

Maintenance is an important technical measure to maintain and restore the performance status of equipment and ensure the safety of the production process in industrial production, and is an indispensable part of prediction and health management. However, most of the existing remaining useful life (RUL) prediction methods assume that there is no maintenance or only perfect maintenance during the whole life cycle; thus, the predicted RUL value of the system is obviously lower than its actual operating value. The complex environment of the system further increases the difficulty of maintenance, and its maintenance nodes and maintenance degree are limited by the construction period and working conditions, which increases the difficulty of RUL prediction. An RUL prediction method for a multi-omponent system based on the Wiener process considering maintenance is proposed. The performance degradation model of components is established by a dynamic Bayesian network as the initial model, which solves the uncertainty of insufficient data problems. Based on the experience of experts, the degree of degradation is divided according to Poisson process simulation random failure, and different maintenance strategies are used to estimate a variety of condition maintenance factors. An example of a subsea tree system is given to verify the effectiveness of the proposed method.

Key words: remaining useful life, Wiener process, dynamic Bayesian networks, maintenance, subsea Christmas tree system

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1 Introduction

Recently, the traditional machinery industry has experienced rapid development. In order to effectively improve production safety and economic benefits, and avoid accident hazards, the use of machinery industry prognostic and health management technologies is gradually increasing, and has been widely studied by many researchers (Li et al., 2019). Predicting the RUL is an important part of Prognostic and Health Management (PHM) (Li et al., 2022). It is an important bridge connecting diagnosis and maintenance, that can prevent the occurrence of accidents in time and effectively and avoid the high costs of total failure (Tamssaouet et al., 2021). Prediction techniques can be classified in different ways (Hu et al., 2020; Cai et al., 2023). The most commonly used classification methods are model-driven methods, data-driven methods and mixed methods (Lee et al., 2014, Liu et al., 2023). The model-driven method constructs the corresponding physical model based on the failure mechanism of the system, and explains the degradation law in detail (Zhai and Ye, 2017). If the degradation mechanism and the factors to influence the system are fully considered, the prediction result will be accurate

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(Lei et al., 2018; Wu et al., 2018). However, the complexity of the system makes its degradation mechanism difficult to explain (Liao and Kottig, 2014). The data-driven approach is effective for condition monitoring and remaining service life prediction (Kumar et al., 2019; Cai et al., 2020).

A statistical model, artificial intelligence technology or similarity analysis technology is used to directly model the obtained monitoring data and explore the product degradation law (Li et al., 2016). The prediction method is based on the analysis of degraded data, and the results are relatively simple, not universal, and require high data integrity (Lei et al., 2018; Cai et al., 2022). Li et al. (2020) proposed a prediction method based on deep learning, which solved the problem that the first prediction time of the remaining service life was difficult to determine. The mixed-drive prediction method combines the above advantages, avoids these disadvantages to some extent, and has been widely applied in recent years (Gou et al., 2020). However, there are still problems such as the difficult combination of models and data (Peng et al., 2019; Hanachi et al., 2018). Maintenance is an important technical means to restore the performance of equipment in industrial production (Chen et al., 2020). The degree of repair can generally be divided into perfect maintenance, imperfect maintenance and minor repair (Wang et al., 2020). However, most of the existing RUL prediction methods assume that there is no maintenance or only perfect maintenance (Han et al., 2021). As a result, the above methods are difficult to apply to the RUL prediction of equipment with imperfect maintenance (Mosayebi Omshi and Grall, 2021; Shahraki et al., 2020). Study the mechanism of the influence of imperfect maintenance activities on the state of health of equipment and accurately quantifying the uncertainty of prediction results are urgent problems (Zhu et al., 2021). However, most of the related research has focused on the study of maintenance free behavior intervention, but according to engineering practice, it is difficult to implement a more unified maintenance operation (Liu et al., 2022). It is important to establish a reasonable and effective performance degradation model to accurately evaluate the health status of multicomponent systems and adjust appropriate maintenance factors (Hesabi et al., 2022). Guida and Pulcini (2009) studied the Weibull process model in depth, and established a model of a repairable system. In order to assess the reliability of CNC machine tools under incomplete maintenance, Li et al. (2021) proposed a method for evaluating the reliability of several CNC machine tools based on the log-linear proportional strength model. At present, many complex systems face problems such as long life cycle, insufficient data collection and individual difference (Hu et al., 2022). The method of forecasting the RUL while considering maintenance still needs to be optimized.

This paper presents a novel approach for predicting the RUL of a multicomponent system while considering maintenance activities. The method incorporates several key elements: the Wiener process is utilized to simulate the initial degradation state of the system, the Poisson process is employed to model the failure time and strength of the components, and the impact of maintenance events and their extent are comprehensively considered in RUL prediction. By addressing the limitations of existing methods that assume either no maintenance or perfect maintenance throughout the system’s lifecycle, this approach provides more accurate RUL estimates that align with the actual operating conditions of the system.

The remainder of the paper is organized as follows: in Section 2, an RUL prediction method is proposed; in Section 3, the subsea tree system is studied, and the results are analyzed and discussed; and Section 4 summarizes the work.

2 Methodology: RUL prediction for a multicomponent system considering maintenance

An RUL prediction method for a multicomponent system based on the Wiener process taking maintenance into account is proposed. The method describes the performance of the system under different maintenance strategies and restores the degraded prediction accuracy of the model, which is proposed using the system component failure time of Poisson process simulation, a comprehensive variety of maintenance. The framework of the proposed method based on the Wiener process is shown in Fig. 1.

First, according to the historical data collected and the experience of experts, the degradation process is divided into early, middle and late stages, and the initial performance degradation model is established by combining the dynamic Bayesian network (DBN) and the Wiener process. Then, the failure nodes and failure interval of each component of the system are studied, which can be obtained from historical data and simulated Poisson process. Based on the failure of each component, the maintenance strategy is coordinated, the maintenance node $h(t)$ and the maintenance degree $g(x)$ are formulated, and the maintenance factors P_M, F_1, F_2, and F_n represent the failure nodes, and T_1, T_2, and T_n are obtained by combining with the physical model and stand for the failure interval.

Initial maintenance mainly considers two aspects, the maintenance node and the degree of maintenance. The appropriate maintenance time is selected according to the severity of the fault, namely, immediate maintenance, group maintenance and extreme maintenance. For the components after a system failure, the maintenance intervention activities combined with the initial prediction model and preliminary maintenance model are established in the preliminary maintenance prediction model. C_i is the parameter that affects the performance, X_i represents the initial performance prediction, P_{Mi} is the maintenance factor under different maintenance activities, M_i represents the influence degree of maintaining the performance prediction, and X_i' represents the performance degradation forecast for consideration of main-

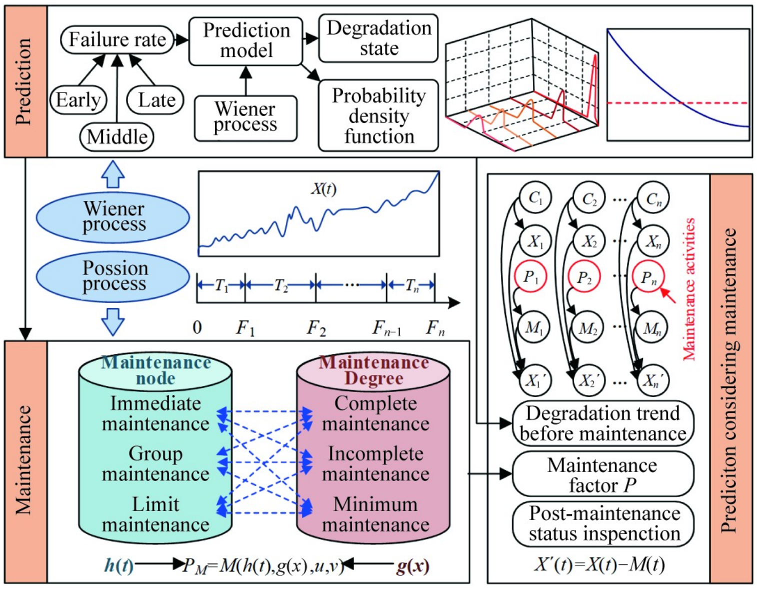

Fig. 1. RUL prediction method based on the Wiener process considering maintenance.

tenance. The proposed method includes four steps: modeling of performance degradation, modeling of preliminary maintenance, modeling of prediction taking maintenance into account and estimation of the RUL.

2.1 Performance degradation modeling

A model consistent with the degradation process of the whole life cycle of the system is established, which is divided into three stages according to the experience of experts, namely, the early test stage, the middle use stage and the late accelerated wear stage. The failure rate of each stage together constituted the bathtub curve. System maintenance generally occurs at the early and middle stages, and the degradation process of each component at different stages can be obtained through an empirical formula and historical data from the Wiener process as a continuous time stochastic process. Describing the random degradation process of the system has important significance. Using the Wiener process to parameterize the estimate of the interconnected historical degradation data, the corresponding shape parameter and scale parameter are obtained, because the initial parameter prediction model in the process of the actual production data in dynamic change, not a fixed value, is uncertain. The empirical formula of failure data and the estimated parameters obtained by the Wiener process are input into the DBN system. There is a series and parallel relationship among the components, and the formula for calculating the reliability of the corresponding relationship is:

$$R_{\text{series}}(t) = \prod_{i=1}^{k} R_i(t); \tag{1}$$

$$R_{\text{parallel}}(t) = 1 - \prod_{i=1}^{k} [1 - R_i(t)], \tag{2}$$

where, $R(t)$ represents the reliability of the system, n is the number of components, and $R_i(t)$ represents the reliability of the i-th component. The overall performance of the system is obtained by the performance degradation of each component and its serial-parallel relationship.

2.2 Maintenance modeling

In actual production, with increasing working time, the reliability of the system will decrease due to structural fatigue, wear defects or other reasons. The model under the assumption of good maintenance assumes that the performance can return to the initial time after maintenance, which is obviously unreasonable and will cause the evaluation result to be higher than the actual reliability level. Therefore, in the remaining service life of the system, considering the prediction of the preliminary maintenance model, it is a reasonable preliminary maintenance process, as shown in Fig. 2. The preliminary maintenance model is based on expert experience. Historical data and the Poisson process are set up first, the fault time and severity of the items constituting the system are determined, and the relevant parameters are obtained by calculating the Poisson process. Then, according to the breakdown state, the corresponding maintenance strategy is formulated to determine the maintenance time node and degree.

Maintenance factor P_M is related to maintenance node $h(t)$, maintenance degree $g(x)$, system state before maintenance u, and state monitoring after maintenance v. Relevant maintenance nodes include three types, $h_1(t)$, $h_2(t)$, and $h_3(t)$ respectively representing immediate maintenance (once a fault is found, maintenance should be taken immediately for the components), unitized maintenance (unified maintenance carried out for the components that failed at different time while the whole system is still on operation), and limit maintenance (maintenance activities after the system breaks

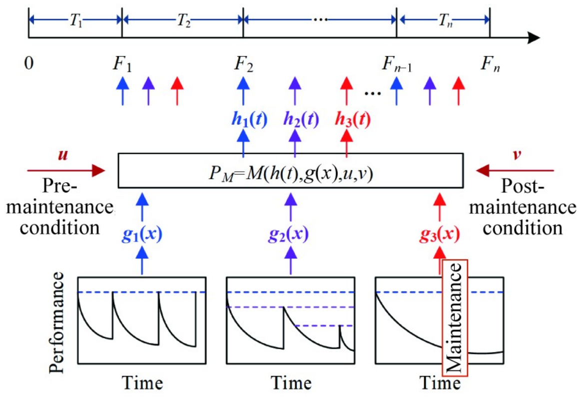

Fig. 2. Preliminary maintenance modeling process.

down). The degree of maintenance consists of full service $g_1(x)$, imperfect maintenance $g_2(x)$ and minimum maintenance $g_3(x)$, and the minimum maintenance means that the system can only restore to the state when the fault happens after the maintenance.

Assuming that the time of fault occurrence follows the Poisson process, i.e., $N(t)$, where $t\geqslant 0$ represents the number of fault events occurring in the time interval $(0, t]$, then $\{N(t), t\geqslant 0\}$ is called a counting process, and the counting process $\{N(t), t\geqslant 0\}$ obeys the Poisson process with a force of λ. Suppose that $\{N(t), t\geqslant 0\}$ in the time interval $(0, t]$, t_1, t_2, $\cdots$, t_n is the time series of fault intervals, and follows the homogeneous Poisson process of intensity λ; then, the mathematical expectation and variance are expressed as:

$$E[N(t)] = \lambda t; \tag{3}$$

$$var[N(t)] = \lambda t. \tag{4}$$

The unbiased estimate of the failure rate λ is:

$$\hat{\lambda} = \frac{N(t)}{t}. \tag{5}$$

The reliability function is expressed as:

$$R(t) = \mathrm{e}^{-\lambda t}. \tag{6}$$

During the initial maintenance process, P_M can be calculated as follows:

$$P_M = M(h(t),\ g(x),\ u,\ v), \tag{7}$$

where, u and v represent the state of the system before and after maintenance, respectively, which can be obtained through the initial prediction model and state monitoring.

2.3 RUL prediction modeling considering maintenance

Maintenance-aware RUL prediction modeling is carried out mainly by maintenance intervention activities based on performance degradation modeling. The specific modeling process is shown in Fig. 3. The Wiener process, as a continuous-time stochastic process, is a mathematical model that can well describe the system performance degradation in the reliability field. The conditional probability distribution between nodes in Bayesian networks can not only describe the deterministic logical relationship among variables, but

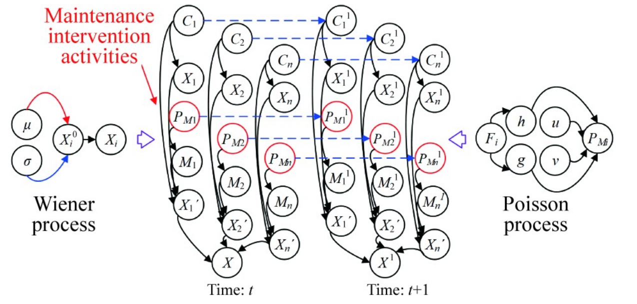

Fig. 3. Modeling of prediction after initial maintenance.

also describe the probabilistic relation of uncertainty among variables. The proposed method combines the Wiener process with the Bayesian network. The use of DBNs for predicting the RUL is significant due to their capacity to model and analyze intricate relationships among variables. By employing DBN, the interdependencies between diverse factors that impact the lifespan of a system or component can be captured accurately. These factors encompass environmental conditions, operational parameters, maintenance activities, and component characteristics. The network can effectively represent these relationships and conduct inference to estimate the RUL or predict failure probabilities. Firstly, a prediction model based on the Wiener process is established. The historical data are analyzed by the EM algorithm, and the drift coefficient μ and the diffusion coefficient σ are obtained iteratively. The physical model of the performance degradation of the system is established by a Bayesian network. μ and σ are input to the Bayesian network as intermediate nodes.

Nodes with an influence relationship between time slices are connected by interchip arcs to perform DBN modeling of the initial prediction model. Then, the failure time and severity are predicted according to the Poisson process, denoted by F. Combined with the maintenance time h, maintenance degree g, pre-maintenance state u and post-maintenance state v, a maintenance model based on the Bayesian network is established to obtain the mean value and probability density function of the maintenance factor P_M. According to the Poisson process, the maintenance factor P_M generated by the maintenance intervention activities was inserted into the established initial prediction model of the DBN in the time slice of fault occurrence, and the modeling of the RUL prediction taking maintenance into account was complete.

2.4 RUL calculation

The RUL is estimated based on the dynamic performance, as shown in Fig. 4. Blue represents the normal performance degradation curve of the system without considering the maintenance situation, while green represents the degradation curve of the system with some recovery after the corresponding maintenance activities are carried out after the occurrence of the fault. When the performance of

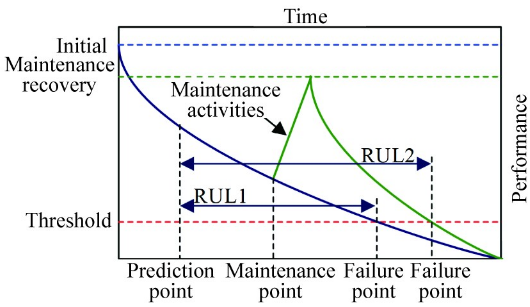

Fig. 4. Remaining useful life calculation model.

the system degrades to the threshold, i.e. the system fails, the time between the prediction point and the failure point is the RUL of the system. Suppose that $A(t)$ describes the performance degradation of the system, and that A_{th} is the failure threshold of the system. More specifically, the RUL can be defined as:

$$T = \inf\left\{t : A(t) \leqslant A_{\text{th}} \middle| A(0) \geqslant A_{\text{th}}\right\}. \tag{8}$$

3 Case study: RUL estimation of a subsea Christmas tree system

3.1 Key structure and maintenance strategy of subsea Christmas tree

The subsea Christmas tree can be defined as a combination of valves and fittings for producing or injecting water to control the flow of products, chemicals, water or gas into the well, and is equipped with valves, pipes, joints, etc. The subsea Christmas tree serves as a valuable case for predicting the RUL due to the complex interactions and dependencies among its components. Factors such as wear, corrosion, and fatigue need to be considered when estimating the RUL of these components, making it be a challenging task. Fortunately, subsea Christmas trees are typically equipped with sensors and monitoring equipment that provide real-time data on parameters such as working status, vibration, temperature, and pressure. Leveraging these real-time monitoring data allows for the establishment and validation of RUL prediction models, thereby enhancing the accuracy and reliability of predictions. Furthermore, as various maintenance plans are implemented throughout the operational period of subsea Christmas trees, this case exhibits strong adaptability to the application scenarios of RUL prediction models. Fig. 5 shows the structure of the subsea Christmas tree system. During normal operation, surface-controlled downhole safety valves continuously transfer oil from the wellhead to the tank. Production main valve (PMV), production wing valve (PWV), production throttle valve, production isolation valve to keep open state. Two chemical injection valves precisely control the flow of glycol and inhibitor injection. In addition, annulus intervention valves, annulus exhaust valves, annulus wing valves (AWVs), and annulus main

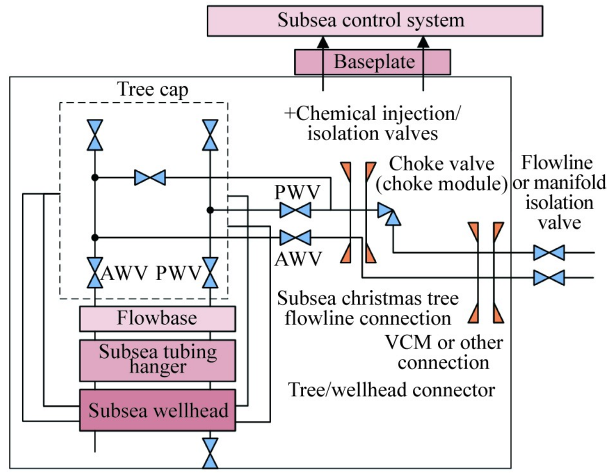

Fig. 5. Structure and composition of the subsea tree system.

valves (AMVs) are used to balance pressure in the upper and lower spaces of the tubing hanger during normal production. The tree body mainly contains various production valves, pipelines and connectors. Valves are classified according to their functional characteristics, which can be divided into process isolation valves, practical isolation valves, check valves, throttle valves and control valves. In addition, frequent maintenance of the ROV can lead to significant maintenance costs due to the environment of subsea Christmas trees. Therefore, it is necessary for maintenance plans to integrate individual maintenance activities into several groups to share costs and further minimize expected maintenance costs over the considered scheduling cycle.

Taking the system composed of key structural components of the subsea tree as the evaluation object, the RUL value is calculated in combination with the maintenance situation, and the proposed method based on the Wiener process considering maintenance is verified.

3.2 Modeling process

3.2.1 *Degradation analysis based on the Wiener process*

In order to compensate for the problem of insufficient data samples, the parameters of the Wiener process are estimated (Cai et al., 2021) after the extension of the exponential distribution. The reliability calculation is as follows:

$$R = \mathrm{e}^{-\lambda t}. \tag{9}$$

This paper mainly analyzes subsea Christmas tree pipelines, connectors, process isolation valves, practical isolation valves, check valves, throttle valves and control valves. The failure rate and maintenance time for each component are shown in Table 1.

Different components have different degradation rates due to their different functions. According to the different failure rates of each component, the performance degradation trend based on the Wiener process is simulated, and the drift parameter μ and the diffusion coefficient σ of the different

Table 1 Failure rate and maintenance data of each component

Component	Failure rate ($10^{-6}/h$)			Maintenance time(h)
	Early	Middle	Late	
Process isolation valves	1.04	0.75	2.64	8
Utility isolation valves	5.42	3.25	13.99	3.7
Check valves	3.91	2.76	10.6	2
Choke valves	9	7.36	24.54	13.6
Control valves	8.94	5.56	10.42	22.9
Connectors	1.33	0.34	1.75	72
Pipelines	1.3	1.59	3.01	19.8

components are obtained. Combining the Wiener process and the physical performance model, a DBN is constructed to evaluate the RUL of the subsea Christmas tree system without maintenance decision. First, the fatigue model of the subsea tree system is established, and the physical performance model of the fatigue crack propagation is the Paris formula, namely:

$$\frac{\mathrm{d}D}{\mathrm{d}n} = C(\Delta K)^M, \tag{10}$$

where, D represents the crack depth, n is the number of stress load cycles, ΔK is the strength factor, C and M are constant parameters, which are generally determined by experience.

$$\Delta K = \lambda\Gamma\left(1+\frac{M}{k}\right)^{\frac{1}{M}}\sqrt{\pi D}, \tag{11}$$

where Γ is the gamma distribution function, and λ and k are the shape parameters and the scale parameters of the Weibull distribution, respectively.

Then, the crack depth during the n-th stress cycle can be expressed as:

$$D(n) = \left\{(D_0)^{1-M/2} + (1-M/2)C\left[\lambda\Gamma\left(1+\frac{M}{k}\right)^{1/M}\right]^M \pi^{M/2} n\right\}^{1/(1-M/2)}, \tag{12}$$

where, D_0 is the initial crack depth.

Next, the sand erosion model is established, which can be represented by the Salama model:

$$E_\mathrm{p} = \frac{\left(1-R_\mathrm{p}\right)V_\mathrm{m}^2 d_\mathrm{s}}{S_\mathrm{p} d_\mathrm{p} \rho_\mathrm{m}}, \tag{13}$$

where, E_p is the rate of sand erosion, R_p is the corrosion resistance coefficient, V_m is the mixture velocity, d_s is the size of the sand and gravel, S_p is the geometric constant, d_p is the pipe diameter of the system valve, and ρ_m is the mixture density.

$$V_\mathrm{m} = V_\mathrm{l} + V_\mathrm{g}, \tag{14}$$

where, V_l and V_g represent the flow velocities of liquid and gas flowing through the subsea Christmas tree system respectively.

Finally, the corrosion model of the subsea tree system is established, which can be represented by the Shell model:

$$V_\mathrm{c} = \frac{1-R_\mathrm{c}}{\frac{1}{V_\mathrm{r}}+\frac{1}{V_\mathrm{t}}}, \tag{15}$$

where, R_c is the corrosion protection factor, V_c is the corrosion rate, V_r is the reaction rate, and V_t is the conversion rate.

$$\log(V_\mathrm{r}) = 4.93 - \frac{1119}{T_\mathrm{p}+273} + 0.58\log(n_\mathrm{c}P_\mathrm{o}); \tag{16}$$

$$V_\mathrm{t} = 2.45\frac{V_\mathrm{l}^{0.8}}{d_\mathrm{p}^{0.2}} n_\mathrm{c} p_\mathrm{o}, \tag{17}$$

where, T_p is the temperature of the liquid flowing through the tree system, n_c is the carbon dioxide fraction in the gas phase, p_o is the operating pressure, V_l is the flow rate of the liquid, and d_p is the diameter of the key component.

In summary, physical models of different influencing factors are established. Each physical model is integrated as the current degradation state x_i of each key component of the subsea tree system, and each component is connected in series and parallel mode to obtain the degradation state X_0 of the overall performance of the system. The drift parameter μ and diffusion coefficient σ are used to update the parameters. The update process is shown in Eq. (18) to establish a DBN model of the overall performance degradation of the subsea Christmas tree system, as shown in Fig. 6.

$$X(t) = X_0 + \mu t + \sigma B(t). \tag{18}$$

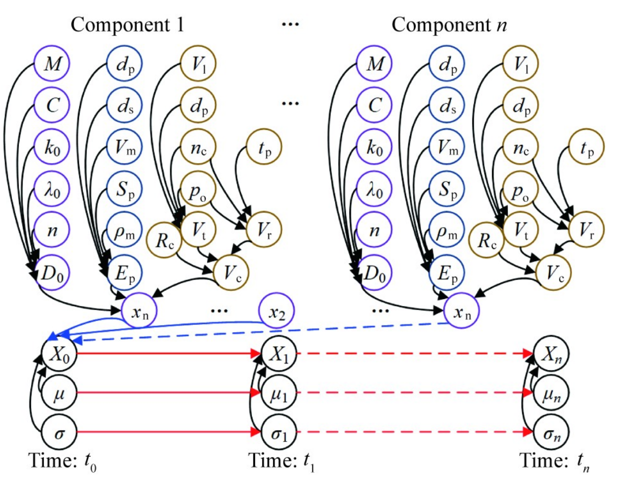

Fig. 6. DBN model of the overall performance degradation of the subsea tree system.

3.2.2 *Preliminary maintenance analysis based on the Poisson process*

The failure time and strength of each key component of the subsea Christmas tree system are analyzed by homogeneous Poisson process (Gupta and Kumar, 2023), and the model is based on the failure rate function.

Table 1 presents the failure rate of each component. Let T_1, T_2, $\cdots$, T_n be the failure time series. The homogeneous Poisson process failure time T_i obeys the Gamma distribution, and the first failure time obeys the exponential distribution; then, the probability density function of the failure time is:

$$f(t)=\frac{\lambda^n t^{n-1}}{\Gamma(n)}\mathrm{e}^{-\lambda t},\ t>0. \tag{19}$$

The probability of failure is:

$$F(t)=P\{T_n\leqslant t\}=\sum_{i=n}^{\infty}\mathrm{e}^{-\lambda t}\frac{(\lambda t)^i}{i!}. \tag{20}$$

The mathematical expectation of the failure time is:

$$E(T_n)=\int_0^{\infty}tf_{Tn}(t)\,\mathrm{d}t=\int_0^{\infty}t\frac{\lambda^n t^{n-1}}{\Gamma(n)}\mathrm{e}^{-\lambda t}\mathrm{d}t=\frac{n}{\lambda}. \tag{21}$$

The occurrence time of the k-th failure in the future is:

$$T_{n+k}=\int_0^{\infty}tf_{T_{n+k}}(t)\mathrm{d}t=\frac{n+k}{\lambda}. \tag{22}$$

The corresponding failure intensity function $\omega(t)$ of the homogeneous Poisson process is shown as follows:

$$\omega(t)=\left(a^{\lambda}\frac{t}{T}\right)^{b^{\lambda}}, \tag{23}$$

where, $a^{\lambda}\geqslant 0$, and $b^{\lambda}\geqslant 1$. The function $\omega(t)$ is essentially a fault intensity function with a monotonically increasing fault intensity.

The maintenance process is modeled considering the maintenance time node and the maintenance degree. The maintenance node is divided into immediate maintenance, group maintenance and extreme maintenance. The maintenance degree is divided into complete maintenance, incomplete maintenance and minimum maintenance. The maintenance node $h(t)$ is determined according to the failure frequency of each component. The fault intensity ζ is the basis for determining the maintenance time node. ζ determines the fault and maintenance time interval $h_1(t)=0$ by expert experience. The fault and maintenance time intervals $h_2(t)$ and $h_3(t)$ of group maintenance and extreme maintenance are obtained according to the monitoring state.

$$h(t)=\begin{cases}\left.\begin{matrix}h_1(t)\\ h_2(t)\end{matrix}\right\},\ \omega(t)\leqslant\zeta\\ h_3(t)=0,\ \omega(t)>\zeta\end{cases} \tag{24}$$

The degree of maintenance $g(x)$ is determined based on the maintenance node and the current performance degradation of each component. Suppose that the failure threshold of each component of the subsea Christmas tree system is $X_j=Th_j$, and the current system performance degradation is $X_j(t)$. When $X_j(t)\leqslant Th_j/a$, the repair operations can achieve a complete repair, i.e., to restore as new, $g_1(x)=1$. When $Th_j/a<X_j(t)\leqslant Th_j/b$, the maintenance is regarded as incomplete, and the maintenance degree $g_2(x)$ varies with the current performance degradation and the fault degree. When $Th_j/b<X_j(t)$, the maintenance is minimum, and the maintenance effect can only return the system to the state at the time of the fault.

$$g(x)=\begin{cases}g_1(x)=1,\ X_j(t)\leqslant Th_j/a\\ g_2(x),\ Th_j/a<X_j(t)\leqslant Th_j/b\\ g_3(x),\ X_j(t)>Th_j/b\end{cases} \tag{25}$$

3.2.3 *RUL prediction analysis considering maintenance*

The RUL prediction for the subsea Christmas tree systems considering maintenance operations is based on the following two steps.

$$X(t)=X_0(t)-M(t); \tag{26}$$

$$Y(t)=1-X(t), \tag{27}$$

where, $M(t)$ represents the amount of performance recovery generated by maintenance intervention activities, and $X(t)$ represents the predicted value of performance degradation during initial maintenance.

$$M(t)=PX_0(t), \tag{28}$$

where, P is the maintenance factor, representing the degree of maintenance activities, and the value range is $0\leqslant P\leqslant 1$. $P=1$ means complete maintenance, i.e., repair to new. $0<P<1$ indicates incomplete maintenance. $P=0$ means minimum maintenance, repair as old, fix fault only, and system performance has not been restored.

$$P=\frac{v-u}{v_0-u}\exp\{-[h(t)(1-g(x)]\}, \tag{29}$$

where, u and v are the states before and after maintaining the random degradation index collected by the sensor, respectively.

3.3 Results and discussions

3.3.1 *Performance degradation analysis*

The initial prediction model of each key component of the subsea tree system is established. The failure rates of different components throughout their lifes are shown in Fig. 7.

Each component conforms to the three-stage degradation process. The performance of each component is in a rapid decline stage, and each component can easily fail. At the mid-term degradation stage, the failure rate of each component is in descending order, i.e., the throttle valve, control valve, practical isolation valve, check valve, process isolation valve, pipeline and connector. The failure rates of the pipeline and process isolation valve are similar, and the

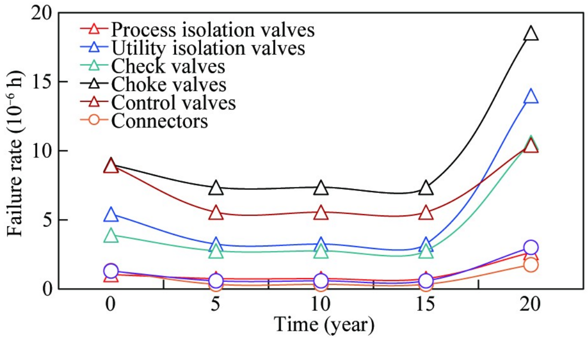

Fig. 7. Failure efficiency of each component of the subsea Christmas tree system.

curves basically coincide. At the last stage of degradation, the failure rates of the throttle valve, practical isolation valve and check valve increase rapidly.

Based on the failure rate of each component, the insufficient data are expanded and the degradation process is transformed into a Wiener process. Combined with the fatigue model, sand erosion model and corrosion model, the performance degradation trend of each component at different degradation stages is obtained, as shown in Fig. 8.

The degradation order of each component performance in the early and middle stages is throttle valve, control valve, practical isolation valve, check valve, pipeline, process isolation valve and connector. Compared with the initial failure rate, the sequence of components remained largely unchanged; however, those of the pipeline and process isolation valves were changed. The process isolation valve plays the role of fluid isolation, equivalent to a switch with relatively high safety and reliability requirements. In the subsea tree system, the valve has a low frequency of use and is in the normally open state. Thus, its performance degradation is in a relatively stable state. At the 20th year, its performance is 0.635, higher than those of the other valves in the middle of degradation. However, due to the long-term exposure of the subsea pipeline to the complex marine environment with high temperature and pressure, corrosion occours. Considering corrosion, fatigue, sand erosion and other factors, the performance degradation is greater than that of the process isolation valve when the failure rate is lower than that of the valve process isolation.

In terms of the whole degradation cycle, the degradation of each component is relatively stable at the beginning and in the middle of the period, and roughly follows a linear or exponential distribution. The throttle valve performance degradation is the fastest, falling below 0.5 in the 11th year, the connector performance degradation is the slowest, and at the end of the middle degradation its performance remains above 0.9. In the late stage of degradation, the performance of each component drops sharply. The fastest decline rate is for the practical isolation valve, which decreases from 0.658 to 0.147. When the performance degradation exceeds 0.5, urgent maintenance is needed. The performance degradation of the other components is at an intermediate level. Fig. 8 shows the overall performance degradation curve of the subsea tree system. At the beginning of the degradation, the performance drops sharply to 0.35, far exceeding the failure threshold and the maintenance threshold. In the 15th year, the performance is close to 0. Therefore, in the whole cycle of the system, maintenance is essential, and it is necessary to consider the distribution of system life according to different maintenance strategies.

3.3.2 *Maintenance process analysis*

(1) Fault analysis

The Poisson process is used to analyze the failure time and intensity of each key component. The probability density function of the failure time is shown in Fig. 9. At the initial stage of degradation, the probability density function values of the failure time of each component are obviously different, and the order of failure probability from large to small is the throttle valve, practical isolation valve, check valve, control valve, pipeline, process isolation valve and connector. Among them, the highest probability of the throttle valve is 0.14, while the lowest probability of the connector is 0.015, and the difference between the two is significant. The probabilities of the line, process isolation valve, and connector decrease steadily, and the probability of failure is almost evenly distributed throughout the life cycle, while the probability density function of the throttle valve

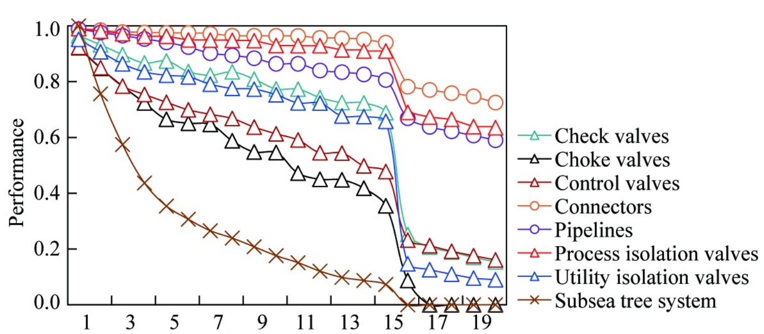

Fig. 8. System performance degradation curve without considering maintenance.

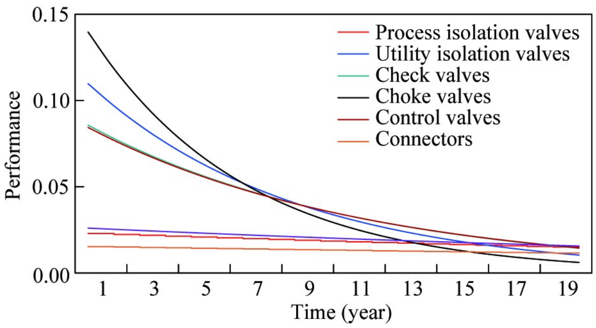

Fig. 9. Probability density function of the failure time.

decreases quickly, and after 15 years, the probability of failure is lower than that of the connector. Therefore, in practical engineering, monitoring and management of convection valve, practical isolation valve, check valve and control valve should be strengthened to achieve the purpose of early failure detection and early maintenance.

Due to the complex environment and long operation cycle of the subsea tree system, there is a lack of arrangement and analysis of its fault data. In order to facilitate maintenance prediction, the number and specific time of failures in the entire life cycle of each component are simulated based on the probability density function of the failure time and the Poisson process. The simulation results are shown in Fig. 10. Moreover, the failure frequencies of the throttle valve, practical isolation valve and check valve are greater. The throttle valve fails in the 1st, 3rd, 4th, 6th, 13th and 15th years, respectively. The practical isolation valve fails in 5.5, 6, 7.4, 8.9, 10.8 and 12.6 years.

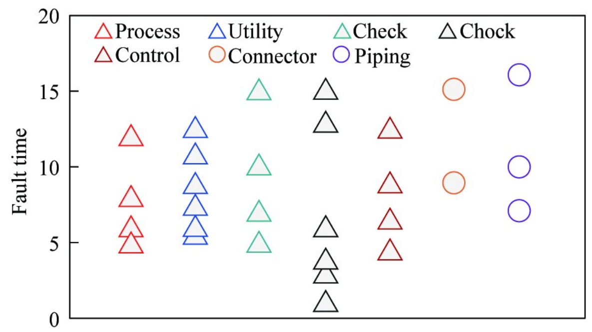

Fig. 10. Simulation diagram of the failure time.

Fig. 11 shows the fault intensity relationships of the components at different times. It can be seen from Fig. 11 that the fault intensity of each component of the subsea tree system increases with time. The throttle valve has the lowest initial failure intensity and the fastest growth tendency. The failure intensity of the connectors is relatively high and increases essentially linearly. The intensity of the pipeline failures is slightly lower than that of the connector failures. The fault resistance of the process isolation valve is at an intermediate level at the initial stage, but its growth rate is slow. After 16 years, the fault resistance becomes the lowest

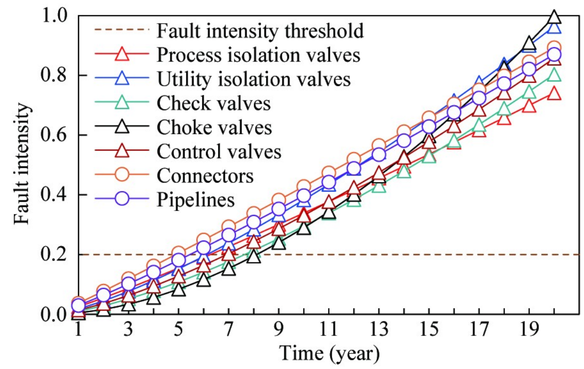

Fig. 11. Graph of the failure intensity at different times for each component.

of all components. The practical isolation valve failure intensity is always in the top three. The overall distribution of the failure intensity of each component is concentrated.

(2) Maintenance analysis

Based on the fault intensity and fault intensity threshold of each component in Fig. 12, the maintenance node for each component after a fault occurs can be determined. ζ is the basis for determining the maintenance time node. $h_1(t)$= 0; the fault and maintenance time intervals $h_2(t)$ and $h_3(t)$ of group maintenance and extreme maintenance, respectively, were obtained according to the actual monitoring state. Based on expert experience and historical data, the fault strength threshold ζ is set to 0.2. As shown in Fig. 12, below this threshold strength, the time required for different components to take immediate maintenance measures is as follows: 6.4 years for the process isolation valve, 6.2 years for the service isolation valve, 7.8 years for the check valve, 8.2 years for the throttle, 7 years for the control valve, 5.2 years for the connector, and 5.5 years for the pipeline.

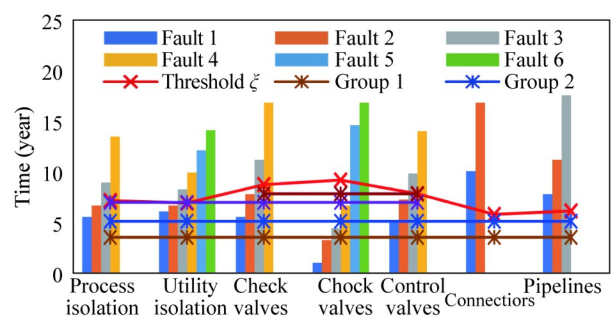

Fig. 12. Maintenance node for each component.

Before the time node where each component needs to adopt an immediate maintenance strategy, the fault degree of different components or the same component can be comprehensively considered to adopt the minimum maintenance and group maintenance strategy. The first group maintenance concerns only the two failures of the throttle valve. At the same time, since the throttle valve is repaired after two failures, its degree of repair will also decrease to a certain extent. The second group maintenance involves the third failure of the throttle valve and the first failure of the control valve. The third group maintenance involves the first and second failures of the process isolation valve, the first and second failures of the practical isolation valve, the first failure of the check valve and the first similar failure of the throttle valve. The fourth group repair involves the second failure of the check valve and the second failure of the control valve. Different maintenance nodes will also have some impact on system performance recovery.

Fig. 13 shows the degree of maintenance. The specific maintenance nodes and the current performance degradation of each component determine the degree of maintenance. The higher the maintenance level, the stronger the performance recovery. The overall degree of maintenance is the product of each maintenance degree, and with increasing maintenance time, the overall degree of maintenance gradually decreases.

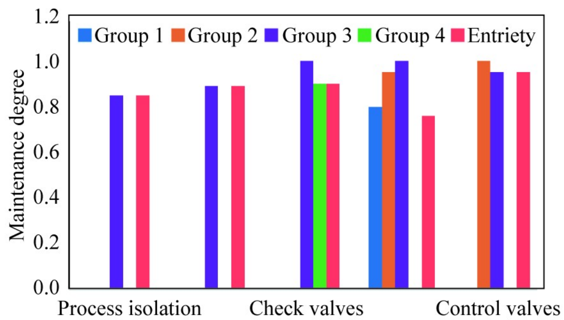

Fig. 13. Degree of group maintenance for each component.

As it can be seen from Fig. 13, the group maintenance of the process isolation valve is the third group maintenance, and the degree of maintenance is 0.85. Indeed, it experienced two failures, but no maintenance measures were taken. An increase in the delay time leads to the deterioration of its ability, which has a certain impact on the degree of repair recovery. The group maintenance of the practical isolation valve is the third group maintenance, and the maintenance degree is 0.89. The maintenance degrees of the third maintenance group and the fourth maintenance group are 1 and 0.9, respectively. The maintenance degrees of the throttle valve undergoing the first group maintenance, the second group maintenance and the third group maintenance are 0.8, 0.95 and 1, respectively, and the overall maintenance degree of the group maintenance stage is 0.76. The maintenance degrees of the second group maintenance and the third group maintenance of the control valve are 1 and 0.95, respectively.

Fig. 14 shows the degree of immediate maintenance. The maintenance degrees of the process isolation valves are 0.9 and 0.88, respectively, and the overall maintenance degree is 0.792. The maintenance degrees of the practical isolation valves are 0.85, 1, 0.81 and 0.98, respectively. The

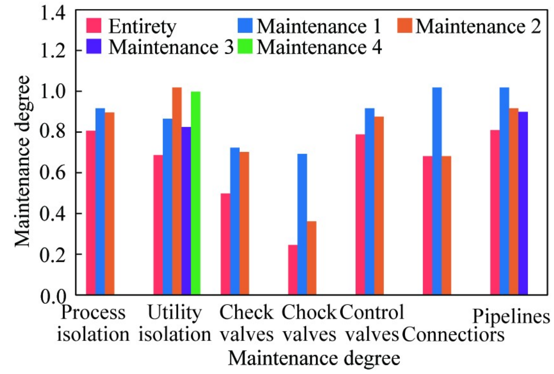

Fig. 14. Degree of instant maintenance for each component.

maintenance degree of check valves is 0.71 and 0.689 respectively. The maintenance degrees of the throttle valves are 0.68 and 0.355, respectively. The degree maintenance of the control valves are 0.9 and 0.86, respectively. The maintenance degrees of the pipelines are 1, 0.9 and 0.883, respectively, and an overall maintenance degree is 0.7947. Among them, the throttle valve requires the minimal maintenance; other components obtain a certain degree of incomplete maintenance.

3.3.3 *Performance prediction analysis considering maintenance*

The performance degradation of the subsea tree system was predicted by integrating the initial prediction results, the maintenance nodes and the degree of maintenance of each component. Fig. 15 shows the main structural components of the subsea tree system considering maintenance and performance prediction results of the system. At the beginning, the practical isolation valve degrades rapidly and remains more intensive; therefore, the performance fluctuates greatly. The performance degradations of the connector, pipeline and process isolation valve are low, with relatively small fluctuations. The control valve has undergone complete repair, and its performance is restored from 0.754 to 1. In the middle of the period, most components changed from group maintenance to immediate maintenance. The prompt maintenance response has interrupted the tendency of performance deterioration and relieved the deterioration trend of the components to some extent, causing them to fluctuate

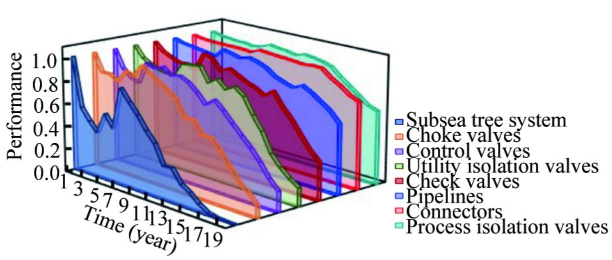

Fig. 15. Prediction of the component performance during initial maintenance.

slowly in a small range and extending the remaining life. In the 20th year , the performance prediction results for each component are as follows: 0.755 for the connector, 0.638 for the process isolation valve, 0.61 for the pipeline, 0.32 for the check valve, 0.18 for the control valve, 0.16 for the utility isolation valve, and 0.113 for the throttle valve.

3.3.4 *RUL calculation*

The failure thresholds for different components and systems were set based on expert experience and historical data: 0.7 for the process isolation valve, 0.2 for the utility isolation valve, 0.45 for the check valve, 0.1 for the throttle valve, 0.2 for the control valve, 0.6 for the connector, 0.6 for the pipeline, and 0.0015 for the subsea tree system. The RUL is shown in Fig. 16. To sum up, the normal and stable operation of the system is inseparable from the maintenance support. The connectors and pipelines show minimal changes in predicted RUL before and after maintenance. Specifically, both connectors have an RUL of 20 years before and after maintenance, while the pipeline's RUL is 19.5 years without maintenance and 20 years with maintenance. Therefore, the connectors and pipelines are least affected. The preliminary RUL prediction after the initial maintenance is around 19 years, which is more reliable compared with the 20-year design life of the subsea trees. The RUL of the process isolation valve is 18.5 years, 19.2 years for the practical isolation valve, 18.5 years for the check valve, 20 years for the throttle valve, and 19.75 years for the control valve. The RUL of the subsea tree system is 15.2 years without maintenance, and 19.1 years with maintenance.

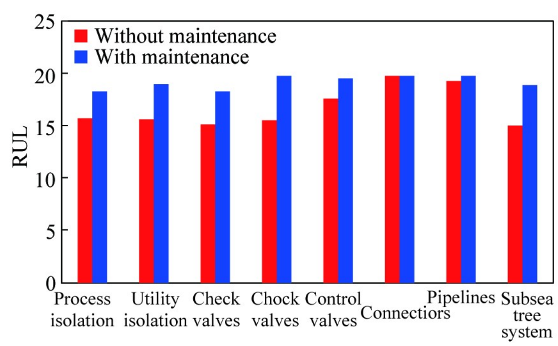

Fig. 16. RUL for the components and systems with or without maintenance.

4 Conclusions

An RUL prediction method based on the Wiener process is proposed in this study, which considers the influence of maintenance nodes and maintenance degree on the prediction. The subsea tree system is used as an example to demonstrate the structure and function of key components such as the throttle valves, convenient isolation valves, and check valves, and the proposed method is verified. The verification results indicate that both the maintenance time node and maintenance degree have an impact on the performance recovery of the components. Compared with group maintenance, immediate maintenance has a greater effect on the performance recovery of each component in the system. Furthermore, the level of maintenance also determines whether the system can be restored to a like-new condition. Without maintenance, the RUL of the subsea tree system is estimated to be 15.2 years, while with maintenance, the RUL extends to 19.1 years, indicating a significant deviation. By considering the effect of maintenance in the prediction process, the proposed method effectively calculates the RUL of the subsea tree system, bringing it closer to real-life scenarios. This finding emphasizes the importance of incorporating maintenance process analysis when calculating the RUL of systems in practical applications.

Competing interests

The authors declare no competing interests.

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