Reliability Engineering and System Safety 226 (2022) 108652

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

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

# A reliability-and-cost-based framework to optimize maintenance planning and diverse-skilled technician routing for geographically distributed systems

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ARTICLE INFO

*Keywords:*
Maintenance scheduling
Diverse-skilled technician routing
Geographically distributed system
Multi-objective decision making
Technician team composition

ABSTRACT

We present an agile maintenance framework where technician assignment and maintenance schedules are planned jointly to ensure timely operation and maintenance (O&M) services. Such an agile framework can quickly respond to organizational scheduling requirements while controlling service costs and not compromising machine reliability. For preventive maintenance (PM) and replacement tasks, a diverse-skilled technician organizing and routing model (D-STORM) is developed for geographically distributed systems with the following decision variables: (1) the scheduled maintenance start time, (2) the appropriate maintenance level (i.e. PM or replacement) for a network of machines, (3) the composition of technician teams subject to constraints controlling the number of technicians per team and their skill levels, (4) the optimal service route for each team. And the two objectives are: (1) maximizing the total reliability improvement and (2) minimizing the total service cost. Other than traditional maintenance policies, we propose a machine-team-technician assignment approach to provide a flexible and unified maintenance framework that can incorporate diverse-skilled technicians and multi-level maintenance operations. Numerical studies show significant advantages in terms of improved reliability and reduced costs, providing a set of alternative solutions for global original equipment manufacturers (OEMs). Moreover, Pareto solutions help OEMs to adopt the most appropriate maintenance scheme for their practices.

## 1. Introduction

The effectiveness and continuous operation of global manufacturing factories are critical for product quality, productivity, and profitability. However, the condition of production machines tends to degrade over time, requiring maintenance operations to ensure their reliability in satisfying prescribed demands [1–3]. Outsourcing maintenance services performed by personnel with specialized maintenance skills constitute a significant portion of the product-service package offered by many original equipment manufacturers (OEMs) [4]. OEMs are increasingly transitioning from being exclusive machine manufacturers to becoming service providers capable of predicting the degradation of their fielded machines and dispatching technician teams that provide operation and maintenance (O&M) services [5]. The routing of technician teams is a unique problem that arises alongside the conventional challenges of managing machine reliability, performing opportunistic maintenance, and assigning service tasks. This operational problem of maintenance scheduling and routing of service technicians has been studied in the existing literature and is referred to as the maintenance planning and technician routing problem (MPTRP) [6].

Leading OEMs possess global service networks composed of numerous factories in multiple locations. Generally, OEMs (the lessor) that lease their machines tend to also provide maintenance operations to their customers (the lessees) [7]. Each lessee may lease multiple machines as part of a multi-unit system. OEMs often retain a limited pool of technicians with varying skill levels to support maintenance activities at their customer sites. Therefore, in order to design a framework to meet the demands of multiple maintenance operation scheduling, this paper studies an improved version of the MPTRP that further accounts for the

*Abbreviations:* O&M, operation and maintenance; PM, preventive maintenance; D-STORM, diverse-skilled technician organizing and routing model; OEM, original equipment manufacturer; MPTRP, maintenance planning and technician routing problem.

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https://doi.org/10.1016/j.ress.2022.108652
Received 8 January 2022; Received in revised form 5 June 2022; Accepted 8 June 2022
Available online 9 June 2022
0951-8320/

**Nomenclature**

*Sets*

$\mathcal{N}$ set of nodes including maintenance center (index $i,j \in \mathcal{N} = \{0, 1, 2, \ldots, L\}$)
$\mathcal{L}$ set of lessee enterprises (index $i,j \in \mathcal{L} = \{0, 1, 2, \ldots, L\}$)
$\mathcal{A}$ set of possible service routes between nodes
$\mathcal{M}$ set of all leased machines (index $m \in \mathcal{M} = \{1, 2, \ldots, M\}$)
$\mathcal{S}$ set of service technicians (index $s \in \mathcal{S} = \{1, 2, \ldots, S\}$)
$\mathcal{K}$ set of formed teams (index $k \in \mathcal{K} = \{1, 2, \ldots, K\}$)
$\mathcal{Q}$ set of service skills (index $q \in \mathcal{Q}$

*Input parameters*

$\beta_{mn}, \eta_{mn}$ parameters in Weibull distribution of machine $m$ at the $n$th cycle
$\varepsilon_{mn}$ environment factor for machine $m$ at the $n$th cycle
$a_{mn}$ age reduction factor for machine $m$ at the $n$th cycle
$I_m$ machine importance coefficient for machine $m$
$C_{im}^{PM}$ maintenance cost of the preventive maintenance action for machine $m$ in factory $i$
$C_{im}^{RM}$ maintenance cost of the replacement action for machine $m$ in factory $i$
$F^k$ fixed cost of dispatching maintenance team $k$ from maintenance center
$c_{ij}$ travel cost rate from the node $i$ to node $j$
$t_{ij}$ travel time from the node $i$ to node $j$
$T_{im}^{PM}$ maintenance duration of the preventive maintenance action
$T_{im}^{RM}$ maintenance duration of the replacement action
$P_i$ penalty per unit time for performing maintenance in factory $i$
$v$ maximum number of technicians in each maintenance team
$q_s$ maximum number of machines that technician $s \in \mathcal{S}$ can maintain
$l_m$ reliability constraint of machine $m$ according to the lease contract
$LP_i$ lease period of factory $i$

*Auxiliary decision variable*

$u_{mq}$ binary parameter: 1, if machine $m \in \mathcal{M}$ requires skill $q \in \mathcal{Q}$ to perform the corresponding maintenance operations (i.e. PM or replacement); 0, otherwise.
$r_{sq}$ binary parameter: 1, if technician $s \in \mathcal{S}$ has skill $q \in \mathcal{Q}$; 0, otherwise.
$\lambda_{mn}(t)$ hazard rate of machine $m$ at the $n$th cycle
$T'_{mn}$ actual PM interval of machine $m$ at the $n$th cycle
$H_{mn}(t)$ reliability improvement of machine $m$ after the $n$th maintenance operation

*Decision variable*

$w_{sk}$ binary variable: 1, if technician $s \in \mathcal{S}$ is assigned to maintenance team $k \in \mathcal{K}$; 0, otherwise
$x_{ij}^k$ binary variable: 1, if maintenance team $k \in \mathcal{K}$ travel from node $i \in \mathcal{N}$ to node $j \in \mathcal{N}$; 0, otherwise
$y_{im}^k$ binary variable: 1, if machine $m$ of system $i$ is undergoing PM at time epoch $\gamma_{im}^k$; 0, otherwise
$z_{im}^k$ binary variable: 1, if machine $m$ of system $i$ is experiencing replacement at time epoch $\gamma_{im}^k$; 0, otherwise
$\phi_0^k$ continuous variable: departure time of maintenance team $k \in \mathcal{K}$ from the maintenance center
$\gamma_{im}^k$ continuous variable: maintenance start time of machine $m$ in system $i$ that performed by maintenance team $k$

composition of maintenance teams with technicians of different maintenance skills. Hereafter, we refer to this modification of the operational problem as the "improved MPTRP". To control costs, OEMs typically utilize a pool of technicians who are qualified to perform various maintenance and repair activities. We consider a setting where skill levels vary from one technician to another and are related to the maintenance actions being performed. Specifically, we consider two types of maintenance actions. The first is an imperfect preventive maintenance (PM) action and the second is a complete replacement. In our setting, imperfect PMs are assumed to require technicians with a nominal skill level, whereas replacement actions will require more skilled technicians.

Our objectives in this paper are to maintain a high level of quality of service and machine reliability by dispatching appropriate technician teams while controlling the service costs incurred by the OEM. The lessor (OEM in this case) is typically faced with a bi-objective decision problem, maximizing total machine reliability improvement and minimizing total service cost. The traditional approach for solving this problem is to transform this bi-objective problem into a single objective, which is the weighted sum of the two objectives [8]. However, determining the optimal weights of the two objectives is not trivial. Sometimes, the weights may vary based on the priorities of different lessees. For example, some manufacturing enterprises may focus more on machine availability versus reliability. In other words, it is more important to keep the machine running than to minimize the risk of unexpected failure. In contrast, enterprises that manufacture assets that are critical to human safety, such as aircraft engines will tend to give a relatively high priority to reliability and are less driven by maintenance costs [9–10]. Traditional approaches will tend to provide a single solution by optimizing the weights applied to the two objectives discussed earlier. However, one of our goals is to provide multiple solutions that reflect different levels of weight combinations, and thus, provide more flexibility to how we prioritize the two objectives in a flexible manner.

In this paper, we propose a bi-objective maintenance framework specifically designed for the leasehold service network, where OEMs lease multi-unit series production systems to their global client enterprises. For the series production system, once one machine is receiving maintenance operations, the whole system will be shut down. Therefore, one machine predictively maintained or replaced will arise an opportunity for other non-repair machines. Under this context, the proposed framework determines the following decision variables: (1) the scheduled maintenance start time, (2) the appropriate maintenance level (i.e., PM or replacement) for a network of machines, (3) the composition of technician teams subject to constraints controlling the number of technicians per team and their skill levels, and (4) the optimal service route for each team. Based on the obtained Pareto solutions (each solution consists of the four decisions mentioned above), OEMs have the knowledge to arrange a limited pool of technicians with varying skill levels to support O&M services at their customer sites.

With the development of the service-oriented manufacturing mode, the significance of maintenance activities and maintenance management has considerably grown in all sectors of OEMs. It has attracted many researchers to assign in improving cost-effectiveness, availability level, service efficiency, etc. It plays an important role in maintaining availability, reliability levels, and safety requirements by rationalizing the appropriate maintenance policy to reduce system downtimes, increase machine robustness, and minimize maintenance costs. There is a rich body of literature that is dedicated to studying the maintenance outsourcing for leased machines or the production system consisting of multiple leased machines. Ben Mabrouk et al. [11] developed a PM policy for the leased machine that includes a basic warranty and a possible extended warranty period, where the PM interval is obtained by maximizing the lessor's expected total profit. Xia et al. [12] extended the PM management to the multi-unit leased system, where group PM sets are optimized by considering the leasing profit saving to avoid unnecessary system downtime. Zhang et al. [13] proposed a condition-based maintenance policy for the leased system to determine the optimal inspection cycle and PM threshold by considering the lessees' satisfaction and the lessor's market share. Meanwhile, owing to the Internet of Things and sensing technology, system reliability modeling and analysis have become hotspots in the field of maintenance management. Ma et al. [14] developed a condition-based maintenance policy for a two-unit system to maintain its normal operation and minimize the total cost. Wang et al. [15] studied a performance-balanced system operating in a shock environment, and a probabilistic model was derived by a two-step finite Markov chain embedding approach to schedule detailed maintenance actions. it is worth noting that, the reliability models in these studies are used as the constraint rather than the objective function to guide PM scheduling. Meanwhile, existing works develop the preventive maintenance policy for local production systems, which cannot handle the real-life service scenario of multi-factory production systems.

Multi-unit production systems have been geographically leased in different sites, which triggers the requirement to study the service sequencing and routing optimization in maintenance management [16–18]. Mazidi et al. [19] addressed the generation maintenance scheduling for deregulated power systems by taking cost minimization and profit maximization as twin objectives. Li et al. [20] studied an operational problem of restoring the disrupted critical infrastructure composed of geographically distributed machines with multiple maintenance teams. Guastaroba et al. [21] studied the multi-period technician scheduling and routing problem based on a set of jobs requiring services, and each job required a set of skills to be completed. However, these event-based studies mainly focus on the implementation and route planning of predetermined maintenance tasks. In other words, they do not necessarily fit modern manufacturing factories where maintenance scheduling is highly dependent on dynamically evolving degradation predictions. In reality, maintenance schedules optimized based on machine degradation can significantly maximize availability without risking unexpected failures due to the visibility provided by sensor data. Si et al. [22] proposed a service-oriented global optimization model to study the maintenance planning and technician routing problem for multi-location multi-unit production systems. Manco et al. [23] developed a reliability threshold-driven maintenance policy for multi-location multi-unit production systems based on the dynamic criticality analysis. And Akl et al. [24] developed a simulation-optimization framework to determine the optimum frequency of the scheduled machine maintenance and its corresponding technician requirements. As discussed formerly, these maintenance policies often focus mainly on economics, i.e. minimization of total operational (travel, outsourcing, overtime, etc.) costs or maximization of profits. Although economics plays an important role in our studied optimization problem, these traditional objective functions cannot be applied to the problem setting of our improved MPTRP framework.

A multi-objective maintenance scheduling optimization for the multi-unit system was developed by Zhang et al. [25]. Specifically, the maintenance scheduling optimization is formulated as a tri-objective model aiming at minimizing system unavailability, probabilistic risk, and maintenance costs. Jia and Zhang [26] extend the bi-objective maintenance scheduling optimization to multi-location multi-unit production systems. In this paper, they studied the joint optimization of maintenance planning and technician routing for a network infrastructure with the two objectives of minimizing total cost and maximizing reliability. Jafar-Zanjani et al. [27] proposed a bi-objective optimization model to formulate the maintenance planning and scheduling problem for multi-factory production networks, and the objective functions are minimizing maintenance costs and maximizing reliability. The underlying assumption in these studies is that team organizing is predetermined and cannot be changed. The applicability of this assumption is limited in many practical O&M applications. Usually, the utilization efficiency of diverse-skilled technicians may be improved because of dynamic team organizing and proper maintenance schemes. In our approach, we account for variable product-service configurations that need to optimize the multiple maintenance operation scheduling through two optimization perspectives (reliability and economic) to offer a set of Pareto solutions for global OEMs.

To the best of my knowledge, the team organizing and maintenance scheduling under diverse-skilled technician resources have not been appropriately dealt with for geographically distributed systems. Therefore, motivated by the above real-life operational problem of global OEMs, we aim to dynamically compose teams of diverse-skilled technicians, so as to conduct timely maintenance for geographically distributed systems based on their managerial attitudes. To ensure maintenance efficiency and technician utilization, we develop a diverse-skilled technician organizing and routing model (D-STORM). This D-STORM integrates (1) a mapping relationship between technicians with different skills and machine reliability change, and (2) an adaptive optimization model that arranges the holistic scheme for the improved MPTRP. And two optimization objectives are constructed from the perspective of economy and reliability as follows: (1) maximizing the total reliability improvement and (2) minimizing the total service cost. To the best of our knowledge, no other study to date has addressed the improved version of MPTRP that accounts for the composition of the technician team based on their skill levels and maintenance requirements. Therefore, the contributions of this paper can be summarized as follows:

1) We study the improved maintenance planning and technician routing problem (improved MPTRP) faced by OEMs in their daily O&M services. To balance the contradiction of machine reliability improvement and service cost reduction, we develop a bi-objective decision problem to arrange a limited pool of technicians with varying skill levels to perform maintenance schedules for multi-location factories.
2) We develop a diverse-skilled technician organizing and routing model (D-STORM) to formulate the improved MPTRP. The impact of different maintenance operations (i.e. imperfect PM and replacement) on machine reliability and service cost is modeled firstly. After that, we propose the optimization framework to address the following inter-related decisions: (1) the scheduled maintenance start time, (2) the appropriate maintenance level for a network of machines, (3) the composition of technician teams subject to constraints controlling the number of technicians per team and their skill levels, and (4) the optimal service route for each team.
3) To efficiently solve the developed bi-objective model, we develop a hybrid metaheuristic algorithm that is based on a modified k-means algorithm with a two-level simulated annealing algorithm to approximate Pareto-optimal solutions.
4) Based on the improved MPTRP and D-STORM, our proposed maintenance framework provides a set of Pareto solutions to ensure machine reliability by dispatching composed technician teams while controlling service costs. Unlike traditional maintenance policies, our framework is proved to be flexible in two conflicting objectives, making the long-term O&M management of multi-location factories more practical and economical.

The paper is organized as follows. Section 2 describes the improved MPTRP for multi-location factories. Section 3 presents the D-STORM to formulate this problem. Section 4 provides the solution approach and decision-making process for solving D-STORM. Section 5 presents experimentation performed to illustrate the effectiveness of our proposed maintenance framework. Finally, in Section 6, we summarize our findings and present possible extensions.

## 2. Problem description

The goal of this study is to develop a bi-objective optimization model (abbreviated as D-STORM) to solve the improved MPTRP for geographically distributed systems. The objective functions include (1) the maximization of the total reliability improvement and (2) the minimization of the total service cost. The improved MPTRP can be defined on a directed graph $G = (\mathscr{N}, \mathscr{A})$, where $\mathscr{N} = \mathscr{L} \cup \{0\}$ denotes the set of nodes. $\mathscr{L} = \{1, 2, \ldots, L\}$ corresponds to the lessees in different geographical locations, and node 0 corresponds to the maintenance center for technicians and the required spare parts. And $\mathscr{A} = \{(i,j) | i, j \in \mathscr{N}\}$ represents the set of arcs between the nodes. For each arc $(i,j) \in \mathscr{A}$, $t_{ij}$ denotes the travel time from node $i \in \mathscr{N}$ to node $j \in \mathscr{N}$, $c_{ij}$ denotes the corresponding travel cost rate. Let $\mathscr{M}_i = \{1, 2, \ldots, M_i\}$ be the set of leased machines located at lessee $i \in \mathscr{L}$, so that the complete set of leased machines is given by $\mathscr{M} = \cup_{i \in \mathscr{L}} \mathscr{M}_i$. $\mathscr{S} = \{1, 2, \ldots, S\}$ denotes the set of service technicians, and the technician is qualified in certain skill domains. We assume that each team is composed of maximum $v$ technicians and every technician can be assigned to at most one team. $\mathscr{K}$ denotes the set of formed teams. Since the number of teams to be formed is initially unknown, we set the number of teams as $K$. We do not allow empty teams, i.e. there must be at least one technician in every team.

Focusing on the timeliness and diversity of maintenance, this research considers a limited pool of technicians with varying skill levels, and diverse-skilled technicians are distinguished according to the different maintenance operations they can perform. Specifically, we consider two types of maintenance operations: PM and replacement. Therefore, we define the set of technician skills as $\mathscr{Q} = \{1, 2, \ldots, Q\}$. The binary parameter $u_{mq}$ indicates whether machine $m \in \mathscr{M}$ services by the technician with maintenance skill $q \in \mathscr{Q}$ (the level of maintenance operations) and binary parameter $r_{sq}$ indicates whether technician $s \in \mathscr{S}$ has skill $q \in \mathscr{Q}$. In particular, the correspondence between the diverse-skilled technicians and the maintenance level they can implement on the leased machine is unique ($r_{sq} \rightarrow u_{mq}$). This means that, due to maintenance resources and preparation task limitations, technicians can only have one maintenance skill and perform the specified maintenance operation, rather than being able to perform other kinds of maintenance operations.

Based on the above description, the purpose of this paper is to develop a unified prescriptive analytics framework for global OEMs to schedule the maintenance of multi-location factories with a limited pool of technicians with varying skill levels. Considering diverse-skilled technicians and the corresponding maintenance levels (i.e. PM or replacement), we first establish the effect of technician skills on changes in machine reliability. These mapping relationships are later integrated into the D-STORM with two objectives (maximizing the total reliability improvement and minimizing the total service cost), thus forming the vital link between the diverse-skilled technicians and maintenance decision-making. By optimizing the organizing and routing of technician teams that arise alongside the maintenance scheduling for a network of machines, OEMs can select their maintenance scheme according to the emphasis between reliability and economics. Fig. 1 illustrates the main focus and process flow of our proposed maintenance framework.

## 3. Model formulation

In this section, the relationships between different technician skill levels and machine reliability improvements are presented in Section 3.1. And Section 3.2 describes the adaptive optimization model of D-STORM with adaptive decisions and provides the model formulation.

Before the mathematical model is presented, necessary assumptions are first provided:

- MPTRP is an operational problem, we assume that all the time parameters, especially the maintenance duration, as well as the travel time among nodes are integer and deterministic.
- Each machine has an independent and different degradation trend and requires one technician to perform the optimal maintenance action (imperfect PM or replacement).
- Once a maintenance action begins, it will not be interrupted until the maintenance is completed.
- Skill levels vary from one technician to another and are only related to the maintenance actions being performed, and each technician can only have one maintenance skill.
- Travel time between each pair of nodes is related to their geographical distance and varies from node to node.

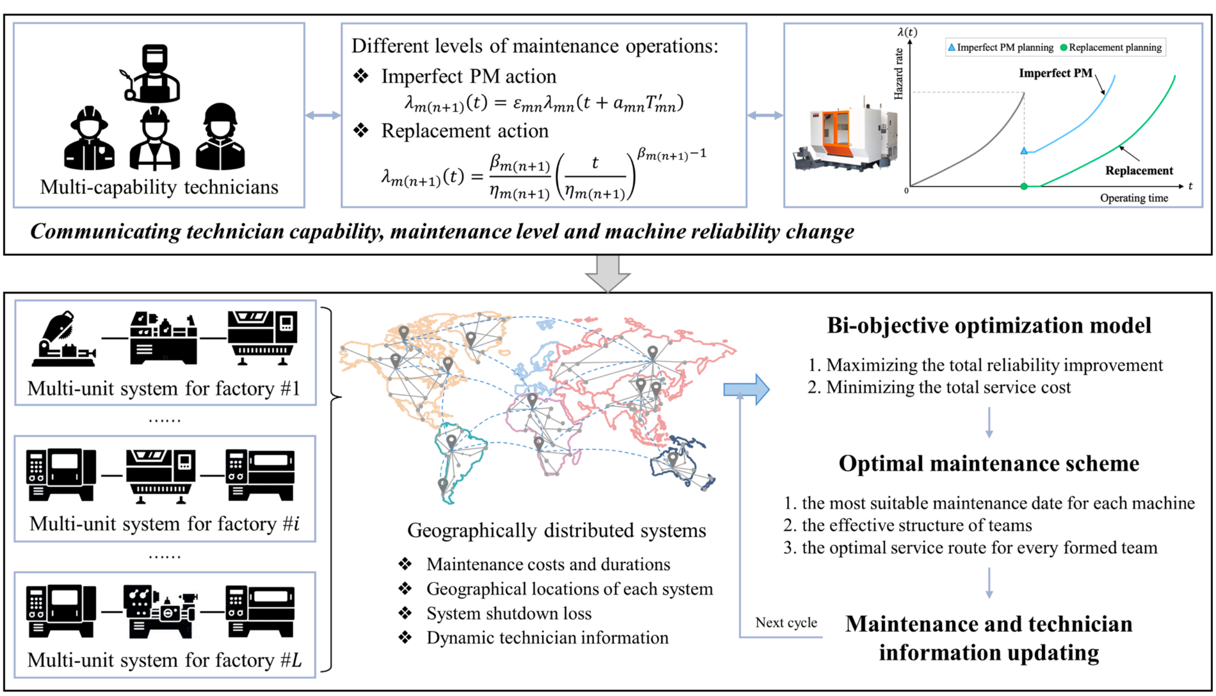


**Fig. 1.** Service-oriented maintenance framework for geographically distributed systems.

- At the beginning of decision-making, all maintenance teams are located at the maintenance center and have the necessary required resources (spare parts and maintenance tools).

### 3.1. Maintenance operations and machine reliability

This research is mainly concerned with the timely and appropriate O&M management for geographically distributed systems under limited technician resources. Without loss of versatility, the hazard rate of machines follows a Weibull distribution, which has been widely used to fit repairable machines and describe the health state in mechanical engineering. Meanwhile, Weibull distribution can simultaneously characterize the "better than old but worse than new" condition after an imperfect PM and the "as good as brand-new" condition after a replacement. And the hazard rate $\lambda_{mn}(t)$ of machine $m$ at the first maintenance cycle ($n = 1$) can be expressed in Eq. (11).

$$\lambda_{mn}(t) = \frac{\beta_{mn}}{\eta_{mn}}\left(\frac{t}{\eta_{mn}}\right)^{\beta_{mn}-1} \tag{1}$$

where $\beta_{mn} > 0$ is the shape parameter, and $\eta_{mn} > 0$ is the scale parameter.

It is well known that the maintenance operation of the current cycle determines the initial condition and distribution of the next cycle. Similar to Jia et al. [26], the effect of different maintenance levels on a machine's reliability is described through a virtual condition model. As shown in Fig. 2, after the $n$th PM action, the initial condition of hazard rate of the $(n+1)$th cycle is less than its calendar condition, thus improving its reliability to varying degrees.

In addition, different maintenance operations not only affect the initial condition of machines but also change the hazard rate distribution for the next cycle. In this paper, we consider a limited pool of technicians with two skill levels. Specifically, for each technician $s \in \mathscr{S}$ dispatched by the global OEM, $q = 1$ represents the PM skill level and $q = 2$ represents the replacement skill level. the relationship between the hazard rate before and after the $n$th maintenance cycle is expressed in Eq. (22).

$$\lambda_{m(n+1)}(t) = \begin{cases} \varepsilon_{mn}\lambda_{mn}\left(t + a_{mn}T'_{mn}\right) & \text{PM} \\ \frac{\beta_{m(n+1)}}{\eta_{m(n+1)}}\left(\frac{t}{\eta_{m(n+1)}}\right)^{\beta_{m(n+1)}-1} & \text{Replacement} \end{cases} \tag{2}$$

where imperfect PM brings the machine to a condition between as-good-as new and as-bad-as old. $\varepsilon_{mn}(\varepsilon_{mn} > 1)$ is the environment factor that captures the effect of the system's environment on the hazard rate, $a_{mn}(0 < a_{mn} < 1)$ is the age reduction factor that shows the initial machine condition $\lambda_{mn}(a_{mn}T'_{mn})$ for the next cycle, and $T'_{mn}$ is the actual PM interval of machine $m$ at the $n$th PM cycle. Replacement makes the repaired machine a brand-new machine, so that the machine obeys a new Weibull distribution for the next cycle.

In general, the machine deteriorates with age, requiring a gradual increase in the frequency of maintenance actions due to the accelerated depreciation. As we mentioned, PM brings the machine to a better state, but starts in not as good as new condition at the next cycle. Replacement is used to restore the machine to its brand-new state. And the time interval between consecutive PM actions is known as PM intervals and has a decreasing trend with increasing the number of maintenance activities performed on the machine. Based on the existing diverse-skilled technician resources, we consider the maintenance sequence optimization to make full use of the limited resources, so as to maximize the overall reliability of multiple leased machines. Therefore, for long-term O&M management, it is essential to find the optimal balance between PM and replacement actions. Fig. 3 represents the idea behind achieving the optimization of the maintenance sequence between PM and replacement actions. As can be seen in Fig. 3, both maintenance scenarios perform three PM actions and one replacement action. And the machine service life with optimizing is significantly longer than that without optimizing.

In this paper, we use variable decision $\gamma_{im}$ to denote the maintenance start time of machine $m$ in lessee $i$. As shown in Fig. 2, the parameters $\gamma_{im}^-$ and $\gamma_{im}^+$ represent the time point before and after the maintenance activities. To mathematically express the impact of maintenance operations on machine reliability, as well as find the optimal balance between PM and replacement actions, we utilize the improvement rate of hazard rate before and after maintenance operations, as described in Eq. (3).

$$H_{mn}(\gamma_{im}) = \lambda_{mn}\left(\gamma_{im}^-\right) - \lambda_{m(n+1)}\left(\gamma_{im}^+\right) \tag{3}$$

Based on the description of machine reliability improvement $H_{mn}(\gamma_{im})$, the relationship between diverse-skilled technicians and the corresponding maintenance effects are established. Meanwhile, different from the individual maintenance decision-making, systemic opportunities arise as a function of the complex economic and degradation interdependencies between machines, thus it remains critical to integrate various maintenance and routing factors into the adaptive optimization model. Similarly, due to different costs and durations of multiple maintenance operations, traditional machine-level cost rate models cannot be used to obtain the scheduled maintenance interval for

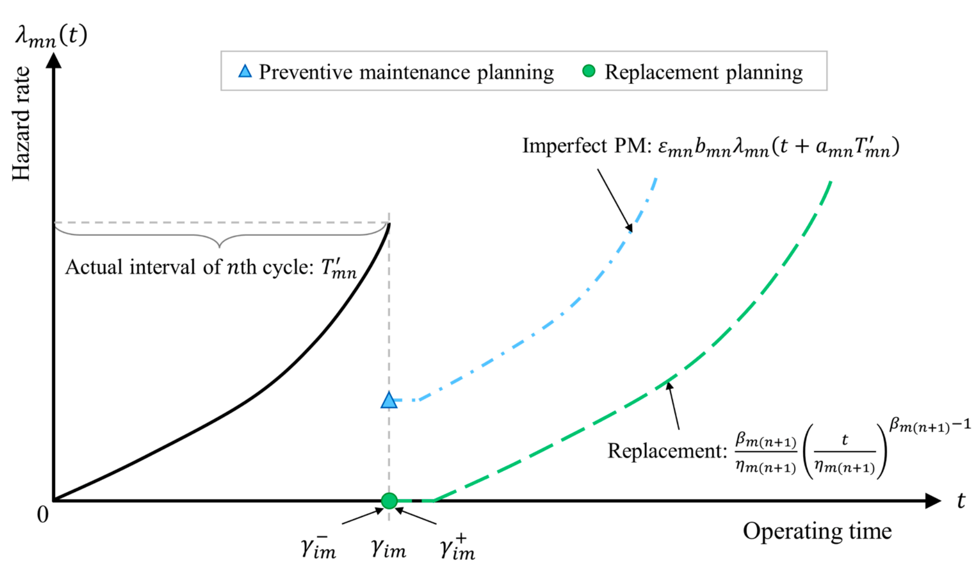


**Fig. 2.** Impact of different maintenance operations on the hazard rate.

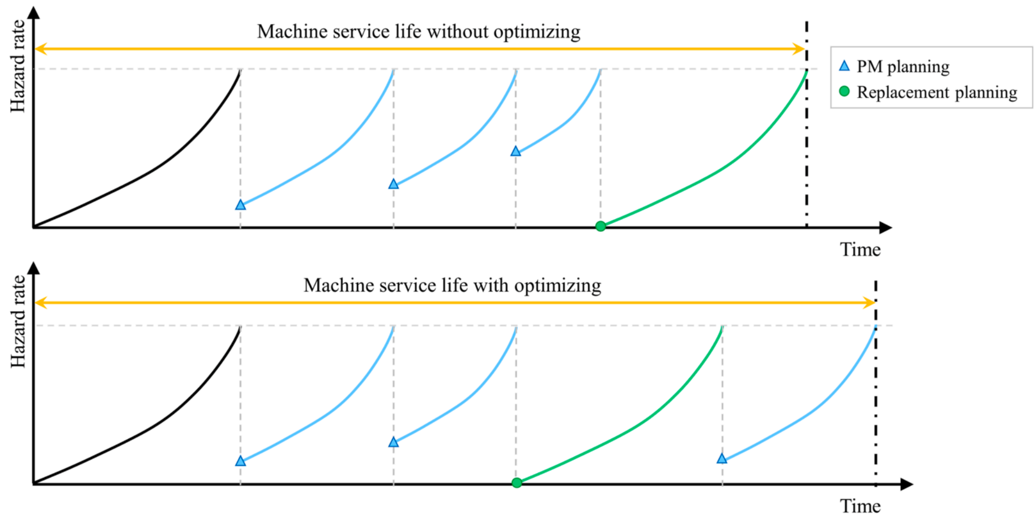


**Fig. 3.** Cyclic maintenance schemes under different maintenance sequences

each leased machine [28]. Therefore, we should not only organize and arrange technician teams but also find out the optimal maintenance level and start time of each machine.

### 3.2. diverse-skilled technician organizing and routing model

In this subsection, we present the mathematical formulation for D-STORM. In this model, we leverage real-time service demands and machine degradation assessment to derive optimal schemes for both the organizing and routing of the lessor's diverse-skilled technicians, as well as the maintenance start time of all the leased machines. We begin by introducing the six main decision variables:

- $w$ defines the *organizing decisions for the lessor's technicians*. Binary variable $w_{sk} = 1$ when technician $s \in \mathscr{S}$ is assigned to maintenance team $k \in \mathscr{K}$, and 0 otherwise.
- $x$ defines the *routing decisions for maintenance teams*. Binary variable $x_{ij}^k = 1$ when maintenance team $k \in \mathscr{K}$ travel from node $i \in \mathscr{N}$ to node $j \in \mathscr{N}$, and 0 otherwise.
- $y$ and $z$ together define the *machine maintenance decisions*. In retrospect, we consider two types of maintenance operations.

  For machine $m$ that is operational at the time of planning, binary variable $y_{im}^k = 1$ when machine $m$ of system $i$ is undergoing preventive maintenance (PM) at the time epoch $\gamma_{im}^k$, and 0 otherwise. Similarly, binary variable $z_{im}^k = 1$ when machine $m$ of system $i$ is experiencing replacement at time epoch $\gamma_{im}^k$, and 0 otherwise.

- Moreover, $\phi$ and $\gamma$ together define the *maintenance start time for machines*. Continuous variable $\phi_0^k$ is the departure time of team $k \in \mathscr{K}$ from the maintenance center. And continuous variable $\gamma_{im}^k$ is the maintenance start time of machine $m$ in system $i$ that is performed by team $k$. Meanwhile, there is a strong correlation between the above two variables, that is, given the departure time and service route of each maintenance team, the maintenance date of each machine can be determined.

There are two objectives: maximizing the total reliability improvement, denoted by $TRI$, and minimizing the total service costs, denoted by $TSC$. For a complete solution $s = (w, x, y, z, \phi, \gamma)$, $TRI(s)$ and $TSC(s)$ are calculated according to Eq. (44) and Eq. (55) respectively.

$$\max\ TRI(\boldsymbol{s}) = \sum_{k\in\mathscr{K}}\sum_{i\in\mathscr{L}}\sum_{m\in\mathscr{M}_i} I_m \cdot H_{mn}\left(\gamma_{im}^k\right) \tag{4}$$

$$\min TSC(\boldsymbol{s}) = \underbrace{\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{L}}\sum_{m\in\mathscr{M}_i}\sum_{s\in\mathscr{S}} y_{im}^k \cdot w_{sk} \cdot C_{im}^{PM} + \sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{L}}\sum_{m\in\mathscr{M}_i}\sum_{s\in\mathscr{S}} z_{im}^k \cdot w_{sk} \cdot C_{im}^{RM}}_{\text{O1) machine maintenance cost}}$$
$$\underbrace{\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{L}} x_{0j}^k \cdot F^k}_{\text{O2) fixed dispatch cost}} + \underbrace{\sum_{k\in\mathscr{K}}\sum_{i\in\mathscr{N}}\sum_{j\in\mathscr{N}} x_{ij}^k \cdot c_{ij} \cdot t_{ij}}_{\text{O3) traveling cost}} + \underbrace{\sum_{k\in\mathscr{K}}\sum_{i\in\mathscr{L}}\sum_{m\in\mathscr{M}_i}\sum_{s\in\mathscr{S}} \max\left\{y_{im}^k \cdot T_{im}^{PM}, z_{im}^k \cdot T_{im}^{RM}\right\} \cdot P_i}_{\text{O4) downtime penalty cost}} \tag{5}$$

Firstly, we begin by elucidating the parameters of the objective function (4). $I_m$ indicates the importance coefficient of machine $m$, which can be derived from the lease contract and the machine importance measures [29]. Specifically, importance measures are extensively used to quantify and rank the importance of different machines within a system. In real-life industrial scenarios, some machines play a more important role in causing or contributing to system failure than others. Important measures are developed to prioritize the machines of a system based on given criteria and can provide guidance for improving system reliability/availability and reducing maintenance costs. In this paper, by considering the importance coefficient $I_m$ as an input parameter into the objective function (4), diverse-skilled technician resources can be allocated based on the prioritization of the machines to maximally improve the total reliability improvement. And $H_{mn}(t)$ defines the reliability improvement that machine $m$ is operational at time $t$ after the $n$th maintenance operation.

Then, we introduce the parameters of the objective function (5). The term $C_{im}^{PM}$ is the cost associated with preform a PM action, and $C_{im}^{RM}$ is the cost for conducting replacement. $F^k$ defines the cost of dispatching maintenance team $k$ from the maintenance center, and this term captures the delicate balance between individual maintenance and group maintenance. $c_{ij}$ and $d_{ij}$ denote the travel cost rate, and the travel time from node $i$ to node $j$, respectively. $P_i$ is the penalty per unit time for performing maintenance in factory $i$. $T_{im}^{PM}$ and $T_{im}^{RM}$ represent the maintenance duration of the PM action and replacement action, respectively. As mentioned above, to perform maintenance operations on the leased machine, technician teams and spare parts must be transported from the maintenance center to the lessee factory where the leased machines are located. Meanwhile, planned maintenance decisions can lead to system downtime. Therefore, the objective function (5) has four main parts to the lessor's expenditures:

O1) Machine maintenance cost is the cost of performing maintenance for machine $m$ by technician $s \in \mathscr{S}$ with different skills. As far as we know, different maintenance levels require different expenses. For example, a replacement action requires the purchase of a new component that is used to replace the old one. It is reasonable to consider that the higher the technician skill level is required, the more expensive the maintenance cost is.

O2) Fixed dispatch cost is a cost associated with technician visits due to the required deployment of technician teams and spare parts. While doing so, the higher the dispatch cost is, the more aggressively the optimization model will try to group the maintenance of machines;

O3) Traveling cost is paid for the transportation of technician teams, spare parts, and repair tools from node $i$ to node $j$. When several machines of the same factory or different factories are jointly maintained, the optimized service routes will form a closed loop, starting from the maintenance center and finally returning to the maintenance center;

O4) Downtime penalty cost occurs when factory $i$ is stopped during the maintenance of machine $m$. Considering each production system consists of multiple machines in series, the dependence between machines indicates that the maintenance duration of each group set is not equal to the cumulative maintenance duration of all the machines in isolation, but equal to the maximum duration.

After describing the objective functions of D-STORM, we further provide and explain model constraints as follows:

$$\sum_{j\in\mathscr{L}} x_{0j}^k = \sum_{i\in\mathscr{L}} x_{i0}^k \le 1 \ \forall k \in \mathscr{K} \tag{6}$$

$$\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{N}} x_{ij}^k = \sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{N}} x_{ji}^k \ \forall i \in \mathscr{L} \tag{7}$$

$$\sum_{k\in\mathscr{K}}\sum_{j\in\mathscr{L}} x_{0j}^k \le K \tag{8}$$

$$\sum_{i\in\mathscr{L}}\sum_{m\in\mathscr{M}_i} y_{im}^k + \sum_{i\in\mathscr{L}}\sum_{m\in\mathscr{M}_i} z_{im}^k \le \sum_{s\in\mathscr{S}} q_s w_{sk} \ \forall k \in \mathscr{K} \tag{9}$$

$$\sum_{s\in\mathscr{S}} q_s w_{sk} \le U_k \ \forall k \in \mathscr{K} \tag{10}$$

$$\sum_{k\in\mathscr{K}} y_{im}^k + \sum_{k\in\mathscr{K}} z_{im}^k = 1 \ \forall i \in \mathscr{L}, \forall\, m \in \mathscr{M}_i \tag{11}$$

$$\sum_{k\in\mathscr{K}} w_{sk} \le 1 \ \forall s \in \mathscr{S} \tag{12}$$

$$0 < \sum_{s\in\mathscr{S}} w_{sk} \le v \ \forall k \in \mathscr{K} \tag{13}$$

$$u_{mq} y_{im}^k + u_{mq} z_{im}^k \le \sum_{s\in\mathscr{S}} r_{sq} w_{sk} \ \forall m \in \mathscr{M}_i, \forall i \in \mathscr{L}, \forall k \in \mathscr{K}, \forall q \in \mathscr{Q} \tag{14}$$

$$\exp\left[-\left(\frac{\gamma_{im}^k}{\eta_{mn}}\right)^{\beta_{mn}}\right] \ge l_m, \ \forall k \in \mathscr{K}, \forall j \in \mathscr{L}, \forall m \in \mathscr{M}_i \tag{15}$$

$$\gamma_{jm}^k = x_{0j}^k \cdot y_{jm}^k \cdot \left(\phi_0^k + t_{0j}\right) + x_{0j}^k \cdot z_{jm}^k \cdot \left(\phi_0^k + t_{0j}\right) \ \forall k \in \mathscr{K}, \forall j \in \mathscr{L}, \forall m \in \mathscr{M}_j \tag{16}$$

$$\gamma_{jm}^k = \sum_{i\in\mathscr{L}}\sum_{m'\in\mathscr{M}_i} x_{ij}^k \cdot \left[\gamma_{im'}^k + \max\left\{y_{im}^k \cdot T_{im}^{PM}, z_{im}^k \cdot T_{im}^{RM}\right\} + t_{ij}\right] \ \forall k \in \mathscr{K}, \forall j \in \mathscr{L}, \forall m \in \mathscr{M}_j \tag{17}$$

$$LP_j > \gamma_{jm}^k > 0 \ \forall k \in \mathscr{K}, \forall j \in \mathscr{L}, \forall m \in \mathscr{M}_j \tag{18}$$

$$\phi_0^k > 0 \ \forall k \in \mathscr{K} \tag{19}$$

$$w_{sk}, x_{ij}^k, y_{im}^k, z_{im}^k \in \{0,1\} \ \forall s \in \mathscr{S}, \forall k \in \mathscr{K}, \forall i,j \in \mathscr{N}, \forall m \in \mathscr{M}_i \tag{20}$$

Constraints (6) guarantee that each organized maintenance team must leave and finally arrive at the maintenance center. Constraints (7) ensure that each team entering the system node should also depart from the same node. Constraints (8) state that the number of dispatched teams is not greater than the total number of formed technician teams. Constraints (9) are maintenance capacity constraints, which limit the number of maintenance operations (including PM and replacement) to be conducted by maintenance team $k$. Constraints (10) limit the maximum number of leased machines that the team $k \in \mathscr{K}$ can maintain. Constraints (11) ensure that each machine $m \in \mathscr{M}_i$ of factory $i \in \mathscr{L}$ is maintained by exactly one maintenance team and only once in the $n$th cycle. Constraints (12) state that technicians can be assigned to at most one maintenance team. Constraints (13) limit the minimum and the maximum number of technicians in each maintenance team. Constraints (14) ensure the compatibility of skill levels between technician teams and the machine they maintained. Constrains (15) limit the lower bound of machine reliability to ensure the operation requirement and avoid the increasing rate of unexpected failures. Constraints (16) and (17) give the formula for calculating the time variable $\gamma_{jm}^k$ (maintenance start time point of machine $m$ belonging to factory $j$). If the maintenance team services factory $j$ directly after leaving the maintenance center, the maintenance start time $\gamma_{jm}^k$ can be obtained from Eq. (16), which is equal to the departure time $\phi_0^k$ plus the travel time $t_{0j}$. And if the maintenance team visits factory $j$ after leaving other factory $i$, the maintenance start time $\gamma_{jm}^k$ can be acquired from Eq. (17), which is equal to the maintenance start time of the previously serviced factory $i$ plus the system downtime due to maintenance activities and the travel time. Constraints (18) restrict the range of variable $\gamma_{im}^k$, the maintenance start time is a positive number and earlier than the lease period of factory $i$. Finally, constraints (19) and (20) define the domains of the other variables.

The optimality of bi-objective optimization problems is understood in the sense of Pareto optimality, and the resolution of bi-objective optimization problems lies in the identification of all elements belonging to the Pareto or efficient set, containing all alternative solutions that are not dominated by any other alternative solution. Therefore, for the proposed D-STORM, a feasible solution $s_1$ is said to dominate another feasible solution $s_2$, if and only if both Rule 1 and Rule 2 hold:

$$TRI(s_1) \ge TRI(s_2) \ \wedge \ TSC(s_1) \le TSC(s_2) \tag{Rule1}$$

$$TRI(s_1) > TRI(s_2) \ \vee \ TSC(s_1) < TSC(s_2) \tag{Rule2}$$

In general, a solution $s_1$ dominates another solution $s_2$, if $s_1$ is at least as good as $s_2$ for all objectives and strictly better than $s_2$ for at least one objective. And a feasible solution is said to be Pareto-optimal (or efficient), if it is not dominated by any other feasible solutions. The Pareto-optimal set is the set of all Pareto-optimal solutions.

## 4. Two-phase solution approach

The main goal of this section is to develop a solution approach to solve the improved maintenance planning and technician routing problem (improved MPTRP). Towards this goal, a two-phase solution approach is developed based on a modified k-means clustering algorithm and a two-level simulated annealing (TSA) algorithm. This hybridization aims to develop a solution approach that is powerful in terms of diversification (global search) and intensification (local search) and intelligently learns information during the optimization process [30,31]. On the one hand, with the development of deep learning, some studies tend to solve group maintenance by classifying the maintenance tasks into clusters based on their similarity or diversity to ensure the diversification of initial auxiliary solutions [32,33]. On the other hand, the Pareto simulated annealing algorithm has been widely utilized to solve multi-objective combinatorial optimization problems, and has been shown to be capable of yielding high-quality solutions in real-time [34, 35]. It has been shown that if the annealing rate is slow enough, the Pareto simulated annealing algorithm converges to the global optimum. Additionally, it has been observed that good results are obtained even with reasonably rapid cooling rates. The modified k-means algorithm is proposed to combine the geographically contiguous and time adjacent maintenance into the same group to reduce search scope and generate initial auxiliary solutions in Section 4.1. Then, starting from the initial auxiliary solution, the TSA algorithm is proposed to strengthen solutions and obtain the set of non-dominated solutions in Section 4.2.

### 4.1. Phase 1: initial auxiliary solution construction

To implement the D-STORM, the first essential issue is to appropriately encode a complete solution $s = (w, x, y, z, \phi, \gamma)$ of the improved MPTRP. This is done with three vectors: machine vector $\boldsymbol{\mu} = (\mu_1, \mu_2, \ldots, \mu_M)$, team vector $\boldsymbol{\kappa} = (\kappa_1, \kappa_2, \ldots, \kappa_K)$ and technician vector $\boldsymbol{\rho} = (\rho_1, \rho_2, \ldots, \rho_S)$. More specifically, $\mu_m (m = 1, 2, \ldots, M)$ denotes the $m$th machine to be maintained, $\kappa_m$ denotes the maintenance team visiting the $m$th machine. And $\rho_m$ denotes the technician with the corresponding skill level to perform the relevant maintenance operation (i.e. PM or replacement) for the $m$th machine. Therefore, a complete solution can be represented by a tuple $\boldsymbol{\pi} = (\boldsymbol{\mu}, \boldsymbol{\kappa}, \boldsymbol{\rho})$.

For the purpose of illustration, an encoding example of a complete solution is described in Fig. 4. In this example, the OEM builds a maintenance center and forms several maintenance teams to conduct maintenance operations for four manufacturing factories. And each factory owns three machines working in series. Based on a given tuple of three vectors $(\boldsymbol{\mu}, \boldsymbol{\kappa}, \boldsymbol{\rho})$ and the skill level parameter $r_{sq}$ of each technician, the maintenance level of each machine can be determined. As shown in Fig. 4, this complete solution indicates that team 1 is composed of technicians 2 and 3 with the replacement skill level. And team 1 first travels to Lessee 4 and performs a replacement action for machine 11. Then, team 1 travels to Lessee 2 and performs the replacement action for machine 2. After that, team 1 continues to the corresponding lessees to perform replacement actions. Finally, they return to the maintenance center after completing all maintenance operations. This complete solution also indicates that team 2 is composed of technicians 1 and 3 with the PM skill level. Team 2 also completes PM actions in sequences as shown in Fig. 4 and finally returns to the maintenance center. Therefore, we can obtain the composition of diverse-skilled technicians and maintenance schemes for a network of machines.

In the improved MPTRP, assigning maintenance tasks with similar maintenance requirements and geographical proximity to the same team is desirable, as it contributes to cost-saving and operational efficiency. However, different from the traditional technician routing problem based on the given service demands, machine degradation needs to be considered to guide the establishment of initial solutions. Meanwhile, the maintenance capacity of each team and the maximum number of machines they can maintain at one dispatch strictly limit the number of serviced machines. Therefore, to obtain the high-quality initial auxiliary solution, we propose a k-means clustering with capacity constraint to classify the maintenance requirements into clusters based on the limitation of machine reliability and team capacity. The detailed steps are presented in Algorithm 1 and Fig. 5.

Specifically, as shown in Fig. 5(b), each node represents a leased machine. The three-dimensional coordinates of each node represent the abscissa value $x_m$ (X-axis), the ordinate value $y_m$ (Y-axis) and the reliability-oriented maintenance requirement $T_m^{R_{mn}(t)=l_m}$ (Z-axis), respectively. The reliability-oriented maintenance requirement of each machine is obtained through the reliability function $R_{mn}(t)$ and reliability constraint $l_m$, as shown in Fig. 5(a). And the reliability of machine $m$ at the current $n$th cycle is calculated in Eq. (2121).

$$R_{mn}(t) = \exp\left[-\left(\frac{\gamma_{im}^{k}}{\eta_{mn}}\right)^{\beta_{mn}}\right] \tag{21}$$

Each cluster represents the machines served by the corresponding team under the limitation of team service ability. And the minimal number of clusters can be eliminated through $K^{\min} = |\mathscr{M}|/U_k$. Then, as shown in Fig. 5(c), the clustering results are transformed into machine vectors $\boldsymbol{\mu}$ and team vectors $\boldsymbol{\kappa}$ to continue solution construction. Based on machine-team matching results, we generate machine vectors in the order of smallest to largest maintenance requirements. Finally, the initial auxiliary solution $(\boldsymbol{\mu}^a, \boldsymbol{\kappa}^a)$ including the machine vector and team vector outputted.

### 4.2. Phase 2: two-level simulated annealing algorithm

Based on the initial auxiliary solution, Phase 2 designs two-level simulated annealing (TSA) algorithm to address our bi-objective maintenance scheduling problem of geographically distributed systems to

**Algorithm 1**
Modified k-means algorithm for initial auxiliary solution construction.

**Input:** $\mathscr{M}$: a set of machine nodes, $(x_m, y_m, T_m^{R_{mn}(t)=l_m})$: three-dimensional coordinates of node $m \in \mathscr{M}$
Construct initial clusters by setting $K$ cluster centers and assigning nodes to clusters randomly
**while** termination criteria not satisfied **do**
**for** each node $m \in \mathscr{M}$ **do**
Calculate $d_{mc}$ (Euler distance between node $m$ and cluster $c$) for each $c = 1, 2, \ldots, K$
Assign node $m$ to cluster $c^*$, where $c^* = \mathrm{argmin}_{c=1,2,\ldots,K} d_{mc}$ and satisfy the capacity constraint
**end for**
Calculate the centroids for the next iteration
**end while**
Construct initial auxiliary solution (machine vector and team vector) based on clustering results
**Output:** an initial auxiliary solution $(\boldsymbol{\mu}^a, \boldsymbol{\kappa}^a)$

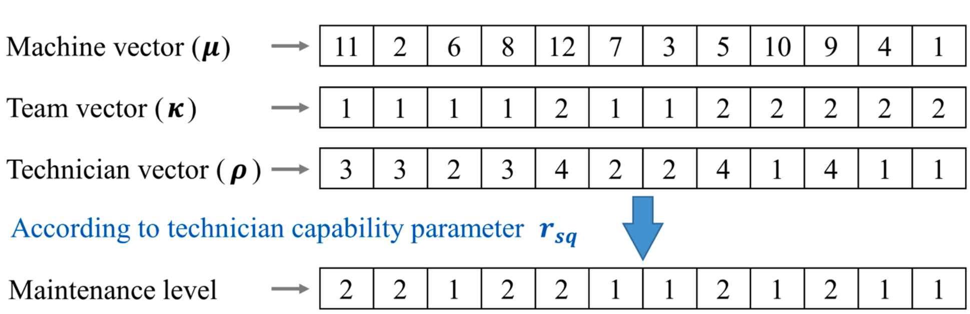


**Fig. 4.** An example of the encoding of a solution.

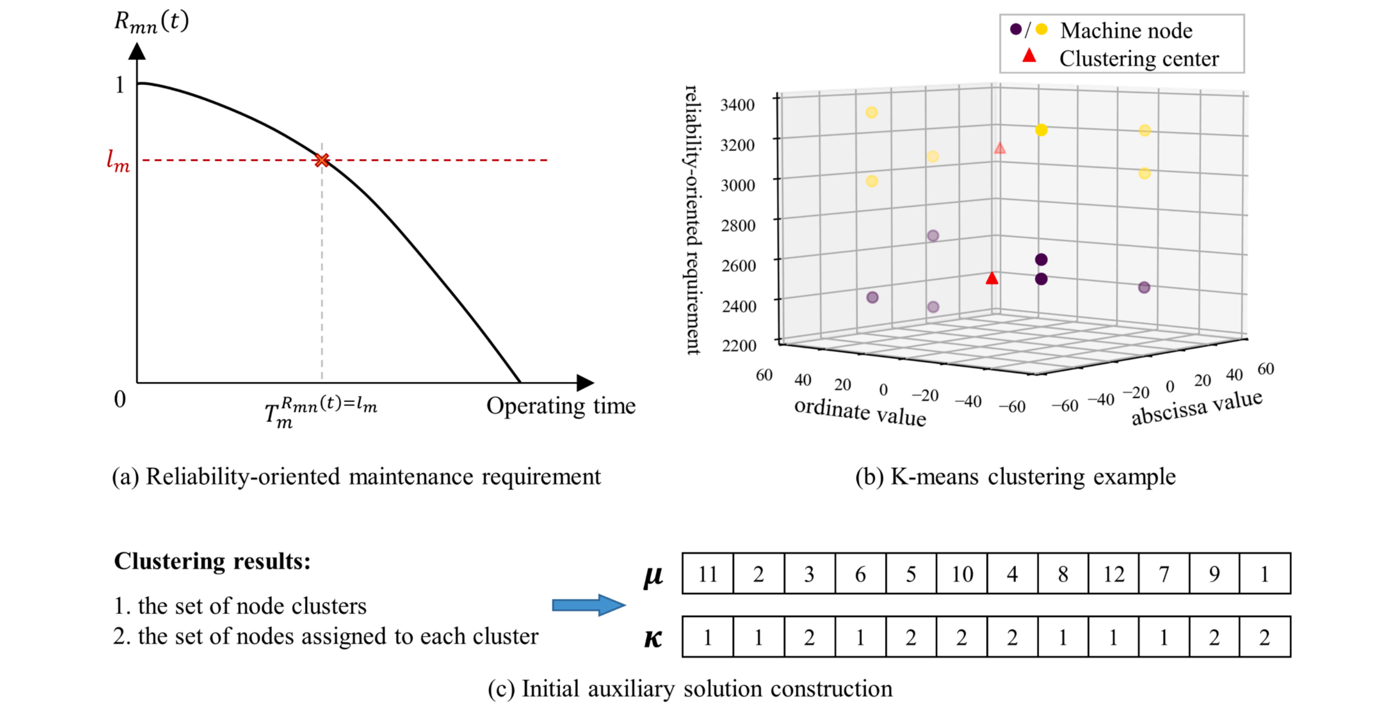


**Fig. 5.** Specific steps of maintenance operation clustering.

obtain a set of non-dominated Pareto solutions. In TSA, the first level aims to generate the service route of each team through the initial auxiliary solution ($\boldsymbol{\mu}^a$, $\boldsymbol{\kappa}^a$). Based on the service route generated in the first level, the second level aims to find the optimal maintenance level (equal to the technician composition with the specified skill) for each machine to obtain the complete solution ($\boldsymbol{\mu}^a$, $\boldsymbol{\kappa}^a$,$\boldsymbol{\rho}$). In the process of the TSA algorithm, it is necessary to determine the acceptance criteria of the new solution. We keep a newly generated solution $\boldsymbol{\pi}'$ if it dominates the current solution $\boldsymbol{\pi}$ based on Rule 1 and Rule 2. Otherwise, $\boldsymbol{\pi}'$ is kept with the acceptance probability $P(\boldsymbol{\pi}, \boldsymbol{\pi}', \boldsymbol{Te})$ calculated from Eq. (22) to avoid trapping into local optimization. Specifically, the initial acceptance probability is high, so even worse solutions have a good chance of being accepted, while ensuring that TPA does not get stuck in any local optimum. In the later stages of the search, the probability of accepting worse solutions decreases and TPA becomes more greedy to focus the search on the potentially optimal regions of the search space.

$$P(\boldsymbol{\pi}, \boldsymbol{\pi}', \boldsymbol{Te}) = \exp\left( - \frac{|TRI(\boldsymbol{\pi}) - TRI(\boldsymbol{\pi}')| + |TSC(\boldsymbol{\pi}) - TSC(\boldsymbol{\pi}')|}{Te} \right) \tag{22}$$

where $TRI(\boldsymbol{\pi}) - TRI(\boldsymbol{\pi}')$ and $TSC(\boldsymbol{\pi}) - TSC(\boldsymbol{\pi}')$ denote the difference between the values of objective 1 and objective 2, respectively. And $Te$ is the current annealing temperature.

Moreover, to extend the search scope, we generate neighborhood solutions during each cycle. In the first level, we generate $N_1$ neighborhood solutions by randomly selecting two different points in $\boldsymbol{\mu}^a$ and exchanging their stations. And in the second level, based on each service route (arranged through vectors $\boldsymbol{\mu}$ and $\boldsymbol{\kappa}$) generated in the first level, we further randomly generate the technician vector $\boldsymbol{\rho}$ while limiting the total number of machines they can maintain. Similarly, we randomly select two points in $\boldsymbol{\rho}$ and exchange the two maintenance operations to obtain a newly generated solution $\boldsymbol{\pi}'$ at the second-level cycle. Finally, the set of non-dominated Pareto solutions $\mathscr{V}$ is obtained. The entire procedure of the TSA is presented in Algorithm 2.

Furthermore, among various dominance comparison mechanisms, nondominated sorting has been shown to be very effective for finding Pareto-optimal solutions [36]. And non-dominated sorting is a procedure where solutions are assigned to different fronts based on their dominance relationships. In the final step of Algorithm 2, an efficient nondominated sort using a sequential search (ENS-SS) strategy is utilized to output the set of non-dominated Pareto solutions $\mathscr{V}$. We assume that the individuals in the population can be categorized into $R$ Pareto fronts, denoted as $F_r$, $r = 1, \ldots, R$. For solution $\boldsymbol{\pi}$, the ENS-SS checks at first whether there exists a solution that has been assigned to the first front $F_1$ and dominates $\boldsymbol{\pi}$. If such a solution does not exist, assign $\boldsymbol{\pi}$ to front $F_1$. If $\boldsymbol{\pi}$ is dominated by any solution in $F_1$, start comparing $\boldsymbol{\pi}$ with the solutions assigned to $F_2$. If no solution in front $F_2$ dominates $\boldsymbol{\pi}$, assign $\boldsymbol{\pi}$ to front $F_2$. If $\boldsymbol{\pi}$ is not assigned to any of the existing fronts, create a new front and assign $\boldsymbol{\pi}$ to this new front. Note that if $r < r'$, solutions belonging to front $F_{r'}$ are dominated by at least one solution belonging to front $F_r$.

## 5. Numerical experiments

We design a series of numerical experiments to validate the effectiveness and performance of the proposed bi-objective optimization model and solution approach for the maintenance scheduling of geographically distributed systems.

### 5.1. Data settings

To illustrate the D-STORM and show the effectiveness of the proposed bi-objective maintenance framework in a real manufacturing environment, the parameters are estimated by the lessor's engineers and listed in Tables 1 and 2. The global OEM is responsible for the O&M

**Table 1**
Travel time between maintenance center and multi-location factories.

| Starting node | Ending node Center | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Center | - | 8 | 7 | 10 | 7 |
| 1 | 8 | - | 13 | 15 | 4 |
| 2 | 7 | 13 | - | 13 | 11 |
| 3 | 10 | 15 | 13 | - | 17 |
| 4 | 7 | 4 | 11 | 17 | - |

**Table 2**
Reliability and maintenance parameter values for each machine.

| Lessee | Machine | $\beta_m$ | $\eta_m$ | $\varepsilon_m$ | $a_m$ | $I_m$ | Maintenance cost ($) | | Maintenance duration (h) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | PM | Replacement | PM | Replacement |
| 1 | 1 | 2.59 | 5900 | 1.045 | 0.187 | 1430 | 3600 | 9400 | 10 | 5 |
| | 2 | 1.81 | 5400 | 1.024 | 0.304 | 1090 | 4000 | 8000 | 9 | 14 |
| | 3 | 2.75 | 5100 | 1.042 | 0.428 | 1160 | 5400 | 8500 | 10 | 13 |
| 2 | 4 | 2.90 | 5400 | 1.019 | 0.329 | 1000 | 4600 | 10200 | 11 | 15 |
| | 5 | 2.73 | 5200 | 1.022 | 0.339 | 1370 | 4100 | 8600 | 19 | 9 |
| | 6 | 2.01 | 5100 | 1.049 | 0.223 | 1440 | 4200 | 7000 | 8 | 11 |
| 3 | 7 | 2.43 | 5000 | 1.026 | 0.197 | 1240 | 3800 | 9900 | 20 | 6 |
| | 8 | 2.06 | 5400 | 1.015 | 0.373 | 1360 | 4300 | 7500 | 9 | 12 |
| | 9 | 3.04 | 5400 | 1.031 | 0.438 | 1190 | 3700 | 11100 | 8 | 9 |
| 4 | 10 | 2.41 | 5700 | 1.045 | 0.26 | 1120 | 4800 | 7700 | 16 | 9 |
| | 11 | 1.85 | 5100 | 1.053 | 0.417 | 1140 | 4700 | 9400 | 18 | 11 |
| | 12 | 2.10 | 5400 | 1.019 | 0.442 | 1100 | 5500 | 9400 | 18 | 13 |

service of four lessee factories, and each factory contains three leased machines working in series. The reliability parameters of each leased series system are determined from the historical failures of different computer numerical control (CNC) machines including lathe, drilling, milling, surface grinding, and welding in a manufacturing setting. In addition to the reliability parameters, costs and durations of imperfect PM and replacement actions are estimated from the recorded previous operations.

For this case study, the travel cost rate $c_{ij}$ is set to $400/h and the deployment cost $F^k$ for dispatching technician teams is set to $20,000/time. Once a machine is scheduled to be maintained, a pressing issue for lessees is to ensure that the machine is restored as soon as possible. Thus, the downtime penalty cost rate $P_i$ is set to $500/h. To express the limited maintenance capacity for teams, the maximum number of technicians in each maintenance team is set to 2. The maximum number of machines that each technician can maintain is 3. And the machine reliability limitation is set to 0.80 according to the minimum machine reliability requirements of the lease contract. Meanwhile, we assume that there are four technicians responsible for the O&M service of multi-location systems, two have the PM skill level, and the other possesses the replacement skill level ($\mathcal{O} = [1, 1, 2, 2]$).

### 5.2. Output of targeted maintenance scheme through non-dominated solutions

To obtain the holistic maintenance scheme for geographically distributed systems and team composition solutions for diverse-skilled technicians, our bi-objective maintenance framework seamlessly integrates machine degradation evolutions, diverse-skilled technician composition, and service route optimization. Firstly, D-STORM is constructed based on the input parameters as described in Section 5.1. After building this bi-objective optimization model, initial auxiliary solutions are generated through a modified k-means algorithm. Then, starting from the initial auxiliary solution, the TSA algorithm is applied to improve the quality of solutions. Finally, by applying the ENS-SS to process nondominated sorting, the 10 non-dominated Pareto solutions as shown in Fig. 6. Specifically, these 10 solutions are the solutions in the final archive population that are not dominated by any other solutions and can be used as the final maintenance scheme. And the corresponding total reliability improvement and total service cost respectively are listed in Table 3.

To clearly explain the detailed O&M information about solutions, we use solution 5 as an example to show and illustrate the global maintenance scheme, as shown in Table 4. This solution indicates that OEM builds two teams to ensure the normal operation of four lessee factories. Team 1 consists of two technicians with the PM skill level, and Team 2 holds the remaining two technicians with the replacement skill level. Starting from the maintenance center, team 1 first travels to lessee 3 and lessee 1 to perform PM actions for machines 7 and 2 in turn. Then, team 1 travels to lessee 2 and conducts PM action for machine 6 at the 1561h. After that, this team travels to lessee 3 at 1582h and performs the PM action for machine 8. Finally, after completing the PM actions of

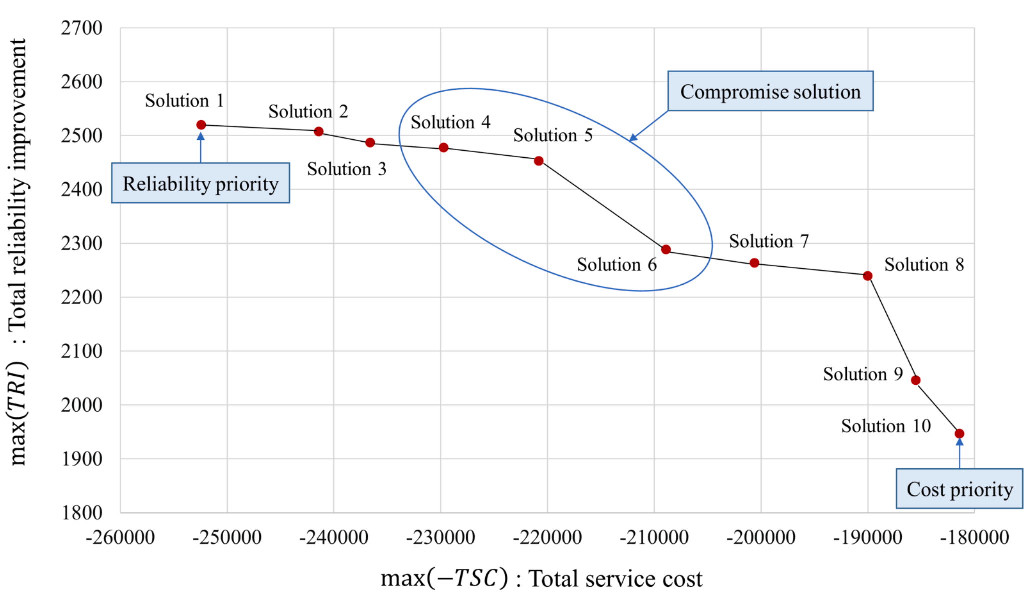


**Fig. 6.** Non-dominated Pareto solutions under general O&M services.

**Table 3**
Two objectives of Non-dominated Pareto solutions.

| Solution | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| *TRI* | 2519.7 | 2507.5 | 2486.7 | 2477.3 | 2453.0 | 2288.4 | 2263.3 | 2239.1 | 2045.7 | 1946.8 |
| *TSC*($) | 252400 | 241400 | 236600 | 229700 | 220800 | 208900 | 200600 | 190000 | 185500 | 181400 |

**Table 4**
Detailed O&M information of solution 5.

| Team 1 | | | | Team 2 | | | |
|---|---|---|---|---|---|---|---|
| Lessee | Machine | Maintenance date | Maintenance operation | Lessee | Machine | Maintenance date | Maintenance operation |
| 3 | 7 | 1517 | PM | 2 | 4 | 1521 | replacement |
| 1 | 2 | 1544 | PM | | 5 | 1521 | replacement |
| 2 | 6 | 1561 | PM | 4 | 10 | 1545 | replacement |
| 3 | 8 | 1582 | PM | 1 | 3 | 1564 | replacement |
| 4 | 12 | 1604 | PM | 3 | 9 | 1584 | replacement |
| | 11 | 1604 | PM | 1 | 1 | 1600 | replacement |

machines 12 and 11 in lessee 4, team 1 returns to the maintenance center. Similarly, team 2 is dispatched to conduct the replacement actions for the other machines, and returns to the maintenance center after finishing all maintenance activities.

Moreover, as shown in Fig. 6, it can be noted that the curve representing the relationship between the total reliability improvement and the total service cost is convex. This further proves the competitive relationship between the two objectives, which shows that with the increase in reliability, further reliability improvement will cost more. At the same time, this also shows the marginal diminishing effect of the OEM in daily O&M management. For instance, from solution 1 to solution 5, the total reliability improvement *TRI* is decreased from 2519.7 to 2453.0, whereas the total service cost *TSC* decreased from $252400 to $220800. And the decreasing rates of the two objectives are 2.65% and 12.52%, respectively. Similarly, from solution 5 to solution 10, the total reliability improvement *TRI* is decreased from 2453.0 to 1946.8, whereas the total service cost *TSC* is decreased from $220800 to $181400. And the growth rates of the two objectives are 20.64% and 17.84%, respectively.

### 5.3. Decision-making guidance under different managerial perspectives

To balance the contradiction of machine reliability improvement and service cost reduction, we develop the bi-objective maintenance framework to arrange a limited pool of technicians with varying skill levels to provide maintenance services for multi-location factories. The key for global OEMs to provide effective services under different managerial perspectives is first to accurately assess the machine's degradation. Moreover, according to different priorities, we need to further compose technicians with different maintenance skill levels into several teams, identify opportunities to dispatch teams, and perform suitable maintenance operations (imperfect PM or replacement) along appropriate routes. Therefore, based on the obtained non-dominated Pareto solutions, we can provide the decision-making guidance on the outsourcing maintenance service for global OEMs in the fuzzy practice environment. We summarize maintenance scheme instructions under different managerial perspectives as follows:

(1) If the outsourcing maintenance service of lessee enterprises requires a cost priority scheme, it means that the OEMs are inclined to optimize the total service cost by sacrificing the achievement of reliability improvement. As long as machine reliability does not exceed the tolerance that would influence the basic availability, the OEM is willing to adopt a lower-cost solution, albeit with not high but acceptable reliability improvement. Specifically, solution 10 with the lowest total service cost *TSC* $181400 and the reliability improvement *TRI* 1946.8 (the dot on the bottom right corner in Fig. 6) can be chosen to arrange the corresponding maintenance scheme under the cost priority. Based on the selected solution 10, the cost-oriented OEMs can arrange the detailed O&M information, and arrange technician teams to perform the corresponding maintenance activities for multi-location lessees along the optimal service sequence.

(2) In contrast, lessee enterprises selling capital-intensive products (e.g., aircraft engines, wind turbines, and oil pipelines) will focus on reliability and be less sensitive to costs. Therefore, if the outsourcing maintenance service of lessee enterprises requires a reliability priority scheme, i.e., satisfying lessee performance outcomes is more important to the OEM and there is a sufficient outsourcing maintenance budget, the Pareto-optimal solution in the top left corner of Fig. 6 is the best choice for maintenance scheme. In other words, for these reliability-oriented OEMs, as long as the cost is not over budget, a higher reliability improvement can be expected. Based on the above analysis, solution 1 with the highest reliability improvement 2519.7 and the total service cost $252400 can be chosen to arrange the corresponding maintenance scheme under the reliability priority.

(3) Further, in addition to the two OEM management perspectives described above, which have a clear priority bias, there is also a management bias. If reducing the total service cost and increasing the total reliability improvement are both crucial targets for the OEM's outsourcing maintenance services, compromise solutions that attempt to satisfy both targets are needed. The compromise solutions are marked by the blue circle in Fig. 6. It shows that the compromise solutions fall in between the cost priority and reliability priority solutions. And the detailed O&M information of solution 5 to guide the maintenance decision-making is listed in Table 4.

In sum, no matter what managerial perspectives OEMs/decision-makers have for the outsourcing maintenance service of geographically distributed systems, Pareto-optimal solutions obtained from the D-STORM and the two-phase solution approach can provide adequate alternative satisfying maintenance schemes. Moreover, in actual industrial sites, failures are gradually accumulated damage with aging, thus affecting the machine reliability. Therefore, for the long-term outsourcing maintenance, maintenance schemes of the cost priority solutions are distributed in early periods intensively, while those of the reliability priority solutions are arranged in longer periods more dispersedly. In practice, OEMs can apply our bi-objective maintenance framework to their O&M cases by inputting real parameters and choosing the most suitable maintenance scheme according to our decision-making guidance.

### 5.4. Sensitivity analysis of reliability limitations

As mentioned before, the suitable Pareto-optimal solution can be chosen according to different types of OEM attitudes toward multi-factory maintenance optimization. In general, each lessee enterprise has a tolerance on the machine reliability to ensure proper use of leased machines. In D-STORM, this tolerance is modeled as a constraint on the lower limit of reliability to guarantee normal operation requirements. The aim of the subsection is to study the impact of different reliability limitations on the final Pareto-optimal solutions. To highlight the effect of reliability limitations, we only restrict the reliability limitation $l_m$ from 0.7 to 0.9 ($l_m \in$[0.7, 0.75, 0.8, 0.85, 0.9]), and the corresponding performance is presented in Fig. 7.

Based on the above analysis of different reliability limitations in Fig. 7, we note that the corresponding Pareto-optimal solutions have a decreasing trend along with one objective (*TRI*) as the reliability limitation $l_m$ increases. On the one hand, the reliability limitation $l_m$ is used to guide the construction of initial solutions. On the other hand, this parameter also limits the search range of feasible solutions. Therefore, as the reliability requirements of the machine increase, OEM needs to dispatch maintenance teams earlier to perform maintenance operations. This shortens the time interval between two continuous maintenance operations, which is reflected in the reliability improvement *TRI* in terms of value reduction. Meanwhile, it is apparent from Fig.7 that results under $l_m = 0.8$ (yellow dots in Fig.7) have the best spread of Pareto-optimal solutions, which can provide much wider and more distinguishable choices for both the reliability improvement *TRI* and service cost *TSC* directions for trading-off and supporting the decision-making.

### 5.5. Sensitivity analysis of diverse-skilled technician resources

Moreover, technicians with different skill levels will directly affect the team construction and O&M services. Therefore, to show the impact of the allocation of technicians on the O&M management, we list all possible combinations of four technicians and obtain the corresponding maintenance schemes. As we mentioned, $q = 1$ means that the technician has the skill to perform PM actions, and $q = 2$ means that the technician has the skill to conduct replacement actions. The different technician skill levels and the corresponding representative solutions are listed in Table 5.

**Table 5**
Different maintenance schemes under different technician allocations.

| Technician allocations | Reliability-priority solution | | Cost-priority solution | |
|---|---|---|---|---|
| | *TRI* | *TSC*($) | *TRI* | *TSC*($) |
| $\mathscr{C} = [1,1,1,1]$ | 2407.8 | 226400 | 1921.1 | 159600 |
| $\mathscr{C} = [1,1,1,2]$ | 2506.0 | 240600 | 2182.4 | 171500 |
| $\mathscr{C} = [1,1,2,2]$ | 2519.7 | 252400 | 1946.8 | 181400 |
| $\mathscr{C} = [1,2,2,2]$ | 2592.6 | 256300 | 2133.6 | 197000 |
| $\mathscr{C} = [2,2,2,2]$ | 2630.1 | 265700 | 2146.2 | 205400 |

The solutions shown in Table 5 indicate that as the technician skill level increases, i.e., the number of technicians with replacement-skill increases, the distribution of Pareto-optimal solutions changes accordingly. And specifically for the analysis, firstly for the reliability-priority solution, i.e., the upper bound scheme with the highest reliability, their *TRI*-value shows an increasing trend. And for the cost-priority solution, the lower bound of the *TSC*-value of the solution also shows an increasing trend with the increase of the replacement operation. Furthermore, the machine deteriorates with age, and it is needed to gradually increase the frequency of maintenance actions due to the accelerated depreciation. Based on our analysis of the balance between PM and replacement, as the O&M service of geographically distributed systems progresses, more technicians with the replacement skill are needed. Therefore, global OEMs can choose the most suitable maintenance scheme to achieve their expected targets by varying the composition of diverse-skilled technicians. Similarly, with the bi-objective maintenance framework, OEMs can generate different maintenance schemes and manageability proposals according to the practices of lessee enterprises.

### 5.6. Solution approach comparison

Apart from the above numerical cases and analysis, the performance of the two-phase solution approach is shown by comparing it with three common algorithms, namely the nondominated sorting genetic algorithm II (NSGA-II), the NSGA-II with the modified k-means algorithm (k-means + NSGA-II), and two-level simulated annealing algorithm (TPA). All experiments are compiled in Python 3 programming language executed on a Pentium 7 CPU with a 3.00 GHz processor and 16GB of RAM. Meanwhile, we use the same geographic location information and

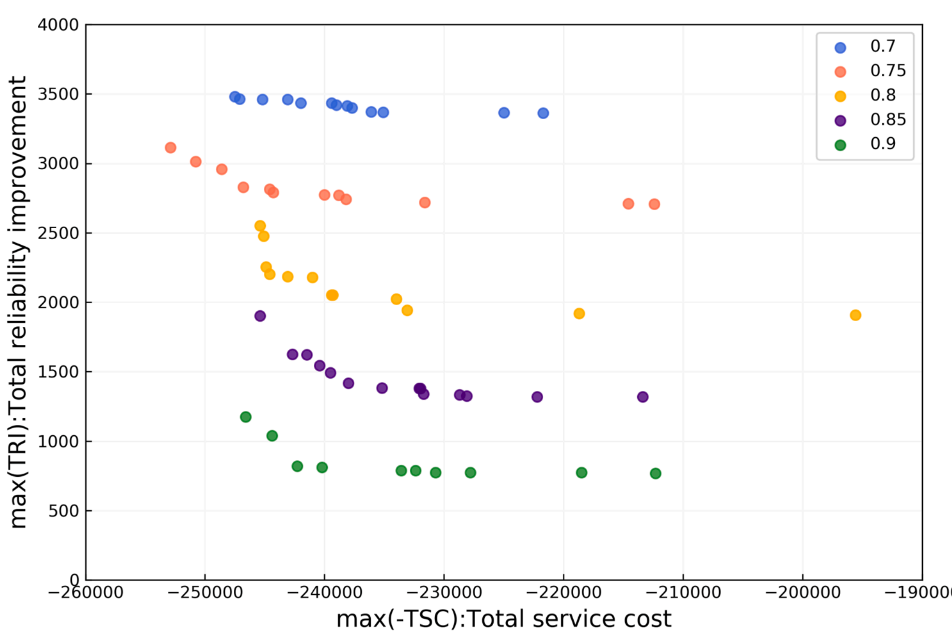


**Fig. 7.** Effect of reliability limitations on Pareto-optimal solutions,

maintenance parameters at each time. As we know, the quality of an algorithm is significantly influenced by the setting of its algorithm parameters. To get a high-performance algorithm, proper tuning of its parameters is carried out by using response surface methodology (RSM). And after conducting RSM, tuned parameters of the NSGA-II, k-means + NSGA-II, TPA, and our proposed two-phase solution approach are listed as follows:

- **NSGA-II**: The size of population $P_{size}^{GA} = 100$, the maximum number of iterations $Itr_{\max}^{GA} = 1000$, the mutation rate = 0.2, and the crossover rate = 0.8.
- **k-means + NSGA-II**: The size of population $P_{size}^{GA} = 100$, the maximum number of iterations $Itr_{\max}^{GA} = 1000$, the mutation rate = 0.2, and the crossover rate = 0.8.
- **TPA**: The initial annealing temperature: $Te_1^{\max} = Te_2^{\max} = 500$, the annealing rate $r = 0.6$, the minimal temperature: $Te_1^{\min} = Te_2^{\min} = 0.01$, the total number of solutions: $N_1 = N_2 = 10$, and the number of non-dominated Pareto solutions in set $\mathscr{V} = 100$.
- **Two-phase solution approach**: The initial annealing temperature: $Te_1^{\max} = Te_2^{\max} = 500$, the annealing rate $r = 0.6$, the minimal temperature: $Te_1^{\min} = Te_2^{\min} = 0.01$, the total number of solutions: $N_1 = N_2 = 10$, and the number of non-dominated Pareto solutions in set $\mathscr{V} = 100$.

Table 6 reports the comparison results between four algorithms. The reported value ($TRI^L$, $TRI^U$, $TSC^L$ and $TSC^U$) is the lower bound and upper bound of two objectives, respectively. The user CPU-time (containing [min, max] value) contains the minimal and maximum computation durations (in seconds) for solving the bi-objective maintenance optimization problem. It can be noticed that compared with the NSGA-II and the NSGA-II algorithm with k-means clustering, the TPA and our proposed two-phase solution approach have better computational time performance. This is because the selection, crossover, and mutation operations of the NSGA-II consume more time, while the convergence and cooling schema of the TPA are faster, thereby increasing the computational performance. Meanwhile, our proposed two-phase solution approach is a little slower than TPA, due to the mechanism that generates the initial solution by the modified k-means algorithm. Also, such a difference (about 1 min) in computational time is acceptable for the operational problem of bi-objective maintenance optimization.

Moreover, as can be seen in Table 7, the NSGA-II and the NSGA-II algorithm with k-means clustering have poor performances. This is due to the lack of diversity resulting from the retention of repeated solutions in the population and the randomness in choosing the parents to reproduce, thus fewer non-dominant solutions are identified. And the performances of the TPA and the two-phase solution approach are similar. As we mentioned in Section 3, to accurately model the improved MPTRP under limited resources, the two objectives of D-STORM are (1) to maximize *TRI* and (2) to minimize *TSC*. Based on the comparison between the best and average values for two objectives, it can be seen that the two-phase solution approach is more consistent and stable than the TPA. This is specifically demonstrated by the smaller difference between the best values (maximum value of TRI and minimum value of TSC) and the average values of the solutions derived from the two-phase solution approach. And the two-phase solution approach has the largest average *TRI*-value and the smallest average *TSC*-value. This is because the k-mean clustering algorithm can obtain an excellent initial solution, which may have better performance than randomly generated solutions. Therefore, compared to the three existing algorithms, the Pareto solutions obtained by the proposed two-phase solution approach has higher stability, while avoiding falling into local optimum.

In the general sense, our proposed maintenance framework leverages existing diverse-skilled technician resources to comprehensively ensure the service quality and reduce the total cost, so as to obtain a set of selected solutions. Different service network sizes, lessee geographical locations, machine maintenance parameters, technician skill levels, and technician team compositions will result in completely different solutions. However, the mechanism of our bi-objective maintenance framework can adapt to these changes and obtain adaptive maintenance and routing decisions. On the one hand, the consideration of two conflicting objectives allows the optimization model to balance the trade-off between the low-cost solution and high-reliability solution to determine the non-dominated Pareto solutions. On the other hand, by purposefully grouping maintenance operations among multi-location lessees, opportunities from anticipated maintenance are leveraged to reduce system downtime and avoid duplicate dispatches.

Meanwhile, different from the existing studies that directly consider the cumulative reliability of all machines as an objective function, this study constructs the total reliability improvement *TRI* as an objective. By setting the minimum reliability constraint for each leased machine while maximizing the total reliability improvement, the constructed maintenance schemes can satisfy the enterprise reliability requirements while extending the maintenance start time as much as possible. In other words, it can achieve an optimal balance between the high reliability and low availability due to early maintenance and the low reliability and high availability due to delayed maintenance. Under the same maintenance resource conditions, the proposed bi-objective maintenance framework can help OEMs to rationalize maintenance resources scheduling and achieve long-term O&M optimization.

**Table 6**
Comparison results among four algorithms for bi-objective maintenance optimization.

| | No. | $TRI^L$ | $TRI^U$ | $TSC^L$($) | $TSC^U$($) | Times |
|---|---|---|---|---|---|---|
| NSGA-II | 1 | 1184.0 | 2114.7 | 183200 | 267800 | [502,522] |
| | 2 | 1268.9 | 2098.1 | 175200 | 266400 | |
| | 3 | 1274.8 | 2113.8 | 179800 | 265900 | |
| | 4 | 1254.1 | 2268.5 | 180600 | 265100 | |
| | 5 | 1251.1 | 2262.6 | 185900 | 263300 | |
| k-means + NSGA-II | 1 | 1205.6 | 1929.6 | 193900 | 263200 | [517,543] |
| | 2 | 1206.1 | 1933.9 | 201200 | 264100 | |
| | 3 | 1205.6 | 1936.5 | 207000 | 263200 | |
| | 4 | 1207.7 | 1922.5 | 200100 | 264900 | |
| | 5 | 1205.6 | 1897.2 | 200500 | 255600 | |
| TPA | 1 | 1869.7 | 2275.1 | 170500 | 252700 | [261,364] |
| | 2 | 1942.6 | 2402.2 | 179300 | 249400 | |
| | 3 | 1921.7 | 2350.5 | 180000 | 248200 | |
| | 4 | 1925.8 | 2512.3 | 179000 | 259000 | |
| | 5 | 1980.8 | 2404.8 | 184000 | 260400 | |
| Two-phase solution approach | 1 | 1853.6 | 2560.5 | 185500 | 253000 | [331,443] |
| | 2 | 1855.3 | 2554.6 | 181700 | 252000 | |
| | 3 | 1887.1 | 2551.0 | 175300 | 253600 | |
| | 4 | 1849.1 | 2538.4 | 179700 | 252300 | |
| | 5 | 1856.8 | 2551.0 | 177600 | 251300 | |

## 6. Conclusions

In this paper, we study an improved maintenance planning and technician routing problem, wherein technician organizing decisions are considered in maintenance scheduling decisions simultaneously. This problem is formulated through a diverse-skilled technician organizing and routing model (D-STORM) that incorporates two important evaluating aspects of O&M services for production systems quality and cost. These aspects are mathematically transferred and modeled through two objective functions: (1) maximizing the total reliability improvement and (2) minimizing the total service cost. Meanwhile, this paper also addresses an agile challenge in maintenance plans by considering the balance between PM and replacement actions. Thus, on the one hand, the attained maintenance framework is shown to be flexible in two conflicting goals. On the other hand, this comprehensive study extends the maintenance scheduling optimization and makes the long-term O&M management of multi-location factories more practical and economic.

**Table 7**
The best and average value of two objectives (TRI and TSC),

| | | Max. | | Min. | | Times |
|---|---|---|---|---|---|---|
| | | $TRI^L$ | $TRI^U$ | $TSC^L$($) | $TSC^U$($) | |
| NSGA-II | #Best | 1274.80 | 2268.50 | 175200 | 263300 | [502,522] |
| | #Average | 1246.58 | 2171.54 | 180940 | 265700 | |
| k-means + NSGA-II | #Best | 1207.70 | 1936.50 | 193900 | 255600 | [517,543] |
| | #Average | 1206.12 | 1923.94 | 200540 | 262200 | |
| TPA | #Best | 1980.80 | 2512.30 | 170500 | 248200 | [261,364] |
| | #Average | 1928.12 | 2388.98 | 178560 | 253940 | |
| Two-phase solution approach | #Best | 1887.10 | 2560.50 | 175300 | 251300 | [331,443] |
| | #Average | 1860.38 | 2551.10 | 179960 | 252440 | |

**Algorithm 2**
Two-level simulated annealing algorithm,

**Input:** ($\boldsymbol{\mu}^a$, $\boldsymbol{\kappa}^a$): the initial auxiliary solution, $Te_1^{\max}$, $Te_2^{\max}$: initial annealing temperature, $r$: annealing rate, $Te_1^{\min}$, $Te_2^{\min}$: minimal temperature, $N_1$, $N_2$: total number of solutions during each cycle

```
Set Te_1 = Te_1^max
if Te_1 ≥ Te_1^min then
Randomly generate N_1 service routes based on (μ^a, κ^a)
Set Te_2 = Te_2^max
if Te_2 ≥ Te_2^min then
Randomly generate service technician vector (ρ) based on each service route to obtain solution π
Calculate TRI(π) and TSC(π) for each solution
Generate N_2 neighborhood solutions π'
Calculate TRI(π') and TSC(π'), and compare the performance of the results
if π' is accepted based on Eq. (22) then
Set π' as the current solution π^now
if π^now is not dominated by any solution in set 𝒱 then
Add π^now into set 𝒱 and remove the solutions dominated by π^now
end if
end if
Update Te_2 to r·Te_2
end if
Update Te_1 to r·Te_1
Generate N_1 neighborhood solutions of service route
end if
```

**Output:** $\mathscr{V}'$: the set of non-dominated Pareto solutions

Most of the studies in existing literature consider the technician routing and maintenance planning separately and try to find the best solution for each. However, it is clear that diverse-skilled technician organizing and multiple maintenance operation scheduling are interconnected and both of them should be optimized together. Meanwhile, individual optimization also leads to the inconsistency between limited technician resources and cost-oriented maintenance requirements. And this inconsistency leads to the mismatch between maintenance planning and maintenance execution, which further impacts the agility of the outsourcing maintenance process. To overcome this operational problem of global OEMs, we study all problems simultaneously through a bi-objective optimization model (D-STROM in this case). And final solutions are obtained with a comprehensive consideration of technician and path constraints. Therefore, daily O&M services do not suffer from delays caused by inconsistency between limited technician resources and dynamic maintenance requirements, and the agility of the maintenance framework when facing disruption or uncertainty can be ensured. To deal with the complexity of D-STORM, a hybrid metaheuristic algorithm is developed based on the modified k-means integrated with two-level simulated annealing to approximate Pareto-optimal solutions. The identified Pareto-optimal solutions can help OEMs to understand the trade-off between two significant objectives and select the global maintenance scheme that coincides with their risk attitude.

Future extensions will focus on integrating time-varying travel speeds into the maintenance framework to provide a more comprehensive scheme to improve the robustness and flexibility of networked O&M management. Meanwhile, a major challenge in the application of decision support tools for offshore wind farms is that maintenance centers are often located in ports near wind farms. The optimization of team starting points between multiple centers should also be studied.

## CRediT authorship contribution statement

**Guojin Si:** Writing – original draft, Methodology, Conceptualization. **Tangbin Xia:** Writing – original draft, Software, Methodology. **Nagi Gebraeel:** Writing – review & editing, Validation, Supervision. **Dong Wang:** Investigation, Data curation. **Ershun Pan:** Visualization, Software. **Lifeng Xi:** Writing – review & editing.

## Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, "A reliability-and-cost-based framework to optimize maintenance planning and diverse-skilled technician routing for geographically distributed systems". Guojin Si, Tangbin Xia, Nagi Gebraeel, Dong Wang, Ershun Pan and Lifeng Xi.

## Data Availability

Data will be made available on request.

## Acknowledgments

This work was supported by the National Natural Science Foundation of China (51875359), Natural Science Foundation of Shanghai (20ZR1428600), Shanghai Science & Technology Innovation Center for System Engineering of Commercial Aircraft (FASE-2021-M7), Ministry of Education-China Mobile Joint Foundation Construction Project (MCM20180703), Oceanic Interdisciplinary Program of Shanghai Jiao Tong University (SL2021MS008), CSSC-SJTU Marine Equipment Forward Looking Innovation Foundation (22B010432).

## References

[1] Jardine AK, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process 2006;20(7):1483–510. https://doi.org/10.1016/j.ymssp.2005.09.012.
[2] Yang S, Bagheri B, Kao HA, Lee J. A unified framework and platform for designing of cloud-based machine health monitoring and manufacturing systems. ASME J Manuf Sci Eng 2015;137(4):040914. https://doi.org/10.1115/1.4030669.
[3] Hu J, Chen P. Predictive maintenance of systems subject to hard failure based on proportional hazards model. Reliab Eng Syst Saf 2020;196:106707. https://doi.org/10.1016/j.ress.2019.106707.
[4] Gao J, Yao Y, Zhu VC, Sun L, Lin L. Service-oriented manufacturing: a new product pattern and manufacturing paradigm. J Intell Manuf 2011;22(3):435–46. https://doi.org/10.1007/s10845-009-0301-y.
[5] Wang W. A model for maintenance service contract design, negotiation and optimization. Eur J Oper Res 2010;201(1):239–46. https://doi.org/10.1016/j.ejor.2009.02.018.

[6] Si G, Xia T, Zhu Y, Du S, Xi L. Triple-level opportunistic maintenance policy for leasehold service network of multi-location production lines. Reliab Eng Syst Saf 2019;190:106519. https://doi.org/10.1016/j.ress.2019.106519.

[7] Chang F, Zhou G, Cheng W, Zhang C, Tian C. A service-oriented multi-player maintenance grouping strategy for complex multi-component system based on game theory. Adv Eng Inform 2019;42:100970. https://doi.org/10.1016/j.aei.2019.100970.

[8] Ebrahimipour V, Najjarbashi A, Sheikhalishahi M. Multi-objective modeling for preventive maintenance scheduling in a multiple production line. J Intell Manuf 2015;26(1):111–22. https://doi.org/10.1007/s10845-013-0766-6.

[9] Safaei N, Jardine AK. Aircraft routing with generalized maintenance constraints. Omega 2018;80:111–22. https://doi.org/10.1016/j.omega.2017.08.013.

[10] Xiang Y, Zhu Z, Coit DW, Feng Q. Condition-based maintenance under performance-based contracting. Comput Ind Eng 2017;111:391–402. https://doi.org/10.1016/j.cie.2017.07.035.

[11] Ben Mabrouk A, Chelbi A. Optimal maintenance policy for equipment leased with base and extended warranty. Int J Prod Res 2022:1–12. https://doi.org/10.1080/00207543.2021.2018139.

[12] Xia T, Xi L, Pan E, Fang X, Gebraeel N. Lease-oriented opportunistic maintenance for multi-unit leased systems under product-service paradigm. ASME J Manuf Sci Eng 2017;139(7):071005. https://doi.org/10.1115/1.4035962.

[13] Zhang Y, Zhang X, Zeng J, Wang J, Xue S. Lessees' satisfaction and optimal condition-based maintenance policy for leased system. Reliab Eng Syst Saf 2019;191:106532. https://doi.org/10.1016/j.ress.2019.106532.

[14] Ma X, Liu B, Yang L, Peng R, Zhang X. Reliability analysis and condition-based maintenance optimization for a warm standby cooling system. Reliab Eng Syst Saf 2020;193:106588. https://doi.org/10.1016/j.ress.2019.106588.

[15] Wang X, Zhao X, Wang S, Sun L. Reliability and maintenance for performance-balanced systems operating in a shock environment. Reliab Eng Syst Saf 2020;195:106705. https://doi.org/10.1016/j.ress.2019.106705.

[16] Goel A, Meisel F. Workforce routing and scheduling for electricity network maintenance with downtime minimization. Eur J Oper Res 2013;231(1):210–28. https://doi.org/10.1016/j.ejor.2013.05.021.

[17] Camci F. Maintenance scheduling of geographically distributed assets with prognostics information. Eur J Oper Res 2015;245(2):506–16. https://doi.org/10.1016/j.ejor.2015.03.023.

[18] López-Santana E, Akhavan-Tabatabaei R, Dieulle L, Labadie N, Medaglia AL. On the combined maintenance and routing optimization problem. Reliab Eng Syst Saf 2016;145:199–214. https://doi.org/10.1016/j.ress.2015.09.016.

[19] Mazidi P, Tohidi Y, Ramos A, Sanz-Bobi MA. Profit-maximization generation maintenance scheduling through bi-level programming. Eur J Oper Res 2018;264(3):1045–57. https://doi.org/10.1016/j.ejor.2017.07.008.

[20] Li Y, Zhang C, Jia C, Li X, Zhu Y. Joint optimization of workforce scheduling and routing for restoring a disrupted critical infrastructure. Reliab Eng Syst Saf 2019;191:106551. https://doi.org/10.1016/j.ress.2019.106551.

[21] Guastaroba G, Côté JF, Coelho LC. The multi-period workforce scheduling and routing problem. Omega 2021;102:102302. https://doi.org/10.1016/j.omega.2020.102302.

[22] Si G, Xia T, Pan E, Xi L. Service-oriented global optimization integrating maintenance grouping and technician routing for multi-location multi-unit production systems. IISE Trans 2021. https://doi.org/10.1080/24725854.2021.1957181.

[23] Manco P, Rinaldi M, Caterino M, Fera M, Macchiaroli R. Maintenance management for geographically distributed assets: a criticality-based approach. Reliab Eng Syst Saf 2022;218:108148. https://doi.org/10.1016/j.ress.2021.108148.

[24] Akl A M, El Sawah S, Chakrabortty RK, Turan HH. A Joint optimization of strategic workforce planning and preventive maintenance scheduling: a simulation-optimization approach. Reliab Eng Syst Saf 2022;219:108175. https://doi.org/10.1016/j.ress.2021.108175.

[25] Zhang S, Du M, Tong J, Li YF. Multi-objective optimization of maintenance program in multi-unit nuclear power plant sites. Reliab Eng Syst Saf 2019;188:532–48. https://doi.org/10.1016/j.ress.2019.03.034.

[26] Jia C, Zhang C. Joint optimization of maintenance planning and workforce routing for a geographically distributed networked infrastructure. IISE Trans 2020;52(7):732–50. https://doi.org/10.1080/24725854.2019.1647478.

[27] Jafar-Zanjani H, Zandieh M, Sharifi M. Robust and resilient joint periodic maintenance planning and scheduling in a multi-factory network under uncertainty: a case study. Reliab Eng Syst Saf 2022;217:108113. https://doi.org/10.1016/j.ress.2021.108113.

[28] Nguyen HSH, Do P, Vu HC, Iung B. Dynamic maintenance grouping and routing for geographically dispersed production systems. Reliab Eng Syst Saf 2019;185:392–404. https://doi.org/10.1016/j.ress.2018.12.031.

[29] Zhu X, Chen Z, Borgonovo E. Remaining-useful-lifetime and system-remaining-profit based importance measures for decisions on preventive maintenance. Reliab Eng Syst Saf 2021;216:107951. https://doi.org/10.1016/j.ress.2021.107951.

[30] Kraus M, Feuerriegel S, Oztekin A. Deep learning in business analytics and operations research: models, applications and managerial implications. Eur J Oper Res 2020;281(3):628–41. https://doi.org/10.1016/j.ejor.2019.09.018.

[31] Mosadegh H, Ghomi S M T F, Süer GA. Stochastic mixed-model assembly line sequencing problem: mathematical modeling and Q-learning based simulated annealing hyper-heuristics. Eur J Oper Res 2020;282(2):530–44. https://doi.org/10.1016/j.ejor.2019.09.021.

[32] Çakırgil S, Yücel E, Kuyzu G. An integrated solution approach for multi-objective, multi-skill workforce scheduling and routing problems. Comput Oper Res 2020;118:104908. https://doi.org/10.1016/j.cor.2020.104908.

[33] Si G, Xia T, Zhang K, Wang D, Pan E, Xi L. Technician collaboration and routing optimization in global maintenance scheduling for multi-center service networks. IEEE Trans Autom Sci Eng 2021. https://doi.org/10.1109/TASE.2021.3132694.

[34] Varadharajan TK, Rajendran C. A multi-objective simulated-annealing algorithm for scheduling in flowshops to minimize the makespan and total flowtime of jobs. Eur J Oper Res 2005;167(3):772–95. https://doi.org/10.1016/j.ejor.2004.07.020.

[35] Singh HK, Ray T, Smith W. C-PSA: Constrained Pareto simulated annealing for constrained multi-objective optimization. Inf Sci 2010;180(13):2499–513. https://doi.org/10.1016/j.ins.2010.03.021.

[36] Niu Y, Kong D, Wen R, Cao Z, Xiao J. An improved learnable evolution model for solving multi-objective vehicle routing problem with stochastic demand. Knowl Based Syst 2021. https://doi.org/10.1016/j.knosys.2021.107378.