Journal Pre-proof

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PII: S0951-8320(21)00019-3
DOI: https://doi.org/10.1016/j.ress.2021.107450
Reference: RESS 107450

To appear in: *Reliability Engineering and System Safety*

Received date: 17 September 2020
Revised date: 30 November 2020
Accepted date: 31 December 2020

Please cite this article as: Dongming Fan , Aibo Zhang , Qiang Feng , Baoping Cai , Yiliu Liu , Yi Ren , Group maintenance optimization of subsea Xmas trees with stochastic dependency, *Reliability Engineering and System Safety* (2021), doi: https://doi.org/10.1016/j.ress.2021.107450

Highlights

- Group maintenance is studied subjected to degradation and unexpected failures.
- Reliability model of subsea Xmas tree is established with stochastic dependency.
- Multiple types of PM strategies are conducted into group maintenance optimization.

Group maintenance optimization of subsea Xmas trees with stochastic dependency

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Abstract: Subsea Xmas trees (XTs) are vital equipment for offshore oil and gas development. Due to a long and continuous operation, components of XTs often become vulnerable subjected to degradation and unexpected failures. Due to the uncertainties of subsea operation and fault tolerance design, current maintenances on heterogeneous components, which are assumed to be independent of each other, perform separately. Only one PM mode (imperfect or perfect) is considered. However, these assumptions impede the application of state-of-the-art research results on the maintenance of this equipment. Therefore, for XTs with stochastic dependency, this study proposes a group maintenance optimization approach that combines maintenance activities to reduce maintenance costs. Reduction factors are introduced to measure the effects of various preventive maintenance (PM) actions, and the optimal component-level PM intervals can be obtained. An improved group strategy can be explored in consideration of stochastic dependency and opportunity maintenance. Utilizing the collaborative particle swarm optimization (CPSO) algorithm, the cost of an optimal group maintenance plan can be minimized while maintaining the availability. The uses and advantages of the proposed group maintenance approach are illustrated by a case study on a Horizon Xmas tree with a 14-component system.

Keywords: Subsea Xmas tree; Group maintenance; Reliability; Availability; Stochastic dependency

Abbreviation

XTs	Xmas trees	HXT	Horizontal Xmas tree
OREDA	Offshore and onshore reliability data	CIV	Chemical injection valves
PM	Preventive maintenance	AVV	Annulus vent valve
CM	Corrective maintenance	XOV	Crossover valve
BOP	Blowout preventer	OM	Opportunity maintenance
ROV	Remotely operated vehicle	PHM	Prognostics health management
VXT	Vertical Xmas tree	CPSO	Collaborative particle swarm optimization algorithm

1 INTRODUCTION

With the development of offshore technologies, many operations that were previously performed on surfaces are moved down to the subsea level. Xmas trees (XTs), as a vital part of subsea production system, are used to control hydrocarbon flow, inject gas and water, and maintain reservoir pressure. Generally, XTs are designed to work for more than 10 years in the subsea environment, during which valves, pipelines and other parts of XTs are in continuous operation so that they are more prone to wear and corrosion failures [1] [2]. As stated by the Offshore and Onshore Reliability Data (OREDA) handbook, degradation contributes 45% of the failure rate at the equipment level [3] as one of the key factors that contributes to the unavailability of XTs.

Maintenance normally includes preventive maintenance (PM) and corrective maintenance (CM) that are carried out to retain a system in operating condition or restore it to an operating condition [4]-[7]. Maintenance optimization aims to determine effective maintenance plans for systems to meet requirements for safety, reliability and availability [8]. Attention has been given to the maintenance of subsea facilities (subsea blowout preventer (BOP) [9]-[11], pipelines [4] [12] [13] and XTs [1] [14] [15]). For BOP, Dui *et al*. [9] made an optimal maintenance plan that considers the criticalities of components to improve the availability of a BOP. Elusakin *et al*. [10] applied condition-based maintenance to BOP maintenance analysis and developed an optimal maintenance strategy for various failure modes. Considering both degradation and external shocks, Liu *et al*. [11] considered BOP as a mission-oriented system and proposed an imperfect maintenance policy to minimize the long-run cost rate. For subsea pipelines, Li *et al*. [4] combined the Bayesian network and Markov approach to develop an optimal maintenance strategy for subsea pipelines. Considering the risk factors in maintenance operations, a maintenance strategy was made with job safety analysis in [12]. Ehsan *et al*. [13] developed a dynamic risk-based methodology for maintenance scheduling of subsea pipelines that are subject to fatigue cracks and minimized the economic risks that are associated with maintenance by suggesting optimum maintenance.

XTs are, however, particular in terms of working mode and system structure compared with BOPs and subsea pipelines. A BOP is mainly in a dormant mode during the service life and is only activated when an undesired event occurs during the drilling process [1] [9], and subsea pipelines are organized in a series structure [4]. The maintenance of these facilities is relatively simple.

As a response to these distinctions, Alves *et al*. [15] proposed periodically tested repairable models and periodically tested nonrepairable models and introduced minimum cut sets and instantaneous availability functions for each component to the maintenance strategy of XTs. Wang *et al*. [1] evaluated the reliability and availability of XTs with different maintenance methods. They proved that both imperfect PM and perfect PM can effectively improve the performance of subsea tree systems. However, these studies are conducted with some assumptions: 1) Maintenances on heterogeneous components are performed separately; 2) Components in XTs are independent; and 3) Only one PM mode (either imperfect or perfect) is considered.

In practice, these assumptions are not always reasonable. For assumption 1), components in XTs deserve various PM intervals due to their different degradation processes. Given that maintenance is conducted for each failure of individual components, the whole system will have a longer downtime. In addition, maintenance on XTs is generally implemented by remotely operated vehicles (ROVs); separate maintenance always means high cost; and the approach of group maintenance is more practicable. For assumption 2), to maintain reliability and safety, XTs include specific components to tolerate faults in case some other components are unreliable. Stochastic dependence thus exists between these components, which means that the degradation of some components may intensify when certain components fail. For assumption 3), PMs on XTs can be perfect or imperfect, namely, hybrid, and different PMs will have different effectiveness against failures.

To release these assumptions, this study aims to identify the optimal group strategies for hybrid maintenance of components of an XT with dependency to minimize cost while maintaining high system availability. The main contributions are described as follows: 1) considering stochastic dependency, an applicable group maintenance strategy for XTs that is subjected to degradation and unexpected failures is developed; 2) multiple types of PM strategies are conducted into group maintenance optimization; and 3) the proposed approach proposes an aperiodic system-level PM plan that considers group maintenance and opportunity maintenance.

The remainder of the study is organized as follows: Section 2 is devoted to the description of the basic structure of XTs with stochastic dependency. A maintenance cost structure and group maintenance frame are described in Section 2. Section 3 focuses on the development of the proposed group maintenance scheduling approach, and all procedures are presented in detail. A case study for subsea Xmas trees is presented in Section 4, and a discussion is presented and conclusions of this study are proposed in Section 5.

Notation	**Description**	**Notation**	**Description**
m	Shape parameter of Weibull distribution	c_l^1, c_l^2	Labor cost for PM_1 and PM_2
η	Scale parameter of Weibull distribution	C_{set}	Setup cost
λ_j^i	Failure rate at *j*th PM cycle of component *i*	c_{set}	Setup cost per unit time
δ^i	Reduction factor of age	c_{spa}^i	Cost for spare part
t_j^i	*j*th PM time point of component *i*	n_j^i	Unexpected failure times of component *i* at *j*th PM interval
t_j^{i-}/t_j^{i+}	The virtual age before/after the *j*th PM action of component *i*	c_c^i	Corrective maintenance cost per unit time of component *i*

A_j^i	Availability at *j*th PM cycle of component *i*	c_p^i	Preventive maintenance cost per unit time of component *i*
ω^{ip}	PM duration of component *i*	T_s^-	The starting time point of *s*th PM action of system
ω^{ic}	CM duration of component *i*	o_j^i	Opportunity maintenance threshold at *j*th PM interval of component *i*;
ω^{io}	OM duration of component *i*	c_o^i	Opportunity maintenance cost per unit time of component *i*
Int_j^i	PM interval	β_φ	Dependency factor
$(Int_j^i)^*$	Optimal PM interval	cri_j^i	Critical decision variable
C_j^i	Total cost at *j*th PM interval of component *i*	$Cut(t)$	Minimal cut set
C_j^{ip}	PM cost at *j*th PM interval of component *i*	Dep	Dependency set
C_j^{ic}	CM cost at *j*th PM interval of component *i*	c_d	System downtime cost per unit time
C_j^{io}	OM cost at *j*th PM interval of component *i*	C_s^d	System downtime cost at *s*th PM interval
T	HXT lifetime		

2 SYSTEM DESCRIPTION AND GROUP MAINTENANCE MODEL

2.1 System description of XTs

A subsea Xmas Tree is located on the top of the subsea wellhead, which provides an interface between the completion string and the piping towards the process system. At its simplest, a subsea XT can be defined as an assembly of valves and fittings that are used for production or injection to control the flow of product, chemicals, water or gas from a well. The injection system, production control system, downhole control system and monitoring and flow control system are systems that are controlled using the subsea XT assembly [1] [16]. XTs can be segmented into two main types: vertical Xmas trees (VXTs) and horizontal Xmas trees (HXTs), as shown in Fig. 1.

A VXT is installed on either a wellhead or a tubing head after the subsea tubing hanger has been installed through the drilling BOP stack and landed and locked into the wellhead or in the tubing head [16]. A VXT can be identified by the location of the production and annulus bore, which is placed vertically through the tree body with the primary valves placed in a vertical configuration. The HXT, which is known as the spool tree, is constructed in a horizontal configuration with production and annulus valves that are located around the tubing hanger. One functional feature is that the HXT may be installed after well drilling and completion but prior to the installation of the tubing with the hanger. This feature is due to the tubing completion being performed via the HXT. This feature opens for easier access for well intervention and tubing recovery since the XT does not have to be retrieved to allow removal of the tubing hanger for well intervention and well workover operations [16]. Hence, HXTs are especially beneficial for wells that are expected to have a higher probability of failure in completion than a failure in XT or a high frequency of well workovers for reservoir management reasons. In this study, we consider HXT as an example to illustrate the proposed approach in further analysis.

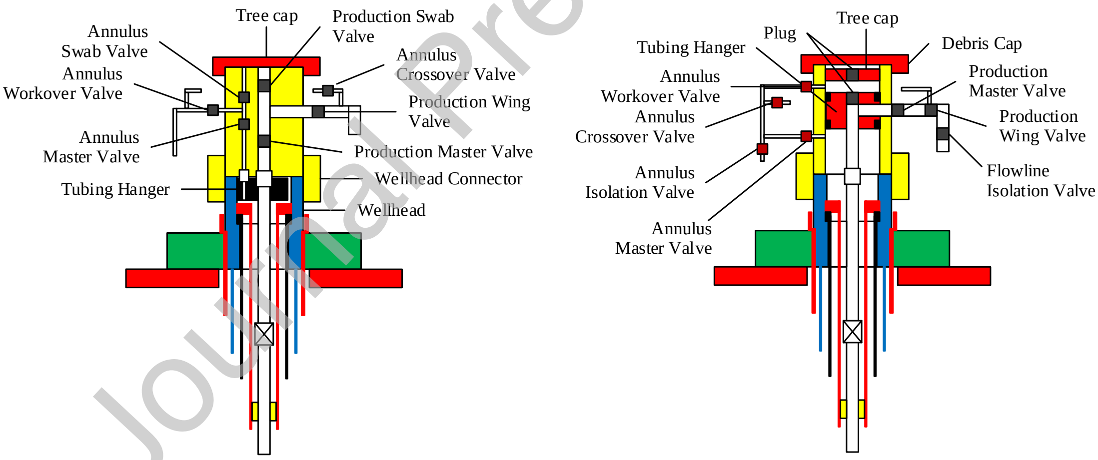


Fig. 1 General configuration of VXT (left one) and HXT (right one) [16].

2.2 Reliability model with stochastic dependency of HXT

During normal working time, a surface-controlled subsurface safety valve continuously opens the oil from the wellhead to storage tanks. The production master valve, production wing valve, production choke valve and production isolation valve are kept open. Two chemical injection valves (CIVs) accurately control the flow of glycol and inhibitor injection. In addition, the annulus workover valve, annulus vent valve (AVV), annulus wing valve and annulus master valve are used to equalize the pressure between the upper space and lower space of the tubing hanger during normal production. In general, each component is indispensable to realize the function of the HXT, and therefore, the components are put in series in the reliability model.

Moreover, to maintain reliability and safety, XTs include specific components for tolerating faults if other components are unreliable. Stochastic dependence among these components thus exists, which means that the degradation of some components may intensify when certain components fail [8] [17]. Some examples are shown here:

- There are two different chemical injection lines in the HXT with different chemicals or compositions, with separate CIV and dedicated injection points at separate locations in the system. If one fails, it is often possible to inject a chemical cocktail via the injection lines that function [16] [18].
- If the AVV cannot be vented through the annulus vent line, the gas can be vented through the crossover valve (XOV), and vice versa [16].

The reliability model with stochastic dependency is shown in Fig. 2.

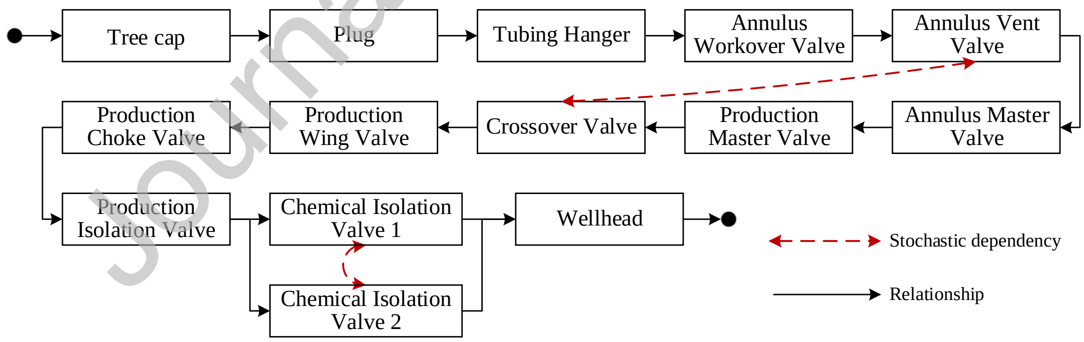


Fig. 2 Reliability model with stochastic dependency of HXT.

2.3 Group maintenance model

Owing to the various degradation processes, PM intervals vary for heterogeneous components [19]. At the system-level of an XT, if PM is conducted every time when any of the components need, frequent downtime will occur in the system. In addition, owing to the subsea environment of

XTs, frequent maintenance by ROVs will generate enormous maintenance costs. Hence, a group maintenance plan is of interest to integrate separate PM activities into several groups to share the setup cost and further minimize the expected maintenance cost in a considered scheduling horizon [20]-[22]. Additionally, during system-level PM shutdown, opportunity maintenance (OM) can be performed on other components that are not preventively maintained [23]. For an XT with n components, the illustration of group maintenance and some consensuses are described in Fig. 3 (a). Regarding component i, t_j^i is the jth component-level PM time point of component i, and T_s is the sth system-level PM time point. Thus, three maintenance scenarios are possible:

Scenario 1: If $t_j^i - T_s > o_j^i$, no action will be implemented for component i at T_s, where threshold o_j^i varies for each component. o_j^i is related to the jth PM interval.

Scenario 2: If $0 < t_j^i - T_s \le o_j^i$, an OM is carried out on component i at T_s.

Scenario 3: If $t_j^i \le T_s$, a PM (PM_1 or PM_2) is carried out on component i at T_s.

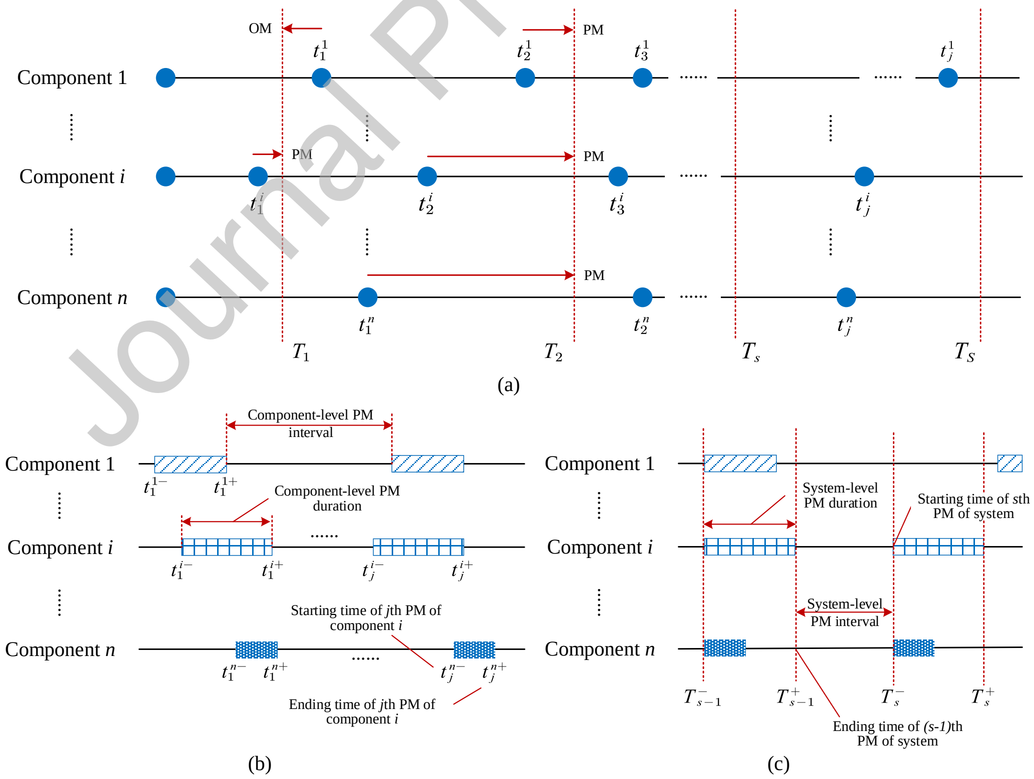


Fig. 3 Illustration of group maintenance.

Component/system-level PM interval and duration are defined. Component-level PM interval means the period from the end of a component-level PM activity to the beginning of the next component-level PM activity, as shown in Fig. 3 (b). Component-level PM interval depends on individual components. After integrating separate PM activities into several groups, the system-level PM interval depends on the group strategy. As shown in Fig. 3 (c), components 1, *i* and *n* are grouped at the *(s-1)*th system-level PM, while components *i* and *n* are grouped at the *s*th system-level PM. System-level PM interval is defined as the period between T_s^- and T_{s-1}^+. In addition, component/system-level PM duration means the period spent by PM of a component/system.

With respect to constructing a specific but realistic model, the following assumptions are made:

1. Components work from brand-new and gradually tear out. In addition, the components of the HXT are heterogeneous;
2. CM will be applied if a component fails between two PM tasks. CM is minimal maintenance, which means recovering a failed component to the degraded state just before failure;
3. PM durations, as well as CM durations of different component are various;
4. Two types of PM strategies are conducted: PM_1 restores components to a previous condition, where accumulated deterioration exists and may subsequently cause a severe breakdown, and PM_2 restores the components that are involved to a good-as-new state;
5. Due to the occurrence of unexpected failures, maintenance and human resources are urgently carried out, which will result in a higher cost per unit time than any type of PM, i.e. $c_c^i > c_p^i$;
6. OM is imperfect similar to PM_1 and is conducted during the PM shutdown of one component.

These assumptions are commonly employed in related studies, such as [1] [15] [24] [25].

3 GROUP MAINTENANCE SCHEDULING WITH STOCHASTIC DEPENDENCY

The procedures of group maintenance of subsea Xmas trees are illustrated in Fig. 4. The developed approach is divided into four steps:

1. Component-level PM interval

2. Stochastic dependency analysis
3. Cost evaluation
4. Collaborative particle swarm optimization algorithm

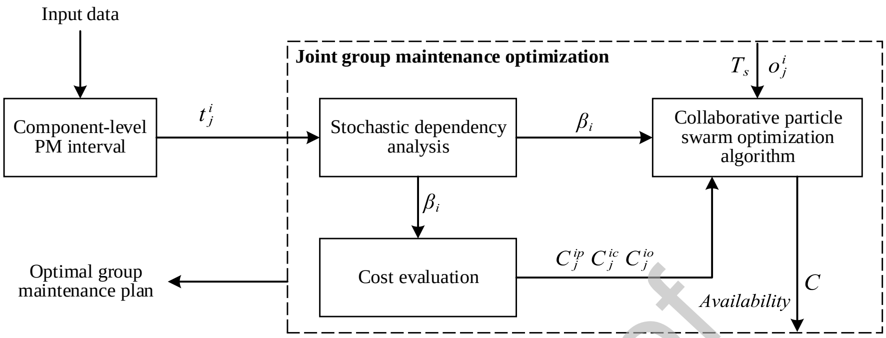


Fig. 4 Group maintenance procedures of subsea XTs.

3.1 Component-level PM interval

To understand the impact of different maintenance modes on facility reliability, we examine the relationship between maintenance and facility reliability. The Weibull distribution [26] [27] is popularly applied to describe facility reliability changes, and thus, the probability density function $f(t)$ is set as the fraction of time:

$$f(t) = \frac{m_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{m_i-1} \times e^{-\left(\frac{t}{\eta_i}\right)^{m_i}} (m_i, \eta_i > 0) \tag{1}$$

where m_i and η_i are the shape parameter and scale parameter, respectively, of component *i*. The cumulative density function *F(t)* and reliability function *R(t)* are set to

$$F(t) = 1 - e^{-\left(\frac{t}{\eta_i}\right)^{m_i}} (m_i, \eta_i > 0) \tag{2}$$

$$R(t) = 1 - F(t) = e^{-\left(\frac{t}{\eta_i}\right)^{m_i}} (m_i, \eta_i > 0) \tag{3}$$

Accordingly, the failure rate is expressed as follows:

$$\lambda(t) = \frac{f(t)}{R(t)} = \frac{m_i}{\eta_i}\left(\frac{t}{\eta_i}\right)^{m_i-1} (m_i, \eta_i > 0) \tag{4}$$

To avoid failure of an HXT, components are preventively maintained with appropriate intervals. Referencing the age reduction theory [28] [29], the outcome of maintenance is that the improved failure rate depends on the selected PM activities. Assume that the age of the component is $t_1^{i-} = t_1$ at the beginning of the first PM action and the virtual age of component *i* at the end of the first PM action is

$$t_1^{i+} = \left(1 - \left(\bar{\delta}\right)^1\right) t_1 \tag{5}$$

$$\bar{\delta} = E\left(\delta_1 + \delta_2\right) \tag{6}$$

where $\bar{\delta}\left(0 < \bar{\delta} < 1\right)$ is the expectation of the reduction factor, where δ_1 and δ_2 are the reduction factors of PM_1 and PM_2, respectively. In practical applications, reduction factors can be obtained by utilizing a Prognostics Health Management (PHM) system [30]. This system can evaluate the health/degradation status of components before/after PM via physical data (temperature, vibration, wear, etc.) that are measured by sensors. If the reduction factor equals to 1, it means that the component will be restored to a good-as-new state, and the virtual age of component after maintenance equals to 0. The virtual age before/after the second PM action of the component is

$$t_2^{i-} = t_1^{i+} + t_2 = \left(1 - \left(\bar{\delta}\right)^1\right) t_1 + t_2 \tag{7}$$

$$t_2^{i+} = \left(1 - \left(\bar{\delta}\right)^2\right) t_2^{i-} = \left(1 - \left(\bar{\delta}\right)^1\right)\left(1 - \left(\bar{\delta}\right)^2\right) t_1 + \left(1 - \left(\bar{\delta}\right)^2\right) t_2 \tag{8}$$

Therefore, the virtual age before/after the *j*th PM of component *i* can be written as

$$t_j^{i-} = t_{j-1}^{i+} + t_j = \sum_{j=1}^{j-1}\left(\prod_{j=1}^{j-1}\left(1 - \left(\bar{\delta}\right)^j\right) t_j\right) + t_j \tag{9}$$

$$t_j^{i+} = \left(1 - \left(\bar{\delta}\right)^j\right) t_j^{i-} = \sum_{j=1}^{j-1}\left(\prod_{j=1}^{j-1}\left(1 - \left(\bar{\delta}\right)^j\right) t_j\right) + \left(1 - \left(\bar{\delta}\right)^j\right) t_j \tag{10}$$

$$\lambda(t_j^{i+}) = \left(1 - \left(\bar{\delta}\right)^j\right) \lambda(t_j^{i-}) \tag{11}$$

In this study, the average availability of components is regarded as the basis for determining component-level PM intervals. The period from one PM to the next PM is composed of two sections: working time and downtime; thus, the availability for the *j*th PM cycle of component *i* can be described as

$$\begin{aligned} A_j^i &= \frac{MUT}{MUT + MDT} \\ &= \frac{t_j^{i-} - t_{j-1}^{i+}}{t_j^{i-} - t_{j-1}^{i+} + \omega^{ip} + \omega^{ic} \cdot \int_{t_{j-1}^{i+}}^{t_j^{i-}} \lambda_j^i(t)\,dt} \end{aligned} \tag{12}$$

where ω^{ip} and ω^{ic} are PM durations and CM durations, respectively, of component *i*; and $\int_{t_{j-1}^{i+}}^{t_j^{i-}} \lambda_j^i(t)\,dt$ is the unexpected failure times within the *j*th component-level PM interval of component *i*. The optimal component-level PM interval $(Int_j^i)^*$, which corresponds to the maximum A_j^i for the availability model is obtained as

$$\begin{aligned} (Int_j^i)^* &= arg \max_{t_j^i(I)} A_j^i(Int_j^i) \\ &\Rightarrow \left. \frac{dA_j^i(Int_j^i)}{d(Int_j^i)} \right|_{t_j^i(I)} = 0 \end{aligned} \tag{13}$$

where $Int_j^i = t_j^{i-} - t_{j-1}^{i+}$.

3.2 Stochastic dependency analysis

As mentioned in section 2.2, XTs are designed to tolerate faults if other components are unreliable. The dependency factor $\beta_\varphi(\beta_\varphi > 1), \varphi = \{1, 2\}$ is introduced to describe the increase in the degradation rate for working components [31]-[33]. This factor can be measured accurately by the degradation status of the component utilizing PHM. For two components with stochastic dependency, the change in the degradation rate can be evaluated by monitoring physical parameters if one component fails.

As shown in Fig. 2, first, the relationships of stochastic dependency between two components in XTs are established in the reliability model. Second, we adopted dependency factor theory to model the status change of these components. As shown in Fig. 5, the initial load shared by two valves will be executed on one component if another component fails at time point *t*. The failure rate of the functional component will increase to $\beta_{\varphi}\lambda(t)$, where $\lambda(t)$ is the original failure rate of the functional component at time point *t*. In this study, we use the concept of the dependency factor without losing generality [34]. Note that dependencies are assumed to be bidirectional.

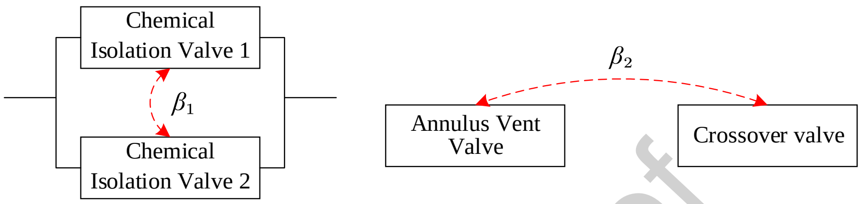


Fig. 5 Schematic of stochastic dependency.

3.3 Cost evaluation

Assume that there are *S* system-level PM activities and the HXT's horizon lifetime will be divided into (*S*+1) PM cycles, as shown in Fig. 6. For the *s*th ($s = 1, 2, \cdots S$) cycle, the maintenance cost consists of two parts: the cost produced during the system-level PM and the cost produced within the system-level PM interval. For the (*S*+1)th cycle, the maintenance cost is only determined by the cost within the system-level PM interval.

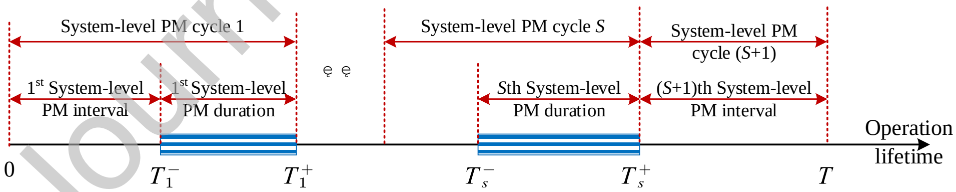


Fig. 6 Illustration of system-level PM cycles.

3.3.1 Cost in system-level PM interval

For the system-level PM interval in any cycle, from 0 to T_1^- in Fig. 6, no PM activity is implemented. Thus, the maintenance cost in the system-level PM interval can include the CM cost and system downtime cost. Hence, we have

$$C_s^{int} = \sum_{i=1}^{n} C_s^{ic(int)} + C_s^{d(int)} \tag{14}$$

where $C_s^{int}(s=1,2,\cdots,S+1)$ is the total cost in the *s*th system-level PM interval and $C_s^{ic(int)}$ is the CM cost, which is related to the unexpected downtime as

$$C_s^{ic(int)} = c_c^i \cdot n_s^i \cdot \omega^{ic}$$
$$= \begin{cases} c_c^i \cdot \int_0^{T_s^-} \lambda_s^i(t)dt \cdot \omega^{ic}, & s=1 \\ c_c^i \cdot \int_{T_{s-1}^+}^{T_s^-} \lambda_s^i(t)dt \cdot \omega^{ic}, & 1<s\leqslant S \\ c_c^i \cdot \int_{T_s^+}^{T} \lambda_s^i(t)dt \cdot \omega^{ic}, & s=S+1 \end{cases} \tag{15}$$

where n_s^i is the unexpected failure time of component *i* within the *s*th system-level PM interval and c_c^i is the CM cost per unit time of component *i*.

$C_s^{d(int)}$ is the system downtime cost due to the negative impacts of the downtime period of the system. It is related to the system structure and dependency. A decision variable cri_s^i is introduced to describe the criticality of the component. If a failure of component *i* leads to a breakdown of the system, $cri_s^i=1$; otherwise, $cri_s^i=0$. Here, we use the concept of a minimum cut set to judge the operating status of the system. Minimal cut sets are the unique combinations of the component failures that can cause system failure. Specifically, a cut set is said to be a minimal cut set if, when any basic event is removed from the set, the remaining events collectively are no longer a cut set [15]. Based on the structure of system, the minimal cut set at time *t* can be obtained and denoted by $Cut(t)$. Dep is defined as the nodes with dependency, which is defined as

$$Dep = \begin{pmatrix} 1 & \beta_\varphi & \cdots & \beta_{\varphi'} \\ 0 & i & \cdots & i' \\ 1 & 2 & \cdots & n \end{pmatrix} \tag{16}$$

where the third row in Dep is the index of components; the second row in Dep represents the dependency components, which is paired with the third row (“0” means there is no dependency component paired with the third row); and the first row in Dep is the factor of dependency (“1” means the dependency factor is equal to 1. There is no dependency relationship between the components of the second row and the components of the third row. For example, $Dep(2,2)=i$ and $Dep(3,2)=2$ mean that component 2 and component *i* are dependent. In addition, the factor of dependency is equal to β_{φ}.

$C_s^{d(int)}$ is calculated in three scenarios:

Scenario 1: If $cri_s^i=1$ && $Dep(2,i)=0$, component *i* is a critical component without any dependency, and the failure of component *i* will make the system break down. Therefore, the system downtime cost can be calculated as

$$C_s^{d(int)}=\begin{cases} c_d\cdot\omega^{ic}\cdot\int_0^{T_s^-}\lambda_s^i(t)\,dt, & s=1 \\ c_d\cdot\omega^{ic}\cdot\int_{T_{s-1}^+}^{T_s^-}\lambda_s^i(t)\,dt, & 1<s\leqslant S \\ c_d\cdot\omega^{ic}\cdot\int_{T_s^+}^{T}\lambda_s^i(t)\,dt, & s=S+1 \end{cases} \tag{17}$$

Scenario 2: If $i\in Dep(2,:)$ && $Cut(t)\subseteq Dep([2:3],i)$, component *i* is dependent on other components. The set of these components constitutes the minimum cut set of the system, meaning to be able to result a system failure, and thus, the system downtime cost can be calculated as

$$C_s^{d(int)}=\begin{cases} c_d\cdot\omega^{ic}\cdot\int_0^{T_s^-}\beta_{\varphi}\lambda_s^i(t)\,dt, & s=1 \\ c_d\cdot\omega^{ic}\cdot\int_{T_{s-1}^+}^{T_s^-}\beta_{\varphi}\lambda_s^i(t)\,dt, & 1<s\leqslant S \\ c_d\cdot\omega^{ic}\cdot\int_{T_s^+}^{T}\beta_{\varphi}\lambda_s^i(t)\,dt, & s=S+1 \end{cases} \tag{18}$$

where $\beta_{\varphi}=Dep(1,i)$.

Scenario 3: $i\in Dep(2,:)$ && $Cut(t)\subsetneq Dep([2:3],i)$, component *i* is dependent on other components. However, the set of these components does not constitute the minimum cut set of the system, and thus, the HXT operates normally. The system downtime cost $C_s^{d(int)}=0$.

3.3.2 Cost in system-level PM duration

For the *s*th ($s=1,2,\cdots S$) cycle in the HXT's lifetime, the cost during this system-level PM can be written as

$$C_s^{dur} = \left[c_{set} + \sum_{i=1}^{n} \left(C_s^{ip(dur)} + C_s^{io(dur)} \right) \right] + C_s^{d(dur)} + \sum_{i=1}^{n} C_s^{ic(dur)} \ (s = 1, 2, \cdots, S) \tag{19}$$

c_{set} shows the setup cost paid for all preparation activities of the maintenance actions. The preparation activities could be, e.g., ROV rental, traveling of maintenance teams and transportation of maintenance tools. The setup cost can be shared when multiple components are preventively maintained to reduce costs [35].

For $C_s^{ip(dur)}$, the PM activities of the HXT include lubrication of valves, physical inspection of the wellhead, etc. The PM cost consists of the cost of labor and spare parts as

$$\begin{aligned} C_s^{ip(dur)} &= \tau_s^i \cdot c_p^i \cdot \omega^{ip} \\ &= \tau_s^i \cdot \left(c_l + c_{spa}^i \right) \cdot \omega^{ip} \end{aligned} \tag{20}$$

where c_p^i is the PM cost per unit time of component i; c_l is the labor cost; c_l^1, c_l^2 represents the labor costs of PM_1 and PM_2, respectively; c_{spa}^i is the cost for the spare part, which depends on the specific characteristics of component i; and τ_s^i is a Boolean value. If $\tau_s^i = 1$, PM activity is implemented on component i within the sth system-level PM duration; if $\tau_s^i = 0$, otherwise.

$C_s^{io(dur)}$ is the OM cost within the sth system-level PM duration as

$$C_s^{io} = \begin{cases} c_o^i \cdot \omega^{io} \cdot \varrho_s^i, & 0 < t_j^{i-} - T_s^- \leqslant o_j^i \\ 0, & otherwise \end{cases} \tag{21}$$

where T_s^- is the starting time of the sth PM on the system; o_j^i is the opportunity maintenance threshold at the jth PM; c_o^i is the OM cost per unit time; and ω^{io} is the OM duration of component i; and ϱ_s^i is a Boolean value. If $\varrho_s^i = 1$, OM is implemented on component i within the sth system-level PM duration; if $\varrho_s^i = 0$, otherwise.

$C_s^{ic(dur)}$ and $C_s^{d(dur)}$ are related to the structure and dependency of HXT. Here, the set Ω_s is introduced to present the preventive maintenance components within the sth system-level PM duration. $C_s^{ic(dur)}$ and $C_s^{d(dur)}$ can be calculated within three scenarios:

Scenario 1: If $Cut(t) \subseteq \Omega_s$, the system will shut down. $C_s^{ic(dur)}$ and $C_s^{d(dur)}$ can be calculated as

$$\begin{gathered} C_s^{d(dur)} = (T_s^+ - T_s^-) \cdot c_d \\ C_s^{ic(dur)} = 0 \end{gathered} \tag{22}$$

where c_d is the system downtime cost per unit time.

Scenario 2: If $Cut(t) \subsetneq \Omega_s$

- Scenario 2.1: $\sigma_i(\sigma_i \in \Omega_s)$ is dependent on other components; these components constitute the minimum cut set of the system. $C_s^{ic(dur)}$ and $C_s^{d(dur)}$ can be calculated as

$$\begin{gathered} C_s^{d(dur)} = c_d \cdot \omega^{ic} \cdot \int_{T_s^-}^{T_s^+} \beta_\varphi \lambda_s^i(t)\, dt \\ C_s^{ic(dur)} = 0 \end{gathered} \tag{23}$$

- Scenario 2.2: $\sigma_i(\sigma_i \in \Omega_s)$ is dependent on other components; these components do not constitute the minimum cut set of the system. $C_s^{ic(dur)}$ and $C_s^{d(dur)}$ can be calculated as

$$\begin{gathered} C_s^{ic(dur)} = c_c^i \cdot \int_{T_s^-}^{T_s^+} \lambda_s^i(t)\, dt \cdot \omega^{ic} \\ C_s^{d(dur)} = 0 \end{gathered} \tag{24}$$

Note that the *s*th system PM duration is written as

$$T_s^+ - T_s^- = \sum_{i=1}^{n} \max\left[(\tau_s^i \cdot \omega^{ip}), (\varrho_s^i \cdot \omega^{io})\right] \tag{25}$$

3.3.3 Total cost in HXT lifetime

The total cost in the HXT's lifetime can be calculated as

$$\begin{gathered} C = C_s^{int} + C_s^{dur} = \sum_{s=1}^{S+1}\left(\sum_{i=1}^{n} C_s^{ic(int)} + C_s^{d(int)}\right) + \\ \sum_{s=1}^{S}\left\{\left[c_{set} + \sum_{i=1}^{n}(C_s^{ip(dur)} + C_s^{io(dur)})\right] + C_s^{d(dur)} + \sum_{i=1}^{n} C_s^{ic(dur)}\right\} \end{gathered} \tag{26}$$

3.4 Collaborative particle swarm optimization algorithm

To address this issue, we choose collaborative PSO as the solution approach due to its adaptability and quick converging capacity [36] [37]. This approach is selected because it has been successful in solving complexity problems, has high efficiency in maintaining the diversity of the swarm, can ease in adjusting parameters, and no requirement for differentiable optimization problems.

We set up *Dim* swarms, where each swarm contains *Num* values. The anterior *S* swarms represent the starting time of system-level PMs, and the posterior *n* swarms represent the opportunity threshold for each component. Set *S*+*n*=*Dim*; the position of the *i*th particle is described as $X_i = (x_{1i}, x_{2i}, \cdots x_{di})\ (i \leqslant Num, d \leqslant Dim)$. If $d \leqslant S$, x_{id} is the value of the starting time point of the system-level PM; if $S < d \leqslant Dim$, x_{id} is the value of the opportunity threshold of the (*d*-*S*)th component. The structure of swarms in collaborative particle swarm optimization (CPSO) algorithm is shown in Fig. 7.

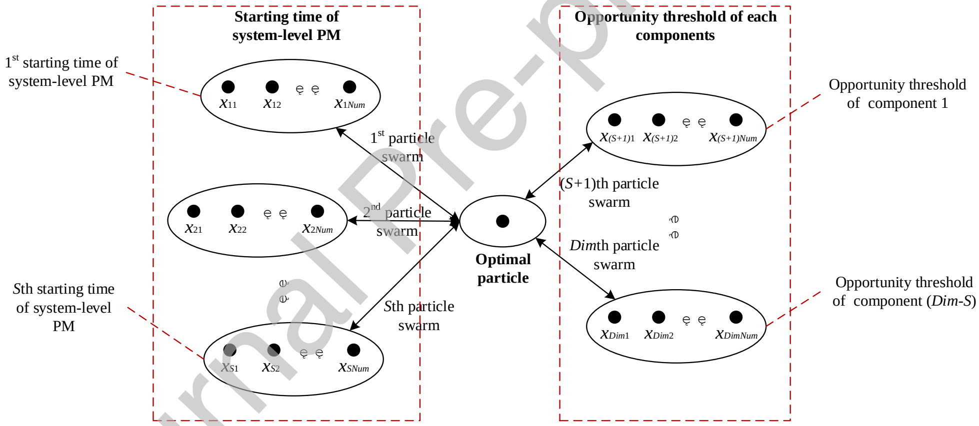


Fig. 7 Structure of swarms in CPSO.

Step 1: *Num* of particles are generated randomly, and the fitness function of each particle is developed by equation (26), which is denoted by fit_i. Rank the fitness functions of all particles in increasing order. The optimal fitness function value and the position of particle i' are also recorded.

$$fit_{best} = fit_{i'} = f\left(x_{1i'}, x_{2i'}, \cdots, x_{Dimi'}\right) \tag{27}$$

Step 2: Let *d*=1, and set the number of iterations, denoted by $Iters_{\max}$.

Step 3: We extract the *d*th value from the position of particle i', which has the optimal fitness function. The original *d*th value is replaced by the values in the *d*th particle swarm in sequence.

The fitness function of the generated particle is generated, which is denoted by $(fit_{i'})'$. A schematic is shown in Fig. 8. If $(fit_{i'})' \leqslant fit_{best}$, the fitness function and the position of the particle are updated; otherwise, fit_{best} does not change.

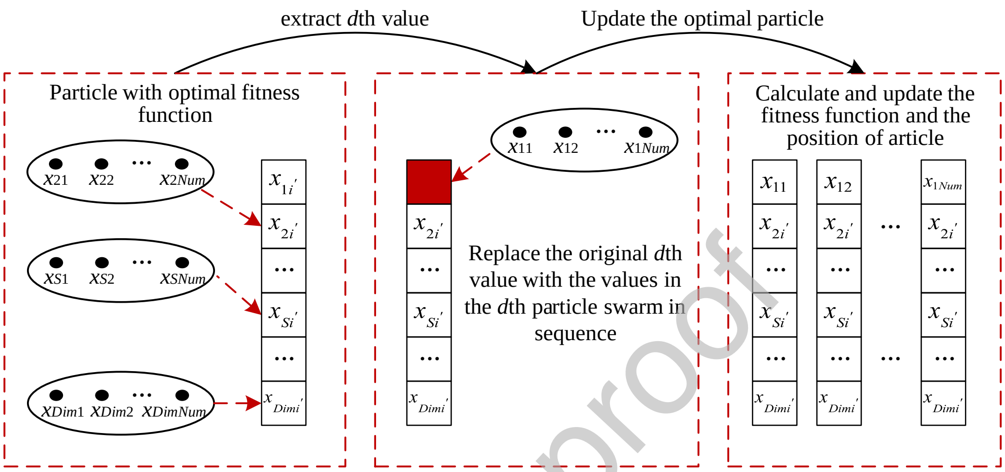


Fig. 8 Schematic of step 3 in CPSO.

Step 4: If $d \leqslant Dim$, let d=d+1 and return to step 3; otherwise, continue to step 5.

Step 5: Update the position and speed of particles as follows:

$$vel_{id}^{Iters+1} = \tau \cdot vel_{id}^{Iters} + c_1 \cdot (pos_{id}^{best} - x_{id}^{Iters}) + c_2 \cdot (pos_{d}^{best} - x_{id}^{Iters}) \tag{28}$$

$$x_{id}^{Iters+1} = x_{id}^{Iters} + vel_{id}^{Iters+1} \tag{29}$$

where $vel_{id}^{Iters+1}$ is the velocity in the dth dimension of particle i at $Iters$th iteration; x_{id}^{Iters} is the position in the dth dimension of particle i at the $Iters$th iteration; pos_{id}^{best} is the best position in the dth dimension of particle i in history; pos_{d}^{best} is the best position in the dth dimension of the particle swarm; τ is an inertia coefficient; and c_1, c_2 are acceleration coefficients, where c_1 is the extent to which particles affect themselves and c_2 is the capability to share the information among particles.

To improve the search accuracy of the CPSO algorithm, the inertia coefficient τ adopts an adjustment strategy that decreases linearly with the number of iterations. The value of inertia coefficient τ can be expressed as

$$\tau = \frac{\tau_{\max} - Iters \cdot (\tau_{\max} - \tau_{\min})}{Iters_{\max}} \tag{30}$$

where $\tau_{\max}$ and $\tau_{\min}$ are the extreme values of τ, and *Iters* is the current iteration. If $Iters \leqslant Iters_{\max}$, set *Iters*=*Iters*+1 and return to step 2; otherwise, continue to step 6.

Step 6: Output the optimum particle and corresponding position values.

4 CASE STUDY

4.1 General parameters of HXT

In this section, the proposed group maintenance optimization of the HXT with stochastic dependency is investigated. The HXT is mainly composed of a tree body, production module, annulus module, choke module and tubing hanger. The tubing hanger, which is installed within the HXT, has metal-to-metal sealing with an electrohydraulic penetrator. With two wireline plugs installed, the tubing hanger may have double sealing over production channels. The workover operation can be conducted by tripping tools through a tubing hanger as long as the XT cap and wireline plugs are retrieved.

As divers cannot reach a subsea installation, maintenance is usually performed by an ROV. Due to the high cost of using ROVs, it is necessary to reduce the frequencies of ROVs by grouping separate maintenance activities. Some general parameters are listed in Table 1, and all parameters are obtained from the following sources: OREDA handbook [3], vendor data [38] and Subsea Engineering Handbook [39]. Based on the description in Section 2.2, C5 is dependent on C8, and C12 is dependent on C13, where $\beta_{\varphi} = 1.2$. Assume that $T = 365$, $c_d = 500$, $c_{set} = 1500$, $\delta_1 = 0.65$, $\delta_2 = 0$ and $c_l^2 = 1.5 * c_l^1$. The historical data in these databases are reliable to a certain extent. However, since the type of XTs and operation environment are not consistent, the relevant data exhibit differences. In practical applications, the data in this proposed approach can be updated according to the field data to obtain a more accurate group maintenance strategy.

Table 1 General parameters of HXT

No.	Components	m_i	η_i	ω^{ip}	ω^{ic}	ω^{io}	c_l^1	c_{spa}^i	c_c^i	c_o^i
C1	Tree cap	1.5155	337	0.5	2	0.4	300	120	1300	220
C2	Plug	1.8231	400	0.8	2	0.6	400	150	1200	150
C3	Tubing Hanger	1.3280	386	0.5	4	0.4	500	100	1400	160
C4	Annulus Workover Valve	1.6527	435	0.5	3	0.4	600	120	1250	200
C5	Annulus Vent Valve	1.3918	355	0.6	2.4	0.4	520	80	1250	180
C6	Annulus Master Valve	1.8663	391	1	4	0.8	450	80	1300	220
C7	Production Master Valve	1.3909	426	0.4	3	0.4	600	100	1250	120
C8	Crossover Valve	2.1427	360	0.4	2	0.4	650	120	1600	200
C9	Production Wing Valve	2.1826	343	0.5	2.4	0.5	550	120	1500	150
C10	Production Choke Valve	2.0819	363	1	2	0.6	560	80	1200	200
C11	Production Isolation Valve	1.4262	368	1	3.5	0.6	560	80	1250	180
C12/C13	Chemical Isolation Valve 1/2	1.5822	333	0.6	3	0.5	40	100	1250	200
C14	Wellhead	1.7625	440	0.4	3	0.3	40	120	1300	200

4.2 Maintenance scheduling of HXT

All components are initially in a new state. Due to the various degradation processes of each component, the PM time points of each component are different. To maximize the average availability of components, the detailed component-level PM intervals for each component can be calculated utilizing the equations in Section 3.1 (as shown in Table 2). "--" in Table 2 means that the component does not need to carry out maintenance activities within lifetime *T*. For component

C2, four PM actions are enough to be taken within the lifetime of HXT to maximize the average availability of C2.

Table 2 Component-level PM intervals

Components	PM time points of each component								
	1st	2nd	3rd	4th	5th	6th	7th	8th	9th
C1	76.3	123.1	166.9	207.9	246	281.4	314.2	344.4	--
C2	116.4	187.7	254.5	316.9	--				
C3	70.9	114.4	155.1	193.2	228.6	261.5	291.9	320	345.9
C4	111.4	179.7	243.7	303.4	359	--			
C5	70.4	113.6	154.1	191.9	227.1	259.8	290.1	318	343.7
C6	117	188.7	255.9	318.6	--				
C7	84.4	136.2	184.7	230	272.2	311.3	347.6	--	
C8	125.9	203	275.3	342.8	--				
C9	122.3	197.2	267.4	332.9	--				
C10	123.1	198.5	269.2	335.2	--				
C11	75.9	122.5	166.1	206.9	244.8	280	312.6	342.7	--
C12/C13	80.3	129.5	175.6	218.7	258.8	296	330.5	362.3	--
C14	122.7	197.8	268.2	334	--				

Given the separate maintenance of individual components, as shown in Table 2, a total of 78 PM activities are required, which will incur a longer downtime and higher cost. This study aims to identify the optimal group strategies for hybrid maintenance on components of an XT with dependency to minimize cost while maintaining high system availability. There are three types of parameters to be optimized, including system-level PM time points, specified maintenance activity for each component at each system-level PM time point, and an opportunity maintenance threshold for each component. To address this issue, CPSO algorithm is used to search for an optimized group maintenance strategy within the HXT's lifetime. The algorithm searches the solution space using the rules described in section 3.4, and the final optimized system-level PM time points are 60.8, 121.7, 182.5, 243.2 and 304.2. The maintenance cost is 93,884, and the system availability is 0.7776.

In addition, the recommendation of maintenance activities on each component can be specified at each system-level PM based on the proposed approach, as shown in Table 3. For instance, XOV (C8) needs three PM cycles, where OM should be carried out at 121.7 and 182.5 and PM_1 should be carried out at 304.2. Note that "--" means that there is no maintenance activity at this system-level PM time point for the component. Moreover, the proposed approach can also provide optimal opportunity maintenance thresholds for each component according to the complex structure of the HXT.

Table 3 Maintenance plan of HXT

Time	Component													
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
60.8	OM	OM	OM	--	--	OM	--	--	--	--	OM	OM	OM	--
121.7	OM	--	PM2	PM1	PM1	--	PM1	OM	OM	OM	OM	OM	OM	OM
182.5	PM1	OM	PM1	PM1	PM1	OM	PM2	OM	OM	OM	PM1	PM1	PM1	--
243.2	PM1	OM	PM1	OM	PM1	OM	--	--	OM	OM	PM1	PM1	PM1	PM2
304.2	PM1	OM	PM1	PM1	PM1	OM	PM1	PM1	--	OM	PM1	PM1	PM1	PM1
Maintenance cost: 93884														
Availability: 0.7776														
Opportunity threshold: 0.3,0.6,0.4,0.2,0.2,0.5,0.2,0.4,0.4,0.5,0.4,0.5,0.5,0.2														

Additionally, a suitable maintenance scheduling contributes to improving the deteriorating HXT system performance, which is subjected to degradation and unexpected failure. The number of system-level PMs s has a direct impact on the maintenance cost. Fig. 9 shows the relationship between system-level PM frequencies and maintenance cost/availability. The maintenance cost decreases when the PM frequency is rather low and then increases when the frequency is higher. The system availability curve shows the opposite trend.

The maintenance cost reaches the minimum at s=5, which complies with the optimal results in Table 3, while the availability reaches the maximum at s=5. Note that both the maintenance cost and the system availability are at a high level when s=1 because the degradation of components in the HXT enable high probabilities of unexpected failures, and thus, the maintenance cost increases when *s* is low. Limited PM downtime interventions simultaneously keep the system availability at a high level. As *s* increases, the maintenance cost gradually decreases ($s \leqslant 5$) and the availability increases ($s \leqslant 6$). When *s* exceeds 4, the maintenance cost is greatly increased and the system availability is sharply decreased due to unnecessary PM actions.

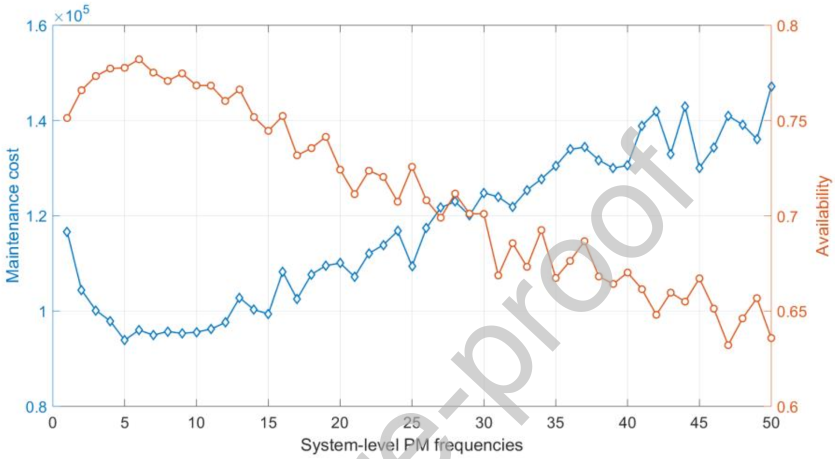


Fig. 9 Relationship between system-level PM frequencies and maintenance cost/availability.

To compare with other maintenance strategies, we consider the periodic group maintenance strategy and group maintenance without an opportunity maintenance strategy as illustrations. As shown in Fig. 10, the proposed group maintenance approach has significant advantages both in maintenance cost and system availability, which verifies the effectiveness of the proposed group maintenance approach.

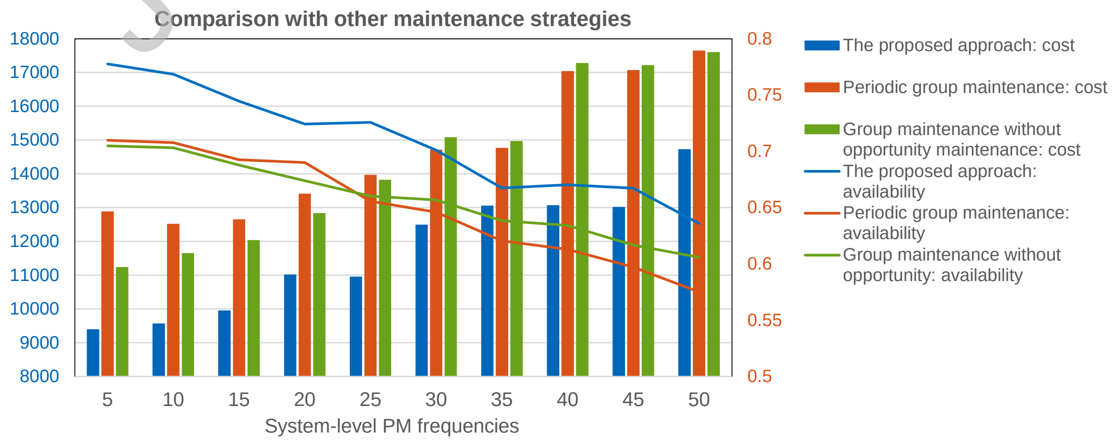
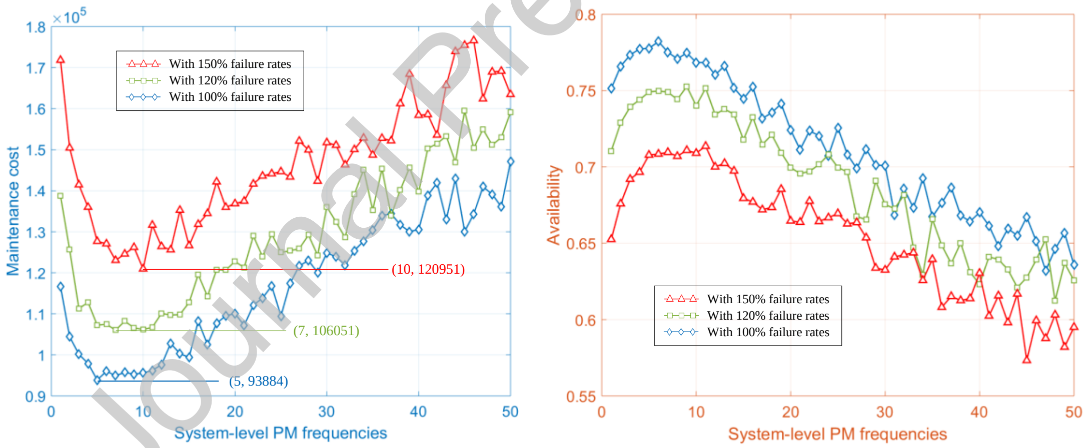


Fig. 10 Comparison with other maintenance strategies.

4.3 Discussions

4.3.1 Effect of failure rate

Since maintenance cost and system availability are related to the failure rates, sensitivity analysis is carried out considering the uncertain factors in actual working conditions. Assume that the prior probability of each component changes to +20% and +50%. The deviance will lead to a shift in the maintenance cost of the HXT and the system reliability. As shown in Fig. 11 (a), with an increase in prior failure rates, the maintenance cost increases and the optimal system-level PM frequencies increase. In addition, the system availability increases with a decrease in prior failure rates, while the gap due to the deviance in prior failure rates gradually decreases as the number of system-level PM frequencies increases. This finding implies that an appropriate increase in system PM frequencies is effective for maintaining costs when some disturbances occur in the HXT system.



(a) (b)

Fig. 11 Effect of failure rates.

With the optimal parameters and maintenance plan shown in Table 3, the impact of failure rates for each component on maintenance cost and system availability is investigated, as shown in Fig. 12. It can be determined that components with stochastic dependency, especially C5 (AVV) and C8 (XOV), have larger impacts on maintenance cost. The impacts of these dependent components on system availability are rather different. C5 is the most influential because 1) C5 deteriorates faster; so it is more prone to unexpected failures and 2) C5 is dependent on C8. When C8 fails, the failure rate of C5 will increase, which will have a greater impact on system reliability. Note that C12 and C13 both have very little impact on system availability. The failure of C12 or C13 will directly cause an increase in maintenance cost during the interval between two system-level PMs. Based on the parallel structure, the HXT will still maintain its operation, and thus, system availability is unchanged.

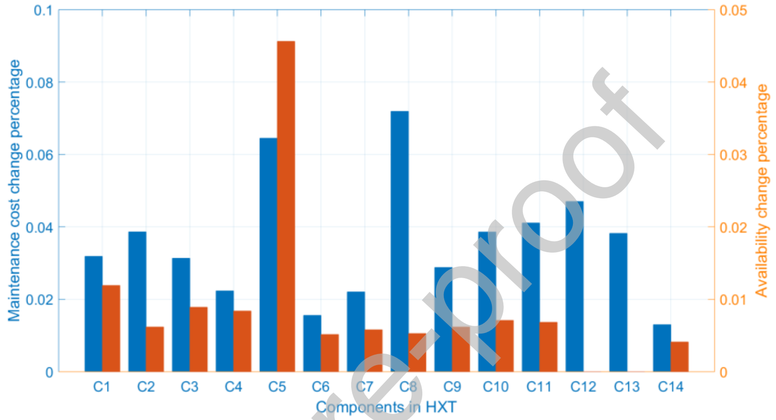


Fig. 12 Effect of various components in HXT.

4.3.2 *Effect of stochastic dependency*

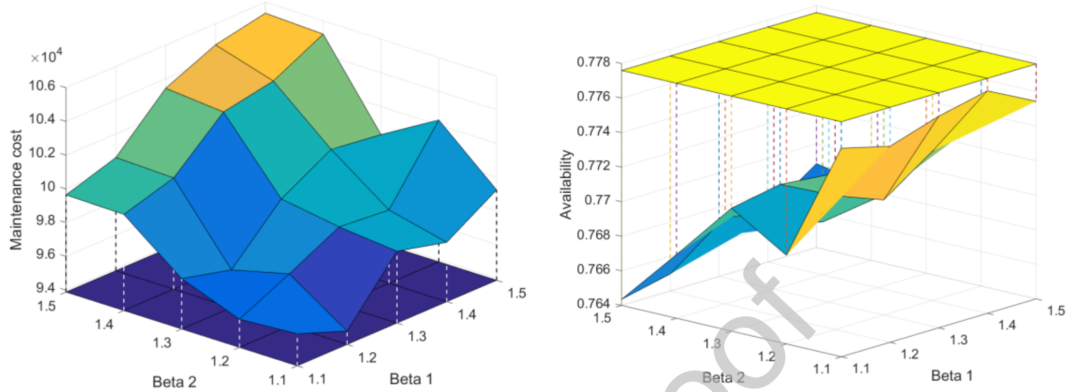
This section carries out a sensitivity analysis of stochastic dependency. Given that stochastic dependency can be disregarded, the calculation of the maintenance cost of the HXT is detailed as follows:

1. Set $\beta_1 = \beta_2 = 1$; the group maintenance plan of the HXT can be obtained utilizing the proposed approach. The optimal parameters (component-level opportunity thresholds and system-level PM time points) are output simultaneously;

2. Re-enter the obtained optimal parameters in the previous step into the group maintenance optimization model;

3. Calculate the maintenance cost and system availability based on the proposed approach.

As shown in Fig. 13 (a) and (b), the surfaces are the results obtained by the previous steps, and the planes are the optimal results that are shown in Table 3. The maintenance cost and system availability are sensitive to stochastic dependency, and as β_1 and β_2 increase, the gap between the surfaces and the optimal planes increases. Moreover, the difference in maintenance costs has a positive relationship with the dependence among components.

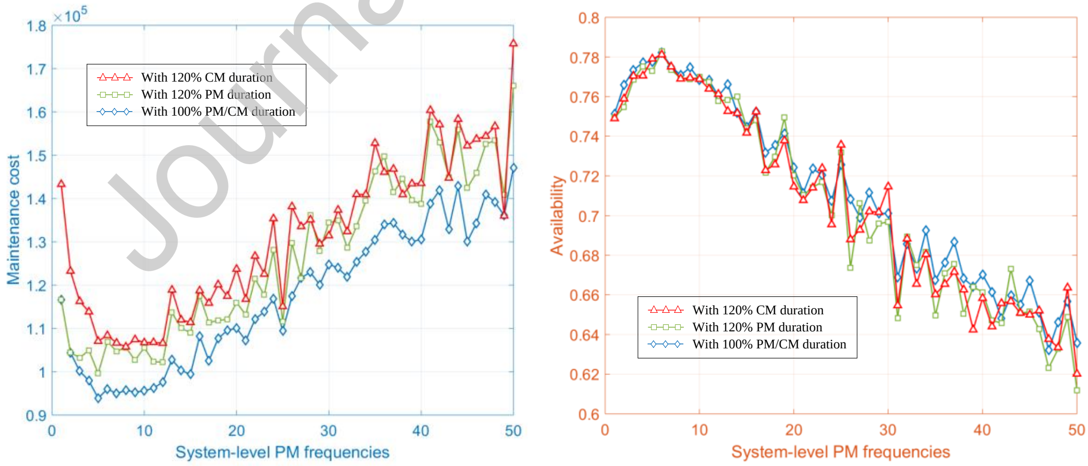


(a) (b)

Fig. 13 Effect of stochastic dependency.

4.3.3 *Effect of PM and CM durations*

A sensitivity analysis is carried out to analyze the effect of PM and CM duration on maintenance cost. Compared with the initial data, the durations of PM and CM are lengthened by 20%, and the curves of the different system PM frequencies and maintenance cost are shown in Fig. 14.



(a) (b)

Fig. 14 Effect of PM/CM durations.

As shown in Fig. 14 (a), the PM duration has a limited effect on the maintenance cost of the HXT when system-level PM frequencies are low. The optimal times of the system-level PM frequencies with 120% PM duration are equal to those with 100% PM/CM duration. Compared with the "120% PM duration", CM duration has a significant effect on maintenance cost, especially when system PM frequencies are low. When the system PM frequency is low, the number of unexpected failures increases during the operation time and causes a high proportion of CM costs. As the system-level PM frequency increases, the "120% CM duration" curve and "120% PM duration" curve tend to coincide. In addition, the optimal number of system-level PM frequencies for "120% CM duration" is 8, which is larger than that with "100% PM/CM duration". Generally, CM durations have a larger effect on maintenance cost than PM duration; thus, taking better advantage (such as performing an OM activity) of CM durations will be effective in reducing maintenance costs.

Moreover, as shown in Fig. 14 (b), the change in PM/CM durations has a slight effect on system availability when the system-level PM frequency is low but a larger difference with the increase in system-level PM frequency. PM/CM durations account for a small proportion of the lifetime T when the system-level PM frequency is low. With an increase in system-level PM frequency, the proportion of PM/CM durations in the lifetime T and the effect on system availability increases.

5 CONCLUSION

This study aims addresses the challenges of degradation and unexpected failures of XTs to identify the optimal grouping strategies by minimizing maintenance costs while maintaining high system availability. This study makes the following contributions: 1) an applicable group maintenance strategy, that is subjected to degradation and unexpected failures and considers stochastic dependency, is developed; 2) multiple types of PM strategies that concern the maintenance plan and optimizing group maintenance cost and system availability are feasible; and 3) an aperiodic system-level PM plan that considers group maintenance and opportunity maintenance is proposed. The proposed approach is available for both the HXT and the VXT, and the HXT is illustrated to verify the effectiveness of the proposed approach. Some conclusions can be obtained:

1. The proposed approach is effective in scheduling a group maintenance plan for the HXT with multiple components. This method can be employed to determine the frequency of system-level PMs within a finite lifetime to reduce overall maintenance costs;
2. An increase in the failure rates of components has a direct influence on maintenance costs, and the increase in cost is proportional to the increase in the failure rate. The impact of increased failure rates can be mitigated by more frequent system-level PMs;
3. Components with stochastic dependency have a larger impact on maintenance cost, especially AVV and XOV. In addition, AVV is the most sensitive component of system availability;
4. It is essential to account for the stochastic dependencies among components since the impacts on maintenance cost and system availability do not consider dependences.
5. By analyzing the influence of PM/CM duration on maintenance cost, CM duration has an obvious effect on maintenance cost compared with PM duration. This analysis can be effective for decreasing the CM duration or performing OM to maintain the system availability.

Future research can improve the proposed group maintenance approach by considering random maintenance duration models and logistic support constraints. Another important research direction could be the extension of predictive maintenance with real-time data of the HXT.

6 Conflict of interest statement

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

Author statement

Dongming Fan: Conceptualization, methodology, writing-review & editing, investigation

Aibo Zhang: Methodology, validation, formal analysis
Qiang Feng: Project administration, writing-review & editing
Baoping Cai: Funding acquisition, project administration
Yiliu Liu: Writing-review & editing, data curation
Yi Ren: Supervision, project administration

Acknowledgement

This research is collaboratively funded by the National Key Research and Development Program of China [No. 2019YFE0105100] and IKTPLUSS Program of Research Council of Norway [AutoPRO, No. 309628].

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