Journal of Manufacturing Systems 68 (2023) 443–454

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Multi-level predictive maintenance of smart manufacturing systems driven by digital twin: A matheuristics approach

Qiang Feng [a,1], Yue Zhang [a,1], Bo Sun [a,*], Xing Guo [a], Donming Fan [a], Yi Ren [a], Yanjie Song [b], Zili Wang [a]

[a] *School of Reliability and System Engineering, Beihang University, Beijing 100191, China*
[b] *Chinese Academy of Sciences, Beijing, 100864, China*

A R T I C L E I N F O

Keywords:
Digital twin
Predictive maintenance
Smart manufacturing system
Dynamic decision
Matheuristics

A B S T R A C T

Digital twin technology is gradually being applied to smart manufacturing systems and is providing valuable information for predictive maintenance of swarms of machines, but also raises the need for more accurate and real-time decision making. However, there is still a shortage of research in this area. This paper proposes a general multi-level predictive maintenance decision-making framework driven by digital twin, considering component dependencies, the variable time scale of decisions, and comprehensive maintenance resources, in which an optimal maintenance schedule can be obtained in real time and then fed back to the physical space, so as to realize closed-loop control. A maintenance decision-making optimization model is then formulated based on integer linear programming to minimize total maintenance costs while meeting required production capacity. Further, a novel matheuristics algorithm (i.e., the interoperation of metaheuristics and mathematical programming techniques) is introduced for various maintenance decision scenarios. Finally, a case study of an offshore oil and gas production system consisting of eight subsea Christmas trees is examined, and the effects of changes in production capacity, failure thresholds, and maintenance resources on the multi-level optimization of decision-making solutions are discussed.

1. Introduction

1.1. Background

Recent developments in internet technology, the Internet of Things, cloud computing, big data, and artificial intelligence have accelerated the integration of information technology with manufacturing systems, and data owned by enterprises have become increasingly rich, both of which are driving the manufacturing industry toward smart manufacturing [1]. The Digital Twin (DT) is a key technology with characteristics including interactive feedback between cyberspace and physical space, data acquisition, fault prediction, and iterative optimization for decision-making, and has become a focus of research in smart manufacturing [2]. DT models have been successfully applied in a wide range of manufacturing fields, from precision parts to full machines, and have been extended to the whole shop floor.

In particular, DT has been widely applied in smart manufacturing systems, because it provides a real-time representation of the physical machine and generates data such as measures of asset degradation. The accessibility and ubiquity of data facilitate better prediction and maintenance of production processes and systems, and thus improve productivity [3]. However, when using DT to make accurate and real-time decisions about predictive maintenance, the complexity of the operational environment and production tasks in manufacturing systems mean that some factors are not fully considered, such as complex dependencies for multi-level systems composed of multiple components, the variable time scale of decisions, and some comprehensive maintenance service resources (maintenance workers, spare parts, etc.).

Abbreviations: DT, Digital Twin; MTTR, mean time to repair; FPS, frequency-priority-selection; ILP, integer linear programming; PM-DT, predictive maintenance decision-making model driven by Digital Twin; ROV, remotely operated vehicle; RUL, remaining useful life; VNS, variable neighborhood search; XT, Christmas tree.

* Corresponding author.
E-mail address: sunbo@buaa.edu.cn (B. Sun).

[1] These two authors contributed equally to this work.

https://doi.org/10.1016/j.jmsy.2023.05.004
Received 21 January 2023; Received in revised form 12 April 2023; Accepted 7 May 2023
Available online 15 May 2023

1.2. Related work

1.2.1. Digital Twin in the manufacturing system

DT has become a widely used technology for integrating cyber and physical worlds. The concept of DT was first presented by Dr. Michael Grieves in 2003, in the University of Michigan's course on product lifecycle management. DT simulates, records, and improves the production process from design to retirement, including the content of virtual space, physical space, and the interaction between them. The most typical application of DT in smart manufacturing is Digital Twin shop-floor [4]. The Internet of Things provides ubiquitous sensing ability to collect data from different factors, businesses, and processes of the shop-floor, such as orders before production (e.g., pertaining to delivery, quantity, cost, and quality), and sensor data (e.g., material stock, human workload, and equipment capacity) [5].

Initially, the main research focus of DT included: 1) scheme evaluation and defect inspection in the design phase [6]—for example Zhang et al. [7] proposed a DT-based approach for designing a hollow glass production line to meet the needs of rapid and individualized design; and 2) operating efficiency improvement—for example Li et al. [8] proposed a DT-based energy management prototype system for an extrusion workshop. Researchers are exploring appropriate ways to improve each link of the manufacturing process by using DT. Due to the complex task scenarios of smart manufacturing systems, a slight failure occurring during production may cause irretrievable losses. Thus, in recent years, many researchers have focused on fault prediction. For example, Guo et al. [9] proposed a DT-based real-time method of predicting remaining useful life (RUL), taking into consideration working conditions and measurement errors. The next problem is how to effectively use the equipment operational information and fault prediction information provided by DT technology to make production and maintenance decisions, and this is still an underexplored area.

1.2.2. Predictive maintenance in the manufacturing system

Predictive maintenance can determine a maintenance schedule for each machine by monitoring mechanical condition, system efficiency, and other indicators [10]. Predictive maintenance in smart manufacturing systems has become a focus of research in recent years because of its potential to ensure safe and stable operation of the whole production system at the same time as reducing maintenance costs [11]. Performing predictive maintenance contributes greatly to reducing machine downtime and costs, and enhancing quality of control and production [12].

Existing optimization methods for predictive maintenance decision-making can be divided into four types: 1) machine learning [13] [14]—for example, Kevin et al. [15] propose a deep reinforcement learning algorithm approach to self-learn optimal maintenance decision policies, based on the health state of equipment; 2) mathematical programming [16]—for example, Pisacane et al. [17] proposed a bi-objective mixed integer linear programming (ILP) model and large neighborhood search for maximizing system reliability and minimizing maximum repair time; 3) heuristic algorithm [18] [19]—for example, Feng et al. [20] proposed a competition game approach based on heuristic rules to search for the optimal strategy matrix; and 4) system modeling and simulation [21]—for example, Nordal and El-Thalji [22] presented a novel simulation model, in which predictive maintenance is leveraged into opportunistic intervals.

The trend of key factor analysis in modeling is toward becoming more comprehensive. In initial work, the main considerations included production cycles, fault times, and downtime costs. Then, various maintenance service resources have been considered, such as service engineers with different skill levels [14], various tools [23], and spare parts [18] [24]. Constraint conditions have involved spare parts inventories, ordering time and type, scheduling time and cost, resource performance, etc. For example, Cai et al. [25] proposed a maintenance method taking into account the technical level of maintenance personnel, which reduced the total number of spare parts and maintenance preparation cost efficiently. Tian and Zhang [26] developed a predictive maintenance optimization procedure by considering repair resource requirements, particularly cranes, for failures of different components.

In terms of the object level, predictive maintenance decision-making under DT has gradually developed from the component level, such as tribological machine components [27], to the system level [28], such as gearboxes [29] and CNC machine tools [30]. In recent years, widespread attention has focused on multi-level predictive maintenance for complex systems composed of multiple components, where interdependencies such as failure [13] [31], structural [23], and economic [32] dependencies may exist between components. Dinh et al. [33] proposed a multi-level opportunistic predictive maintenance approach based on a degradation model considering disassembly impacts. Nguyen et al. [34] proposed a predictive maintenance policy with multi-level decision-making by introducing a cost-based group improvement factor incorporating the economic dependencies as well as the location of the components in the system. Chang et al. [24] presented a service-oriented dynamic multi-level predictive maintenance grouping strategy considering economic dependency.

1.3. Motivation and contribution

To address the research gaps described in the previous subsection, we propose a framework, model, and solution method for multi-level predictive maintenance of smart manufacturing systems driven by DT. Our main contributions are as follows.

(1) We propose a general predictive maintenance decision-making framework for smart manufacturing systems driven by DT. Based on monitoring and assessment of the system's condition, an optimal schedule for maintenance is given in real time and then fed back to the physical space, to realize closed-loop control of operation and maintenance.
(2) Our predictive maintenance decision-making optimization is formulated as an ILP model that minimizes total maintenance costs while meeting required production capacity, considering component dependencies, the variable time scale for decisions, and comprehensive maintenance resources.
(3) We introduce a novel matheuristics algorithm as a general decision-making framework for various maintenance decision scenarios, featuring a variable neighborhood search (VNS) combined with mathematical programming.
(4) We demonstrate our approach using a case study of an offshore oil and gas production system consisting of eight subsea Christmas trees. We also discuss the effects of changes in failure threshold, production capacity, and maintenance resources on the multi-level optimization of decision-making solutions under DT.

1.4. Overview

The rest of the paper is structured as follows. Section 2 describes the data flow of the predictive maintenance framework driven by DT. Section 3 formulates the predictive maintenance decision-making optimization as an ILP model. On this basis, Section 4 introduces a novel matheuristics framework for various maintenance decision scenarios. Section 5 provides a case study featuring a multi-level offshore oil and gas production system. Section 6 concludes the paper and outlines possible directions for future research.

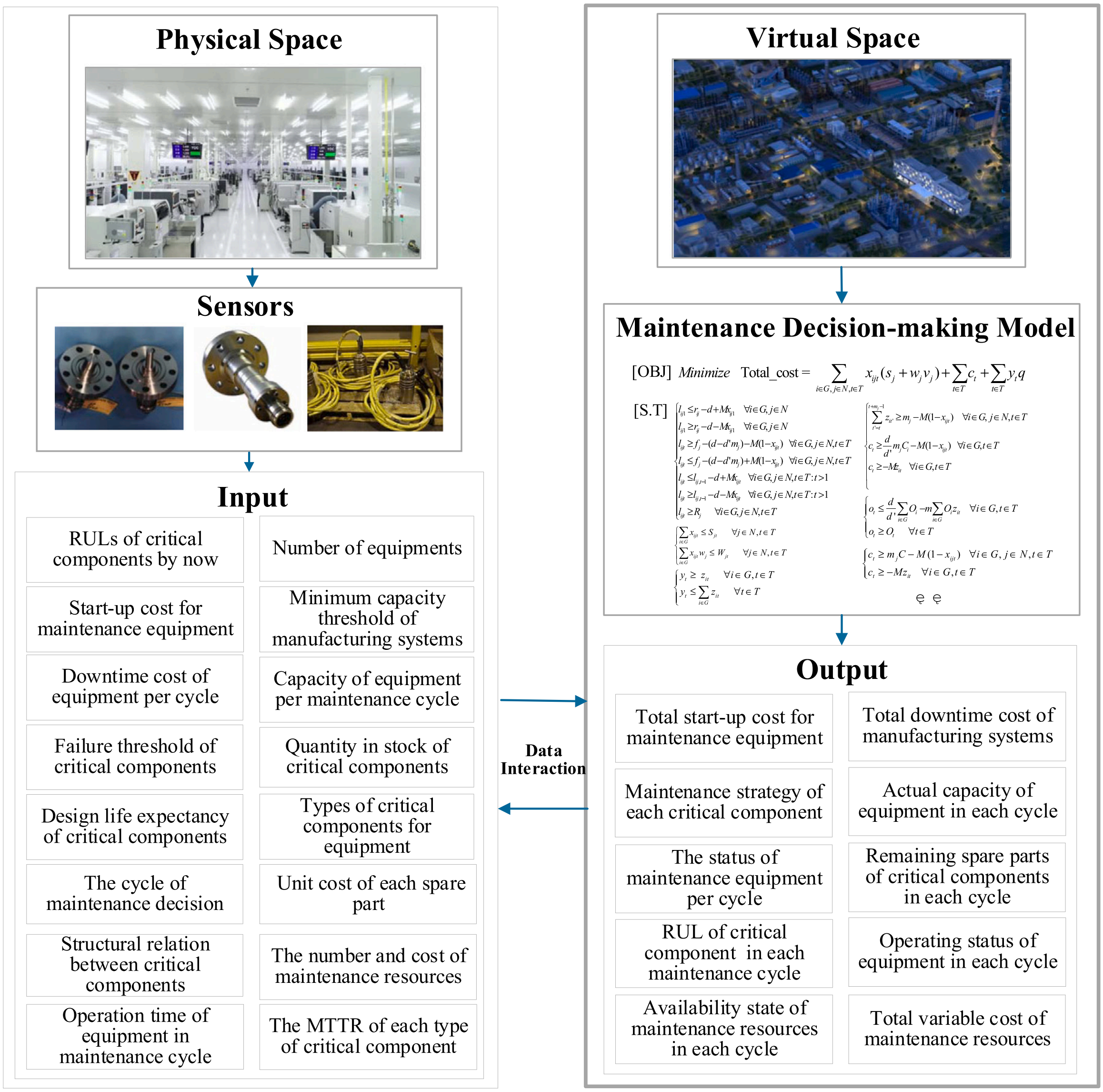

Fig. 1. The predictive maintenance decision-making framework driven by DT.

2. Data flow of the predictive maintenance framework driven by DT

In a DT model, in the physical space, running status data are obtained for all components in each facility through sensors and other devices. The data support layer collects, transmits, and saves the acquired data, and then interacts with the virtual space. Based on the monitoring and condition assessment of the current system, the optimal maintenance decision-making schedule is given in real time and then fed back to the physical space, to realize closed-loop control of operation and maintenance. As summary of the multi-level predictive maintenance decision-making framework driven by DT in smart manufacturing systems is shown in Fig. 1.

2.1. Input data

In the proposed predictive maintenance decision-making model driven by DT (denoted as PM-DT), it is necessary to set the basic parameter information for the manufacturing system in advance. The degradation state of equipment can be evaluated through real-time condition monitoring data collected by sensors, providing a basis for PM-DT. Predictive maintenance is performed periodically to maintain a low probability of failure during the whole production life cycle of the manufacturing system. The required real-time input information is summarized in Table 1.

2.2. Output decision-making

Based on DT technology, we propose a variable time scale for decisions. The production cycle of the smart manufacturing system can be dynamically configured according to the requirements of managers and markets. At the same time, the maintenance decision-making cycle based on the production cycle can also be adjusted in real time. For the proposed PM-DT model, the real-time output maintenance decision information is summarized in Table 2.

3. Problem formulation based on integer linear programming

The proposed multi-level PM-DT model considers component dependencies, the variable time scale of decisions, and comprehensive maintenance resources, and determines how to meet the production system's required production capacity while minimizing total maintenance costs, to achieve optimal economic efficiency of maintenance management for the manufacturing system.

Table 1
Required real-time input data and descriptions.

Parameter	Description
Number of facilities	The total number of facilities in the manufacturing system.
Number of critical components	From importance analysis and literature-based research, critical components that greatly influence reliability are identified.
Production cycle	A complete production cycle for the specific smart manufacturing system.
Maintenance decision interval	The minimum time interval for scheduling maintenance decisions, based on the production cycle.
RULs of critical components	The remaining useful life is used to monitor the current operating status of critical components in each facility.
Downtime cost for each facility per unit of time	The cost of facility downtime for maintenance is determined based on facility capacity and market prices.
Failure threshold of the RUL for each critical component	To ensure normal operation of the facility, maintenance activity should be arranged before components' remaining useful life falls below a threshold value.
Design life expectancy of critical components	After maintenance, the remaining useful life of the component is reset to the designed life expectancy.
Structural dependence between critical components	According to the structural correlation, maintenance of one component can lead to the replacement or disassembly of other working components, which will affect the maintenance strategy and maintenance time.
Cost of maintenance equipment and technicians	Maintenance technicians are required to operate professional maintenance equipment corresponding to components when replacing spare parts.
Minimum production capacity threshold in the manufacturing system	The minimum production capacity of the whole system in each maintenance decision interval is used to ensure stable output capacity in the total production cycle.
Production capacity of a facility per unit time	This parameter is used to evaluate the output capacity and downtime cost of the system.
Quantity of spare parts in stock Unit cost of each spare part	Maintenance activities are closely related to spare parts, especially for large and expensive spare parts in smart manufacturing systems.
MTTR of critical components	Mean time to repair is used to evaluate the impact of component maintenance time on facilities' downtime.

To develop this model, we establish a general formulation as an ILP model. The parameters and decision variables of the ILP model are formulated as follows:

Sets:

GSet of facilities in a manufacturing system, $i \in G, g = card(G)$.

NSet of all critical components, $j \in N, n = card(N)$.

TSet of maintenance decision-making cycles, $t \in T$.

Parameters:

qStart-up cost for the maintenance equipment each time (i.e., a fixed cost)·

o_iProduction capacity of facility i per unit time.

O_tMinimum capacity threshold of the manufacturing system in cycle t.

r_{ij}Remaining useful life of component j in facility i at the current time.

R_jRUL threshold of component j.

f_jDesign life expectancy of critical component j.

dScaling relation between maintenance decision-making interval and RUL.

d'Scaling relation between unit maintenance time and RUL.

s_jUnit cost of spare part for critical component j.

S_{jt}Total number of spare parts for component j in stock in cycle t.

w_jThe number of maintenance workers required to repair component j.

Table 2
Output maintenance decision information and descriptions.

Parameter	Description
Maintenance time node	Maintenance activities are scheduled for each component of all facilities in all maintenance decision-making intervals during the whole production cycle.
Availability state of maintenance resources	Denoted as Boolean data, representing available or unavailable.
Current cost of maintenance resources	The cost of maintenance resources under the current maintenance plan is obtained by calculating the unit costs of spare parts and various other maintenance resources.
RULs of components at each interval	Based on the maintenance plan, components' RULs at all decision-making intervals from the current to the end of the production cycle can be obtained.
Total downtime cost of manufacturing system	The downtime cost under the current maintenance plan is obtained based on the status of each component and the market prices in each time interval.
Actual capacity of equipment	The production capacity at each time interval under the current maintenance plan is obtained according to the status of each component in all facilities.
Current quantity of spare parts in stock	This quantity is obtained based on the replacement status of each component under the current maintenance plan.
Operating status of each facility in system	Denoted as Boolean data, representing running or down.

v_jCost of a maintenance worker per maintenance activity.

W_{jt}The number of available maintenance workers for component j in cycle t.

m_j Maintenance time of component j, $m = \max\{m_j\}, j \in N$.

C_i Downtime loss caused by facility i per unit time.

MA large number that is greater than the maximum design life expectancy of components.

Decision variables:

x_{ijt}Binary variable indicating whether component j in facility i needs to be repaired in cycle t (x_{ijt}=1) or not (x_{ijt}=0).

z_{it} Binary variable indicating whether facility i needs to be shut down for maintenance in cycle t (z_{it}= 1) or not (z_{it}= 0).

y_t Binary variable indicating whether the maintenance equipment is activated in cycle t (y_t= 1) or not (y_t= 0).

l_{ijt}Non-negative consecutive integer variable indicating the RUL of component j in facility i at the end of cycle t.

c_tNon-negative dependent variable indicating downtime loss of the whole system in cycle t.

o_tNon-negative dependent variable indicating production capacity of the whole system in cycle t.

Objective function:

The objective function is to minimize the total maintenance management cost, including the total fixed cost of start-up of the maintenance equipment, the total variable cost of maintenance resources, and the economic loss caused by downtime maintenance.

$$Minimize\text{Total\_cost} = \sum_{t\in T} y_t q + \sum_{i\in G, j\in N, t\in T} x_{ijt}\left(s_j + w_j v_j\right) + \sum_{t\in T} c_t$$

Constraints:

The above objective function and variables are subject to seven groups of linear constraints expressed in Eqs. (1)–(7), as follows.

(1) Constraints to restrict the RULs of components in all facilities.

$$\{l_{ij1} \le r_{ij} - d + Mx_{ij1} \forall i \in G, j \in N \tag{1 -1}$$

$$\{l_{ij1} \ge r_{ij} - d - Mx_{ij1} \forall i \in G, j \in N \tag{1 -2}$$

$$\{l_{ijt} \ge f_j - \left(d - d'm_j\right) - M\left(1 - x_{ijt}\right) \ \forall i \in G, j \in N, t \in T \tag{1 -3}$$

$$\left\{ l_{ijt} \leq f_j - \left(d - d' m_j\right) + M\left(1 - x_{ijt}\right) \ \forall i \in G, j \in N, t \in T \right. \tag{1 -4}$$

$$\left\{ l_{ijt} \leq l_{ij,t-1} - d + M x_{ijt} \forall i \in G, j \in N, t \in T : t > 1 \right. \tag{1 -5}$$

$$\left\{ l_{ijt} \geq l_{ij,t-1} - d - M x_{ijt} \forall i \in G, j \in N, t \in T : t > 1 \right. \tag{1 -6}$$

$$\left\{ l_{ijt} \geq R_j \forall i \in G, j \in N, t \in T \right. \tag{1 -7}$$

Constraints (1−1)–(1−7) are to maintain the stable operation of the manufacturing system by limiting the variation of RULs of components in each facility in all cycles as follows:

A. When $x_{ijt} = 0$, $t = 1$ indicates that component j in facility i does not need to be repaired in the first maintenance decision cycle. Constraints (1−1) and (1−2) specify that the component works normally according to the current input parameter r_{ij} in the current cycle, and the RUL degrades with running time as $l_{ij1} = r_{jj}$-d. Similarly, $t > 1$ represents the ordinary cycle t, and constraints (1−5) and (1−6) specify that the RUL degrades continuously from the last cycle as $l_{ijt} = l_{ij,t-1}$-d. Constraints (1−3) and (1−4) become redundant identical equations by using the big M method.
B. When $x_{ijt} = 1$, component j in facility i needs to be repaired in the maintenance decision cycle t. Constraints (1−3) and (1−4) stipulate that after maintenance at the end of the current cycle, the RUL is restored to the design life, denoted $l_{ij1} = f_j$, and constraints (1−5) and (1−6) become redundant identical equations by using the big M method.

Constraint (1−7) indicates that in the whole production cycle, each maintenance operation should be carried out before the RUL falls the set threshold R_j, so as to ensure that the degradation of all components is maintained within a reasonable range, supporting normal operation of the manufacturing system.

(2) Constraint to determine the structural dependence of components in the manufacturing system.

$$x_{iat} \geq x_{ibt} \forall i \in G, t \in T \tag{2}$$

Constraint (2) describe the structural dependency that in the same facility and same time cycle, if component b needs to be repaired, component a should be operated first.

(3) Constraints on limited maintenance resources for each component in multiple facilities in all cycles.

$$\left\{ \sum_{i \in G} x_{ijt} \leq S_{jt} \forall j \in N, t \in T \right. \tag{3 -1}$$

$$\left\{ \sum_{i \in G} x_{ijt} w_j \leq W_{jt} \forall j \in N, t \in T \right. \tag{3 -2}$$

Constraint (3−1) stipulates that the total number of j-type components to be scheduled for maintenance cannot exceed the total number of j-type spare parts S_{jt} in the current cycle t. Constraint (3−2) stipulates that the total number of required maintenance workers for component j cannot exceed the total number of callable maintenance workers W_{jt} for component j in the current cycle t.

(4) Constraints on facility downtime and loss due to maintenance time

$$\left\{ \sum_{t'=t}^{t+m_j-1} z_{it'} \geq m_j - M\left(1 - x_{ijt}\right) \forall i \in G, j \in N, t \in T \right. \tag{4 -1}$$

$$\left\{ c_t \geq \frac{d}{d'} m_j C_i - M\left(1 - x_{ijt}\right) \ \forall i \in G, t \in T \right. \tag{4 -2}$$

$$\left\{ c_t \geq -M z_{it} \forall i \in G, t \in T \right. \tag{4 -3}$$

$$\left\{ c_t \geq m_j C_i - M\left(1 - x_{ijt}\right) \ \forall i \in G, j \in N, t \in T \right. \tag{4 -4}$$

$$\left\{ c_t \geq -M z_{it} \forall i \in G, t \in T \right. \tag{4 -5}$$

Because any component maintenance will lead to facility shutdown, we adopt the logical relationship that the downtime should be the largest MTTR of components in the current round of group maintenance. When the production equipment is far away from the manufacturing system's operation platform, or the equipment components are too complex, the maintenance time is often greater than or equal to the set maintenance decision-making cycle. In contrast, for manufacturing systems with a simple structure or convenient maintenance operation, the maintenance time is often less than the set maintenance decision-making cycle. Therefore, two sets of constraints are established:

A. When $d/d' \leq 1$, i.e., the set maintenance decision-making cycle is less than or equal to maintenance time, constraints (4−1)–(4−3) are adopted. Specifically, $x_{ijt} = 0$ indicates that component j in facility i does not need to be repaired in decision cycle t. In this case, constraints (4−1) and (4−2) are redundant identical equations for z_{it} and c_t. $x_{ijt} = 1$ indicates that component j in facility i needs to be repaired in decision cycle t. In this case, constraint (4−1) describes the limiting relationship between the maintenance time and the downtime by summing the downtime variable z_{it} from the current time t to the time of component maintenance $t + m_j$-1, and constraint (4−2) calculates the downtime loss of the whole system based on maintenance time and downtime loss per unit time C_i. Constraint (4−3) specifies the relationship between the shutdown state z_{it} and the downtime loss c_t.
B. When $d/d' > 1$, i.e., the set maintenance decision-making cycle is more than the maintenance time, constraints (4−4)–(4−5) are adopted, and are similar to constraints (4−2)–(4−3). The difference to situation A is that the maintenance time will not affect the downtime states in subsequent time periods.

(5) Constraints on start-up of the maintenance equipment.

$$\left\{ y_t \geq z_{it} \forall i \in G, t \in T \right. \tag{5 -1}$$

$$\left\{ y_t \leq \sum_{i \in G} z_{it} \forall t \in T \right. \tag{5 -2}$$

Based on the shutdown state z_{it}, these constraints limit the start-up state of maintenance equipment y_t. Constraint (5−1) limits the lower bound and constraint (5−2) limit the upper bound by summing the shutdown state variables z_{it}.

(6) Constraints to guarantee that the total production capacity of the manufacturing system in each cycle exceeds the corresponding threshold.

$$\left\{ o_t \leq \frac{d}{d'} \sum_{i \in G} O_i \left(1 - z_{it}\right) \forall i \in G, t \in T \right. \tag{6 -1}$$

$$\left\{ o_t \geq O_t \forall t \in T \right. \tag{6 -2}$$

$$\left\{ o_t \leq \frac{d}{d'} \sum_{i \in G} O_i - m \sum_{i \in G} O_i z_{it} \forall i \in G, t \in T \right. \tag{6 -3}$$

$$\{ o_t \geq O_t \forall t \in T \tag{6 -4}$$

Due to the various proportional relationships between maintenance time, maintenance decision-making cycle, and the deign life expectancy, two sets of constraints are established as follows:

A. When $d/d' \leq 1$, i.e., the set maintenance decision-making cycle is less than or equal to maintenance time, constraints $(6-1)$ and $(6-2)$ are adopted. Specifically, constraint $(6-1)$ specifies the influence of equipment shutdown on the production system. Constraint $(6-2)$ limits the lower bound of the total production in any decision cycle t to be greater than the set threshold O_t in the corresponding cycle.
B. When $d/d' > 1$, i.e., the set maintenance decision-making cycle is far more than the maintenance time, constraints $(6-3)$ and $(6-4)$ are adopted. These are similar to constraints $(6-1)$ and $(6-2)$. The difference to situation A is that the maintenance time will affect the facility's production in each cycle.

(7) Constraints to define the value domains for all variables.

$$x_{ijt}, z_{it}, y_t \in \{0, 1\} \forall i \in G, j \in N, t \in T \tag{7}$$

4. A novel matheuristics method for various maintenance decision scenarios

The solving efficiency of ILP decreases exponentially with the increases in data size and various constraints, and the optimality of heuristics cannot be determined. Matheuristics algorithms combine the robustness of mathematical programming and the high efficiency of a metaheuristic algorithms, and have been widely used in various optimization mode[35] [36].

In this section, we introduce a novel matheuristics algorithm as a general decision-making framework for various maintenance decision scenarios. The proposed matheuristics combines with VNS and ILP, denoted VNS-ILP, which can ensure the quality of solutions within a controllable and reasonable time range.

Neighborhood search is a class of local search-based optimization algorithms that explore the solution space by iteratively moving from one solution to its neighbors in the search space. The goal is to find the best possible solution to a given problem by searching within the vicinity of the current solution. There are many variants of the neighborhood search algorithm, including Local Search (LS), Variable Neighborhood Search (VNS), Tabu Search, and Simulated Annealing, etc. Compared to other neighborhood search algorithms, VNS has the advantage of being able to explore a larger search space by switching between different neighborhood structures during the search process, which can lead to better solutions. Additionally, VNS can be easily adapted to different problem domains, making it a versatile and effective optimization algorithm. Compared with basic VNS, the contributions of the proposed VNS-ILP are as follows:

(1) According to the variable characteristics, the frequency-priority-selection (FPS) operator is designed in the shaking procedure to adaptively change the neighborhood structure.
(2) ILP is used in the local search procedure by calling CPLEX solver, which guarantees the accuracy of its results.

4.1. ILP solver in local search

In the process of the local search, we call the ILP solver CPLEX to optimize a subset of binary variables in each iteration. We use the VNS framework and design an adaptive operator to select a subset of decision variables to be fixed, and then call the ILP solver to optimize the model based on the remaining unfixed decision variables. The designed operator is used to determine which subset of existing solutions can be optimized by the ILP solver to form different solution structures.

Table 3
Input parameters of the VNS-ILP algorithm.

Parameter	Meaning
P_{max}	The maximum number of iterations before terminating the algorithm
G_{max}	The maximum number of selected facilities in the neighborhood search
N_{max}	The maximum number of iterations before terminating the neighborhood search
α	The initial number of selected facilities in the neighborhood search, set as 30% of total facilities
θ	The step size for each iteration, set as 5% of total facilities

Once the maintenance components and the maintenance service opportunity (time node) are known, the current RUL of each component in the system and decision variables related to the facilities' downtime can be determined quite effectively. Based on the above principle, we generate the new solution from the existing solution by changing x_{ijt} variables in the ILP optimization. We denote a solution as S, and hence the value of decision variable x_{ijt} for solution S can be denoted as $x_{ijt}(S)$. In our proposed VNS-ILP algorithm, when given solution S, the ILP solver is used to find a new neighbor solution S' as follows: (i) select a subset G of all facilities related to decision variables x_{ijt}; (ii) fix $x_{ijt} \leftarrow x_{ijt}(S)$ for each component i, facility j, and time node t; (iii) unfix x_{ijt} for all $x_{ijt} \in G$; and (iv) call the ILP solver to optimize the problem and return S'. To obtain a new solution S' better than the current solution S, it is very important to design a suitable criterion to select a subset G of decision variables x_{ijt}. Consequently, the adaptive operator is designed in a shaking procedure to select the corresponding subsets G and change the maintenance service opportunity and the sequence of facilities maintenance in the current solution S.

4.2. The framework and operator of VNS-ILP

In each local search of the algorithm, we use the adaptive operator to select subset G for ILP optimization, which directly determines the neighborhood structures for implementing VNS. In our proposed application, as the manufacturing system is working constantly and all components of different facilities degrade, real-time RUL values can be transmitted to the simulation platform through sensors, based on DT technology. Thus, a maintenance plan can be arranged consisting of the maintenance service opportunity, denoted as time node t, and the selection of components in the system for maintenance, denoted as (i,j). Accordingly, maintenance resources can be scheduled, including the spare parts in stock for component j in time node t, maintenance workers, and tools for repair.

The neighborhood search is based on facility characteristics (Lines 5–19 in the **Algorithm**), and we design the FPS operator. The FPS operator selects a subset G of all facilities and then unfixes all time nodes related to each selected facility. To ensure that each facility has the adaptive frequency to be optimized, the G facilities with the least number of optimizations are preferentially selected in each iteration, and the value of G varies dynamically with the step size of θ, in the given interval of $[\alpha, G_{max}]$ according to the improvement of each optimization. The mentioned parameters are explained in detail in Table 3.

By performing the above FPS operator in the VNS, all binary decision variables x_{ijt} related to the selected facilities and time nodes are unfixed and optimized by the ILP solver (Line 8 and Line 10 in the **Algorithm**), while the other binary variables remain fixed to the current solution. When a new solution is found and adopted as the current solution, the new string S' can be constructed.

Algorithm. VNS-MIP (P_{max}, g_{max}, N_{max})

Algorithm: VNS-MIP (P_{max}, g_{max}, N_{max})

Initialization: Initialize a solution S_0 with value f_0
Fix $x_{ijt} \leftarrow x_{ijt}(S_0)$ for all x_{ijt} decision variables
Let $f_{best} \leftarrow f_0$
Let $P \leftarrow 0$
Do while ($P \leq P_{max}$)
  Let $g \leftarrow \alpha$, $N \leftarrow 0$
  Do while ($g \leq g_{max}$)
    Apply ***FPS*** operator to select a set of G facilities
    Unfix x_{ijt} decision variables for all cycles related to G facilities
    Call the MIP solver to find new neighbor solution S' with the value f'
    If ($f' < f_{best}$) **Then**
      Let $f_{best} \leftarrow f'$, $g \leftarrow \alpha$, $N \leftarrow 0$
    Else
      Let $N \leftarrow N+1$
    End If
    If ($N2 > N2_{max}$) **Then**
      let $g \leftarrow g+1$, $N \leftarrow 0$
    End If
  End Do
  Let $P \leftarrow P+1$
End Do
Return f_{best}
End

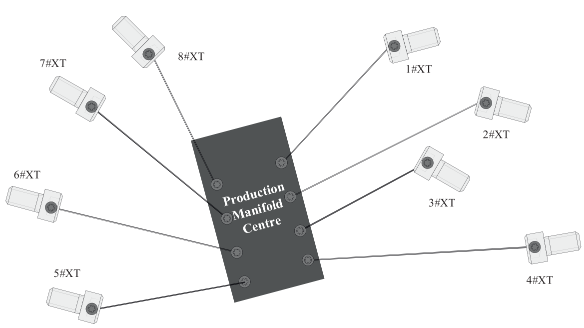

Fig. 2. The distribution diagram of the offshore oil and gas production system.

5. Case study

5.1. Description of XTs and data input

In this section, we use an offshore oil and gas production system as a representative smart manufacturing system. This system is applicable to deep water operations and can help achieve safe and controllable subsea oil and gas production [37]. An important piece of equipment in the offshore oil and gas production system is the subsea Christmas tree (XT) (an underwater device used for controlling the pressure of oil and gas), which has fifteen key components [38].

Over the last few decades, the complexity and functionality of XTs

Table 4
Detailed comparison for scenarios with different degrees of network damage.

Input	Value
Number of XTs	8
Number of critical components	15
Production cycle	1 year
Maintenance decision interval	1 month
Oil production of XT per interval	16,505 barrels of oil, approximately 5% range with time.
Minimum oil production threshold for the whole subsea production system	66,020 barrels of oil, approximately 5% range with time.
Price of crude oil per barrel	$40 per barrel
Design life expectancy of critical components	**Various valves:** approximate range is from 120 to 180 months **Others:** approximately 240 months
Failure threshold of the RUL for each critical component	Approximately 10% of its design life expectancy
The rental fee for the start-up of repair ship	Approximately $10,500,000 per time
Unit cost of spare parts for each critical component	**Various valves:** ranging from $500,000 to $600,000 **Others:** ranging from $300,000 to $500,000
Quantity of spare parts in stock	Uniformly distributed in the range of 3–5
Number of ROVs	**Various valves:** Uniformly distributed in the range of 8–10 **Others:** Uniformly distributed in the range of 12–15
Rental fee for one ROV	**ROV for various valves:** Approximately $1400,000 per time **ROV for others:** Approximately $1600,000 per time

Table 5
Input parameters of 15 key components.

No.	Component	Rj	fj	sj	wj	vj
1	Surface controlled subsurface safety valve, SCSSV	11	144	0.5	8	1.4
2	Production master valve, PMV	13	168	0.5	8	1.4
3	Production wing valve, PWV	12	156	0.5	8	1.4
4	Production choke valve, PCV	14	180	0.5	8	1.4
5	Crossover valve, XOV	9	120	0.5	8	1.4
6	Annulus master valve, AMV	10	132	0.5	8	1.4
7	Annules wing valve, AWV	9	120	0.5	8	1.4
8	Annulus vent valve, AVV	11	144	0.5	8	1.4
9	Chemical injection valve, CIV	10	132	0.5	8	1.4
10	MEG chemical control valve, MEGCCV	13	168	0.5	8	1.4
11	Methanol injection valve, MIV	9	120	0.5	8	1.4
12	Tubing hanger, TH	18	240	0.3	10	1.4
13	Tree cap	23	300	0.3	10	1.4
14	Flowlines	22	288	0.3	10	1.4
15	Connector	18	240	0.3	10	1.4

have increased, and any failure or damage to an XT will be a serious incident. Therefore, predictive maintenance of the offshore oil and gas production system is very important. However, because XTs are commonly located very far from the coast, divers cannot reach subsea installations. Maintenance is usually performed by a remotely operated vehicle (ROV), and a repair ship carries the ROV and the spare parts needed from the floating produce storage offshore facility (FPSO) to the XT's location. The maintenance time is long, the maintenance resources are limited, and the cost is high. After field investigation and based on information provided by a producer and supplier, the distribution diagram of the offshore oil and gas production system is shown in Fig. 2, and the data input is summarized in Table 4.

Fifteen key components of XTs and their corresponding values are listed in Table 5. Rj denotes the threshold of RUL (months), fj denotes the design life expectancy (months), sj denotes the unit cost of spare parts (million dollars), wj denotes the number of ROVs, and vj denotes the rental fee for an ROV (million dollars).

The current RULs of critical components in each XT are listed in Table 6, and the oil production of each XT per interval is listed in Table 7.

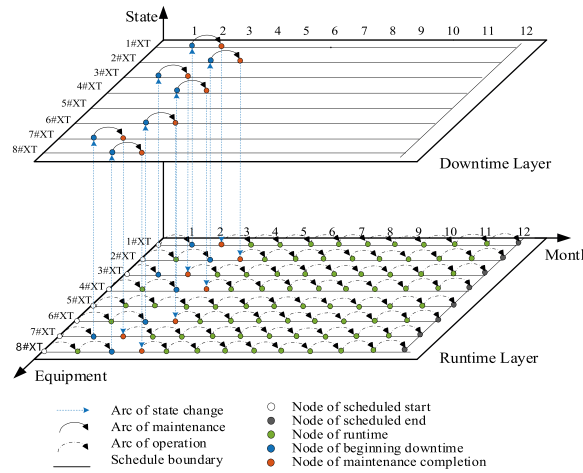

Fig. 3. The optimal maintenance schedule (system-level).

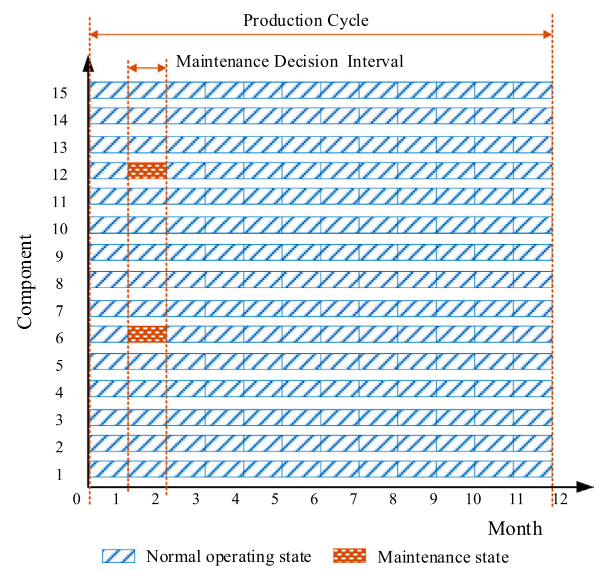

Fig. 4. The optimal maintenance schedule for 1#XT (component-level).

Table 6
The current RULs of critical components in each XT.

Components Facilities	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1#XT	96	146	98	54	101	18	59	108	91	120	46	33	136	258	36
2#XT	116	77	28	169	26	46	88	122	16	40	61	230	61	106	109
3#XT	85	48	116	151	57	127	82	102	65	80	64	198	112	36	129
4#XT	57	94	24	59	91	42	24	21	50	140	78	180	255	242	25
5#XT	107	158	96	165	26	26	24	106	132	76	120	224	236	191	79
6#XT	49	75	67	112	98	76	76	93	114	120	110	107	35	97	190
7#XT	73	106	64	145	29	71	58	121	24	149	84	53	30	262	159
8#XT	41	97	55	30	19	55	14	26	49	83	14	57	171	83	127

Table 7
Oil production of XT per interval.

Intervals Facilities	1	2	3	4	5	6	7	8	9	10	11	12
1#XT	16669	15911	16607	17269	16166	15713	16245	15993	17017	16342	17251	17186
2#XT	17263	17225	16524	16023	16014	16922	16355	16480	16850	17193	16686	16901
3#XT	16857	15909	17289	15710	15782	17161	16278	16618	16567	17177	16628	17015
4#XT	16512	16377	17166	16398	16645	16875	16156	16600	16197	16944	16464	16006
5#XT	16622	15900	17303	16653	15852	16453	15735	16175	17011	16336	15905	15974
6#XT	16954	16489	17034	16948	17196	17053	15865	17116	17095	16131	16447	16811
7#XT	15933	15810	16500	16511	17174	17297	16882	16473	16144	16023	16344	16642
8#XT	16977	16303	16524	16261	16854	16193	16977	15890	16451	17136	16315	17278

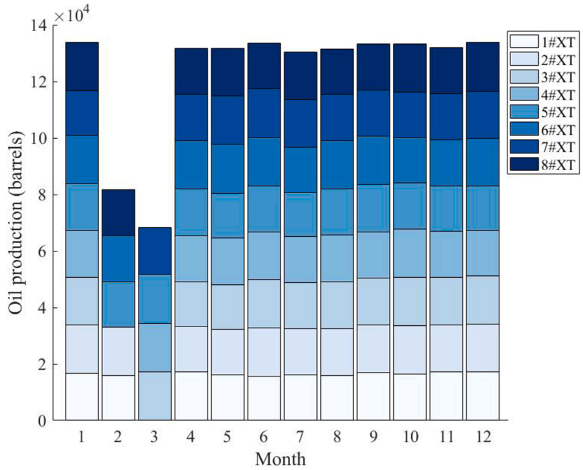

Fig. 5. Oil production capacity for each period.

5.2. Results analysis

In this subsection, we verify the proposed PM-DT model and analyze the obtained maintenance schedule. Computational experiments are conducted on a Linux PC server with two 2.30 GHz Intel Xeon (R) CPUs and 128 GB RAM. The PM-DT model was coded by AMPL (a mathematical programming language), and CPLEX (version 12.6.0.1) was used as the optimization solver.

The results of the predictive maintenance decision-making schedule are obtained for the whole production cycle of 12 months. The optimal maintenance schedules are shown in Fig. 3 (system-level) and Fig. 4 (component-level).

As shown in Fig. 3, for the whole system, we can see that the maintenance decision are focused on February and March, and thus share the fixed cost of the start-up for the maintenance equipment, which reflects the characteristics of opportunity maintenance. Taking the 1#XT at the component level as an example, as shown in Fig. 4, we can see that the components to be repaired are managed in the same period, which is because this group maintenance can reduce the downtime cost.

The frequency of maintenance is related to the failure threshold of different components, the various maintenance resources required, the oil production capacity threshold, etc. If production output must be high, the amount of downtime must be limited. Maintenance resources also limit which parts can be repaired at the same time. Accordingly, for the optimal maintenance schedule obtained, the variation in oil production capacity in each period is as shown in Fig. 5.

Relying on DT technology, the RULs of all components of XTs can be dynamically transmitted into the decision-making model in real time. From the obtained maintenance decision-making schedule, we take two typical components of 8#XT as examples to show the changes in RUL. As shown in Fig. 6(a), the RUL of component No.8 (annulus vent valve, AVV) decreases steadily over time. The red line represents a threshold of 15 months for AVV, so no repairs are required during the one-year production cycle. In contrast, for component No.5 (crossover valve, XOV) shown in Fig. 6(b), it is necessary to carry out maintenance before the RUL reaches the threshold.

6. Discussion

6.1. Analysis of algorithm efficiency

Based on the above production system, five more cases on different scales are generated by enlarging the number of facilities and components by a certain proportion, in order to analyze the efficiency of algorithms. The details of each case are summarized in Table 8.

Table 8
Details of cases on different scales.

Case		Number of facilities	Number of critical components	Number of maintenance decision cycles
Case 1	F8C15T12	8	15	12
Case 2	F40C30T12	40	30	12
Case 3	F80C60T12	80	60	12
Case 4	F100C75T12	100	75	12
Case 5	F110C80T12	110	80	12
Case 6	F120C90T12	120	90	12

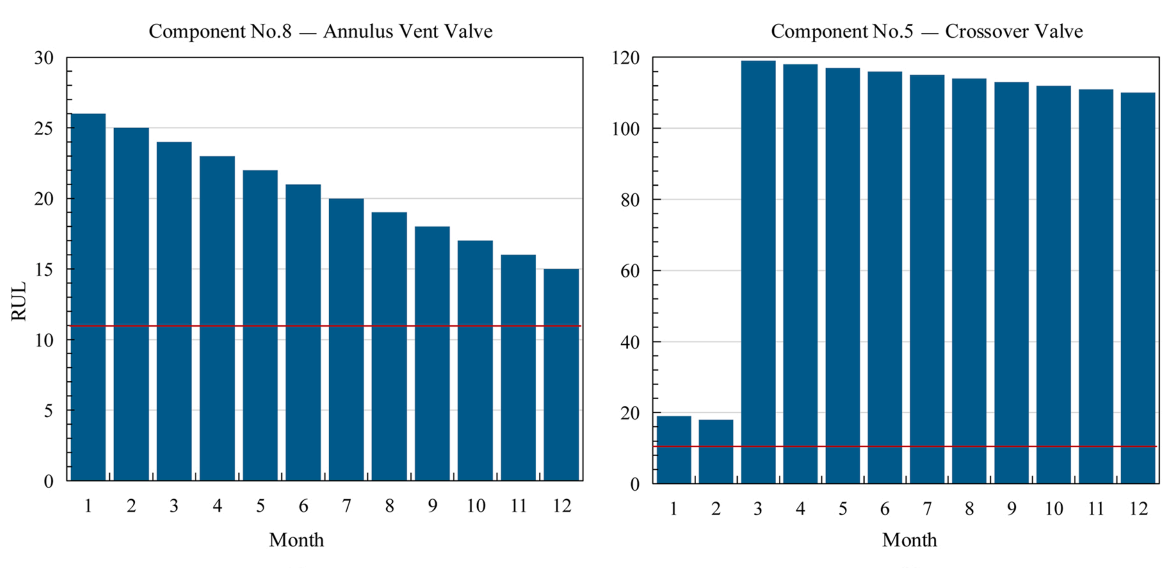

Fig. 6. Changes in RUL for two typical components of 8#XT.

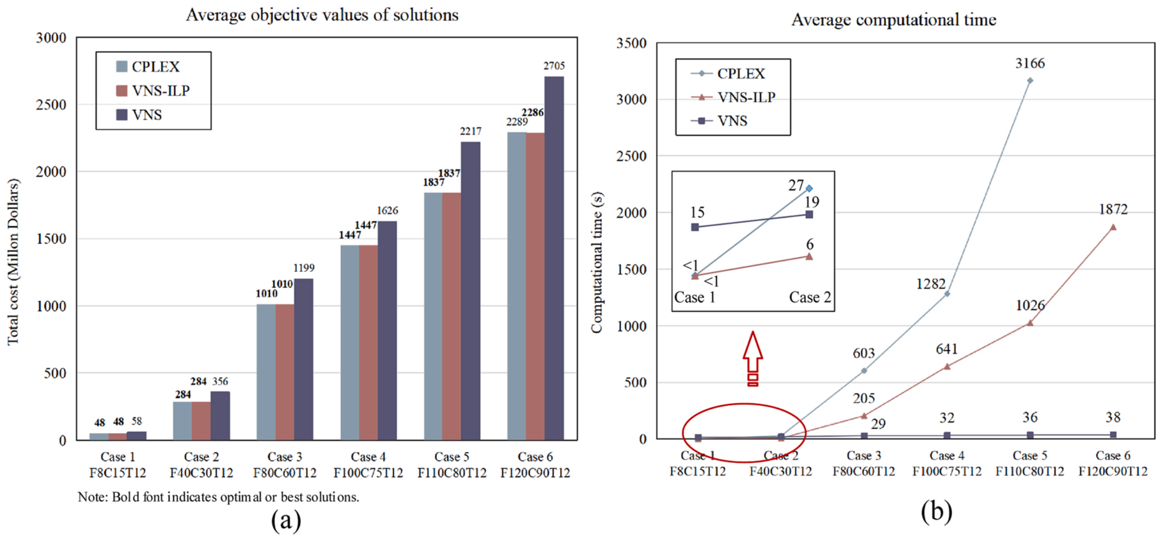

Fig. 7. Comparison of the objective value and computational time.

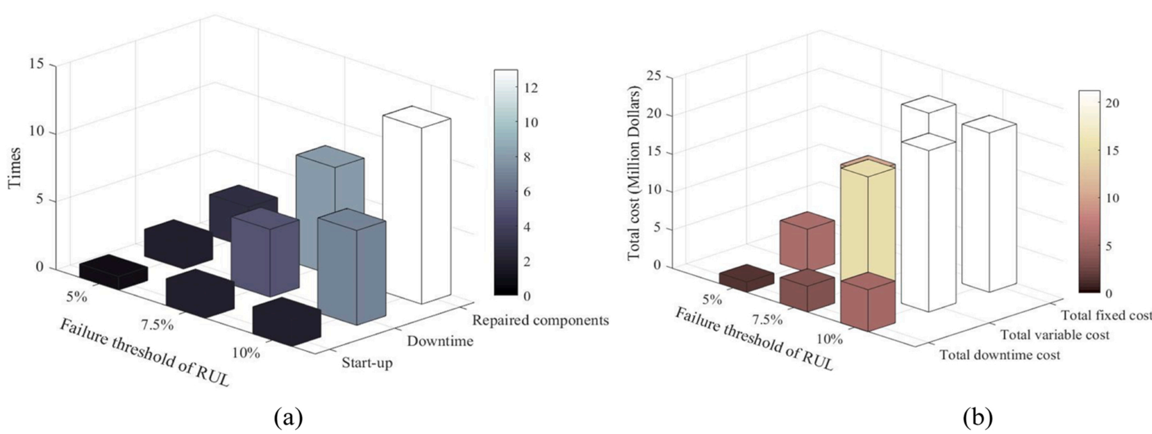

Fig. 8. Comparison of optimal solutions with different levels of failure threshold.

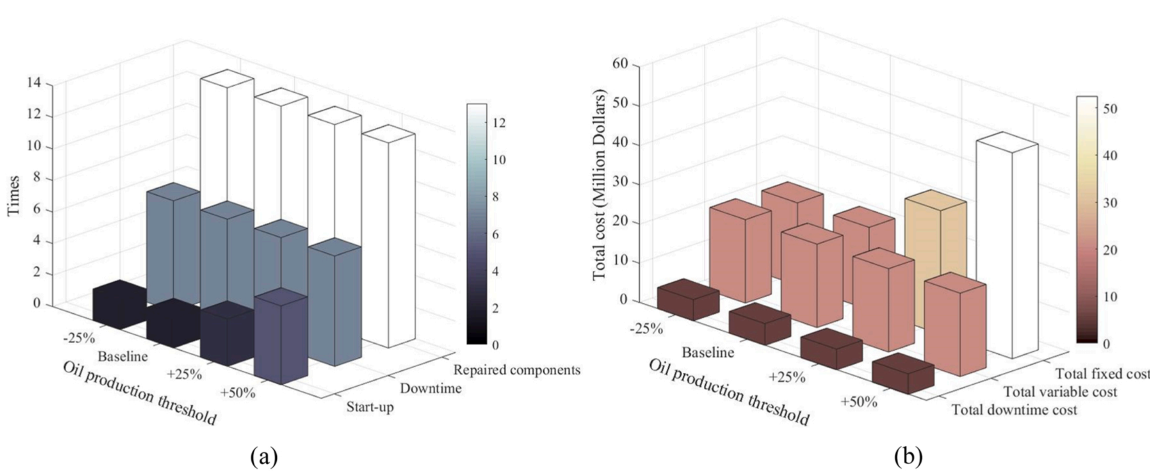

Fig. 9. Comparison of optimal solutions with production threshold of different levels.

Due to the global optimality of the exact algorithm, the solution obtained by CPLEX solver is taken as the baseline to measure algorithm optimality and solution efficiency. To perform comprehensive algorithm comparisons, different algorithms were tested on the above cases, including an exact algorithm, matheuristics algorithm, and VNS algorithm. We ran each algorithm 50 times and produced 50 solutions for each instance.

As the data scale of the cases increases, Fig. 7(a) and (b) illustrates the variation trend of average objective values and computational time. Detailed observations of different algorithms are shown as follows:

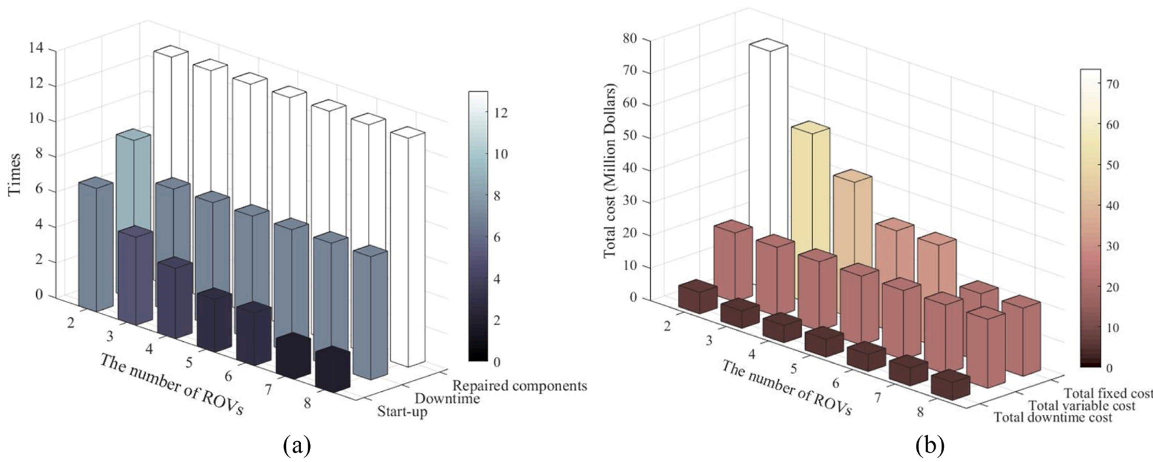

Fig. 10. Comparison of optimal solutions with various numbers of ROVs.

(1) The proposed exact algorithm solved by CPLEX obtains optimal solutions for Case 1: *F8C15T12* within 1 s. However, the computational efficiency and solution optimality decrease exponentially with the size of dataset. For Case 6: *F120C90T12*, the CPLEX solver cannot find any best solutions within a reasonable time of 3600 s
(2) The proposed matheuristics (VNS-ILP) can obtain the best solutions within a reasonable time, and shows good robustness in all scales of cases.
(3) The traditional VNS can obtain good solutions within a reasonable time, while the deviation from the best result increases steadily with expansion of the data scale.

6.2. Effect of failure threshold

Usually, the component failure probability increases exponentially when the component RUL drops to a certain minimum threshold, called the component failure threshold. An increase in the RUL failure threshold indicates a higher standard at which components need to be repaired, and therefore greater system safety. Using the proposed method, we obtain optimal solutions for RUL failure thresholds of 5%, 7.5%, and 10%.

Fig. 8(a) illustrates the variation in start-up for maintenance, downtime and repaired components with changes in the RUL failure threshold. For the case study's production cycle, as the threshold goes from 10% to 5%, the total number of component repairs drops from 13 to 3, and the total downtime decreases by 71.4%, because there are fewer component repairs causing facilities to shut down. This directly affects the total oil production of the whole system. Fig. 8(b) illustrates the variation in total costs, consisting of downtime costs, variable costs of maintenance, and the fixed cost, based on the changes in RUL failure threshold. It can be observed that all types of cost rise steadily with the increase in the RUL failure threshold.

6.3. Effect of oil production threshold

In order to ensure the safe and stable operation of systems, the total oil production of all facilities in each interval should be maintained above a certain threshold. We assume that the threshold of oil production ranges from a 25% reduction to a 50% increase, in increments of 25%; these scenarios are solved using the proposed method, and the optimal solutions are obtained.

Fig. 9(a) illustrates the variation in maintenance start-up, downtime, and component repairs with changes in the production threshold. Because the RUL failure threshold is unchanged, the total number of components repaired remains the same, as does the total variable cost during the whole production cycle. A higher oil production threshold limits the amount of downtime during the same period, thereby increasing the number of maintenance start-ups. Due to the long distances between the FPFO and the XTs, the rental fee for start-up of the repair ship per unit of time is expensive, which significantly increases the fixed cost, resulting in a higher total cost. Fig. 9(b) compares the variation in total costs, consisting of downtime costs, variable costs, and the fixed cost, based on changes in oil production threshold.

6.4. Effect of maintenance resources

For a complex smart manufacturing system, the inventory and market quantity of various maintenance resources at different periods greatly affect the maintenance plan. Specifically, maintenance of components requires the use of professional equipment and spare parts by appropriate skilled workers, the inventory of maintenance resources in each period is limited, and the equipment rental provided by outsourcing companies in the market is also limited. Therefore, the real-time available inventory of various maintenance resources can be monitored to develop the optimal maintenance strategy to minimize total maintenance costs while meeting the constraints of maintenance resources.

In this subsection, the impact of maintenance resources is tested using our case study of an offshore oil and gas production system. Component repairs should be carried out by ROVs leased from an outsourcing company. We consider scenarios where the number of ROVs per interval varies between 2 and 8, solve these scenarios using the proposed method, and obtain the optimal solutions. Fig. 10(a) illustrates the variation in maintenance start-up, downtime, and component repairs with changes in the number of ROVs. Because the RUL failure threshold is unchanged, the total number of components repaired remains the same, as does the total variable cost during the whole production cycle. However, the decline in the number of ROVs available limits the number of components available for repair over the same period, increasing the amount of downtime and maintenance start-up, resulting in a significant increase in the total fixed cost and thus total maintenance costs. Fig. 10(b) compares the variation in total costs, consisting of downtime costs, variable costs, and the fixed cost, based on changes in the number of ROVs per interval.

7. Conclusion

We propose a general predictive maintenance decision-making framework for smart manufacturing systems that is driven by DT and based on monitoring and condition assessment of the current system. In this framework, data flow is analyzed, including available input data and output decision-making, to provide a reference for relevant staff and improve system efficiency. Then, considering component dependencies, the variable time scale of decisions, and comprehensive maintenance resources, an ILP model is formulated to solve the predictive maintenance decision-making optimization problem with the minimum total cost while meeting the production requirements, and then a novel matheuristics algorithm is introduced for various maintenance decision scenarios.

We use an offshore oil and gas production system as a case study, and examine the effects of changes in failure threshold, production capacity, and maintenance resources on maintenance decisions to provide production guidance. In the context of the rapid development of DT, future research can seek to establish a more detailed predictive maintenance decision-making framework driven by DT, to more closely model the actual communication mechanisms across multiple organizations. In addition, the mathematical model for predictive maintenance decision-making under DT should also be improved to formulate a joint optimization model of production planning and maintenance decisions.

Funding

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

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Tao F, Qi Q. New IT driven service-oriented smart manufacturing: framework and characteristics. IEEE Trans Syst Man Cybern-Syst 2019;49:81–91.
[2] Qi QL, Tao F, Hu TL, Anwer N, Liu A, Wei YL, et al. Enabling technologies and tools for digital twin. J Manuf Syst 2021;58:3–21.
[3] Peres RS, Jia X, Lee J, Sun K, Colombo AW, Barata J. Industrial artificial intelligence in industry 4.0-Systematic review, challenges and outlook. IEEE Access 2020;8:220121–39.
[4] Tao F, Zhan H, Liu A, Nee AYC. Digital twin in industry: state-of-the-art. IEEE Trans Ind Inform 2019;15:2405–15.
[5] Tao F, Zhang M. Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing. IEEE Access 2017;5:20418–27.
[6] Guo J, Zhao N, Sun L, Zhang S. Modular based flexible digital twin for factory design. J Ambient Intell Humaniz Comput 2019;10:1189–200.
[7] Zhang H, Liu Q, Chen X, Zhang D, Leng J. A digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access 2017;5:26901–11.
[8] Li H, Yang D, Cao H, Ge W, Chen E, Wen X, et al. Data-driven hybrid petri-net based energy consumption behaviour modelling for digital twin of energy-efficient manufacturing system. Energy 2022:239.
[9] Guo JY, Yang ZJ, Chen CH, Luo W, Hu W. Real-Time prediction of remaining useful life and preventive maintenance strategy based on digital twin. J Comput Inf Sci Eng 2021:21.
[10] Shukla K, Nefti-Meziani S, Davis S. A heuristic approach on predictive maintenance techniques: limitations and scope. Adv Mech Eng 2022:14.
[11] Wu D, Jennings C, Terpenny J, Gao RX, Kumara S. A comparative study on machine learning algorithms for smart manufacturing: tool wear prediction using random forests. J Manuf Sci Eng-Trans Asme 2017:139.
[12] Wang Y, Cai B, Zhang Y, Liu J, Khan JA, Liu Y, et al. Condition-based maintenance method for multicomponent system considering maintenance delay based on remaining useful life prediction: Subsea tree system as a case. Ocean Eng 2022:266.
[13] Xu Y, Sun Y, Liu X, Zheng Y. A digital-twin-assisted fault diagnosis using deep transfer learning. IEEE Access 2019;7:19990–9.
[14] Ong KSH, Wang W, Niyato D, Friedrichs T. Deep-Reinforcement-Learning-Based predictive maintenance model for effective resource management in industrial IoT. IEEE Internet Things J 2022;9:5173–88.
[15] Ong K.S.H., Niyato D., Yuen C., Ieee. Predictive Maintenance for Edge-Based Sensor Networks: A Deep Reinforcement Learning Approach. 6th IEEE Virtual World Forum on Internet of Things (IEEE WF-IoT). Electr Network2020.
[16] Ghaleb M, Taghipour S, Sharifi M, Zolfagharinia H. Integrated production and maintenance scheduling for a single degrading machine with deterioration-based failures. Comput Ind Eng 2020:143.
[17] Pisacane O, Potena D, Antomarioni S, Bevilacqua M, Emanuele Ciarapica F, Diamantini C. Data-driven predictive maintenance policy based on multi-objective optimization approaches for the component repairing problem. Eng Optim 2021;53:1752–71.
[18] Yu VF, Salsabila NY, Siswanto N, Kuo P-H. A two-stage Genetic Algorithm for joint coordination of spare parts inventory and planned maintenance under uncertain failures. Appl Soft Comput 2022:130.
[19] Dinh DH, Do P, Iung B. Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts. Reliab Eng Syst Saf 2022:217.
[20] Feng Q, Bi X, Zhao X, Chen Y, Sun B. Heuristic hybrid game approach for fleet condition-based maintenance planning. Reliab Eng Syst Saf 2017;157:166–76.
[21] Dupuy M.J., Wesely D.E., Jenkins C.S. Airline Fleet Maintenance: Trade-off Analysis of Alternate Aircraft Maintenance Approaches. IEEE Systems and Information Engineering Design Symposium (SIEDS). Univ Virginia, Charlottesville, VA2011. p. 29–34.
[22] Nordal H, El-Thalji I. Lifetime benefit analysis of intelligent maintenance: simulation modeling approach and industrial case study. Appl Sci-Basel 2021:11.
[23] Duc-Hanh D, Phuc D, Iung B. Degradation modeling and reliability assessment for a multi-component system with structural dependence. Comput Ind Eng 2020:144.
[24] Chang F, Zhou G, Zhang C, Xiao Z, Wang C. A service-oriented dynamic multi-level maintenance grouping strategy based on prediction information of multi-component systems. J Manuf Syst 2019;53:49–61.
[25] Cai B, Wang Y, Zhang Y, Liu Y, Ge W, Li R, et al. Condition-based maintenance method for multi-component system based on RUL prediction: Subsea tree system as a case study. Comput Ind Eng 2022;173:108650.
[26] Tian Z, Zhang H. Wind farm predictive maintenance considering component level repairs and economic dependency. Renew Energy 2022;192:495–506.
[27] Desai PS, Granja V, Higgs III CF. Lifetime prediction using a tribology-aware, deep learning-based digital twin of ball bearing-like tribosystems in oil and gas. Processes 2021:9.
[28] Grall A, Dieulle L, Berenguer C, Roussignol M. Continuous-time predictive-maintenance scheduling for a deteriorating system. IEEE Trans Reliab 2002;51:141–50.
[29] Booyse W, Wilke DN, Heyns S. Deep digital twins for detection, diagnostics and prognostics. Mech Syst Signal Process 2020:140.
[30] Luo W, Hu T, Ye Y, Zhang C, Wei Y. A hybrid predictive maintenance approach for CNC machine tool driven by digital twin. Robot Comput-Integr Manuf 2020:65.
[31] Duc-Hanh D, Phuc D, Iung B. Maintenance optimisation for multi-component system with structural dependence: Application to machine tool sub-system. Cirp Ann-Manuf Technol 2020;69:417–20.
[32] Cheng GQ, Zhou BH, Li L. Joint optimization of lot sizing and condition-based maintenance for multi-component production systems. Comput Ind Eng 2017;110:538–49.
[33] Dinh D-H, Do P, Iung B. Multi-level opportunistic predictive maintenance for multi-component systems with economic dependence and assembly/disassembly impacts. Reliab Eng Syst Saf 2022;217:108055.
[34] Nguyen K-A, Do P, Grall A. Multi-level predictive maintenance for multi-component systems. Reliab Eng Syst Saf 2015;144:83–94.
[35] Zhang Y, Feng Q, Fan D, Ren Y, Sun B, Yang D, et al. Optimization of maritime support network with relays under uncertainty: a novel matheuristics method. Reliab Eng Syst Saf 2023;232:109042.
[36] Prata BDA, Fernandez-Viagas V, Framinan JM, Rodrigues CD. Matheuristics for the flowshop scheduling problem with controllable processing times and limited resource consumption to minimize total tardiness. Comput Oper Res 2022:145.
[37] Guo X, Feng Q, Fan D, Wang Z, Ren Y, Sun B, et al. An agent-based dynamic reliability modeling method for multistate systems considering fault propagation: a case study on subsea Christmas trees. Process Saf Environ Prot 2022;158:20–33.
[38] Fan D, Zhang A, Feng Q, Cai B, Liu Y, Ren Y. Group maintenance optimization of subsea Xmas trees with stochastic dependency. Reliab Eng Syst Saf 2021:209.