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Service-oriented global optimization integrating maintenance grouping and technician routing for multi-location multi-unit production systems

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ABSTRACT

With the product-service requirement of modern production enterprises, service-oriented manufacturing and its corresponding operations and maintenance have gained growing attention. Advances in sensor technology and wireless communication, promoting lessors to propose new strategies for intelligent maintenance decision-making of geographically distributed manufacturing enterprises. In this article, we present a comprehensive strategy for solving the maintenance grouping and technician routing problem of multi-location multi-unit production systems. Based on real-time machine degradation, we estimate the failure rate of leased machines and establish a time-varying maintenance cost function to quantify the trade-off between early maintenance and delayed maintenance. Unlike group maintenance of a single system, we integrate the travel time between systems and the maintenance capacity of technician teams into a mixed-integer optimization model to provide the dynamic preventive maintenance scheme. Finally, numerical examples are employed to illustrate the effectiveness of the proposed strategy and explore some managerial insights for the lessor's daily management.

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Service-oriented manufacturing; group maintenance; technician routing; multi-location multi-unit production systems; cost saving

1. Introduction

Fierce market competition combined with rapid updating of technology has resulted in a growing number of manufacturing enterprises needing to rely on Original Equipment Manufacturers (OEMs) to provide production systems and maintenance services (Jin *et al.*, 2016; Xia *et al.*, 2018). According to the service-oriented manufacturing mode, it brings significant advantages to both manufacturing enterprises and OEMs (Gao *et al.*, 2011). On the one hand, leasing helps to avoid high machine investment and provides specialized maintenance support for manufacturing enterprises. On the other hand, the maintenance service brings a new profit growth point and an opportunity to gain practical experience for OEMs (Tarakci *et al.*, 2009; Pascual *et al.*, 2016). For example, Rolls Royce provides repair services for its plane engines in the way of power-by-the-hour. Siemens dispatches maintenance technicians to repair equipment for global factory customers.

The OEM leases various production systems to geographically distributed manufacturing enterprises and is responsible for the maintenance service of all machines in these systems. By monitoring the operating condition of leased machines and considering the dependencies among machines, the real-time maintenance requirements of each production system are scheduled. In addition, based on the predicted maintenance tasks, the OEM dispatches technician teams to conduct timely and appropriate maintenance actions, in order to ensure the reliable operation of production systems. After completing maintenance tasks, the technician teams return to the maintenance center, where they are either reorganized or assigned to complete the next maintenance tasks. For OEMs, therefore, they need to consider not only the most suitable maintenance times for each leased machine, but also the cost-effective arrangements of technician teams to perform maintenance tasks. By developing the comprehensive maintenance schedule for Multi-location Multi-unit Production Systems (MMPSs), it can optimize the availability of leased machines and greatly reduce the total cost.

To deal with the issue caused by outsourcing maintenance and obtain a cost-effective comprehensive maintenance schedule, it is necessary to combine the two problems: maintenance grouping and technician routing. The scheduled maintenance operation can provide sufficient preparation time to organize maintenance resources (technicians, tools, spare parts, etc.) in advance (Xia *et al.*, 2013; Mazidi *et al.*, 2018). Meanwhile, an appropriate Preventive Maintenance (PM) action can reduce the probability of unexpected failures, as well as avoid excessive maintenance (Grall *et al.*, 2002; Pandey *et al.*, 2013). In the multi-unit production system, when PM actions are performed on each machine separately, frequent downtime will increase maintenance costs. Consequently, it is desirable to optimize the maintenance grouping problem to ensure the continuity of production and reduce the repetitive scheduling of teams of technicians.

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When performing group maintenance to a MMPS, unlike the centralized production system, the lessor should jointly maintain the non-adjacent machines.

A second problem that should be taken into consideration is how to obtain a practical service route. This is especially true when the total travel distance of performing the maintenance of several machines together is shorter than performing them separately. Therefore, in addition to considering group maintenance of leased machines, it is required to solve the technician routing problem to further reduce the travel cost. The technician routing problem can be classified as a vehicle routing problem with predicted maintenance tasks, which has been widely studied (Al-Thani *et al.*, 2016; Irawan *et al.*, 2017; Biesinger *et al.*, 2018). To assign maintenance tasks to existing teams of technicians, it is essential to estimate the maintenance capacity of each team and determine their service sequences.

In this context, we consider the following Maintenance Grouping and Technician Routing Problem (MGTRP). Based on the degradation of leased machines, we consider two types of maintenance actions to ensure normal production. Then, we incorporate these maintenance requirements along with: (i) the maintenance capacity of each team in terms of how many machines they can maintain, (ii) the impact of actual maintenance start time on machine degradation, (iii) the travel distance between production systems and the maintenance center, and (iv) the costs associated with system downtime due to PM. By solving the MGTRP for geographically distributed production systems, the OEM can combine PM actions and optimize service routes to ensure system reliability, avoid frequent maintenance downtime, reduce extra travel distance and achieve total cost savings.

This article makes three significant contributions to the area. First, we integrate individual machine degradations, complex maintenance opportunities and network logistics optimization into a global model to achieve the operations and maintenance (O&M) service of a MMPS. Second, we establish time-varying maintenance cost functions for various leased machines and consider the impact of maintenance execution time points on current decisions and subsequent maintenance processes to achieve long-term cost savings. Third, our proposed holistic strategy generates real-time global maintenance schedules by pursuing the minimum total cost. Moreover, we develop the GAKLS algorithm based on a genetic algorithm and iterated local search algorithm to solve the MGTRP efficiently.

The remainder of this article is structured as follows. In Section 2, we review the pertinent literature. In Section 3, we describe the studied problem and propose the optimization model. In Section 4, we propose the GAKLS algorithm for solving the maintenance grouping and technician routing problem. In Section 5, we conduct an illustrative example to show the performance of the proposed strategy. Some numerical experiments are investigated to further discuss the critical parameters in Section 6. Finally, the conclusions deduced from this work are presented in the last section.

2. Literature review

Maintenance scheduling is a fundamental problem in manufacturing enterprises and has been extensively studied in the literature (Xia *et al.*, 2012; Lee and Pan, 2017; Basciftci *et al.*, 2019; Liang and Parlikad, 2020). For promoting the development of a service-oriented manufacturing mode, its corresponding maintenance has gained more and more attention in academia and industry. Traditionally, most existing works focus on the maintenance strategy of single-machine systems (Mabrouk *et al.*, 2016; Hung *et al.*, 2017; Wang *et al.*, 2018). However, these maintenance strategies cannot be applied to multi-unit systems, due to the lack of consideration of the interaction between machines. Meanwhile, it is also an essential feature of modern manufacturing enterprises, which requires various types of machines to cooperate to satisfy the multi-assortment and multi-stage manufacturing process. From the perspective of lessors, the scale of maintenance scheduling expands to consider multi-unit production systems. Recently, in order to capture these dynamics, some scholars have studied the maintenance optimization of the whole production system, and considered different dependencies (economic, structural, stochastic and resource) among leased machines (Zhang *et al.*, 2019). Xia *et al.* (2017) proposed a maintenance optimization strategy that opportunistically advanced scheduled PM actions by optimizing the leasing profit saving. Chang *et al.* (2019) presented a multi-level grouping execution strategy that dynamically grouped the optimal individual service by maximizing service cost saving and availability improvement degree.

Since these maintenance strategies almost exclusively focus on the maintenance scheduling of centralized systems, they are only of limited use for MMPSs. With the improvement of comprehensive logistics management capability, a lot of studies have tried to combine the optimization of technician routing with group maintenance. Camci (2015) presented an approach to schedule maintenance of geographically distributed machines with failure probability predictions, assuming that only one team of technicians is available and each machine is maintained only once. López-Santana *et al.* (2016) extended this problem to further consider that each scattered machine can be maintained multiple times, and multiple teams are waiting to be dispatched. However, these studies only focus on single-machine systems, which cannot be used to satisfy the real-world maintenance requirements.

In recent years, with the consideration of machine dependence, some studies have tried to solve the MGTRP for multi-unit systems. Nguyen *et al.* (2019) presented a dynamic grouping and routing approach, which combined all PM actions into several groups and determined the corresponding maintenance routes by maximizing the total economic profit. Similarly, Jia and Zhang (2019) extended this problem to simultaneously maximize its reliability and minimize the total cost. However, these studies did not consider the maintenance capacity of teams of technicians and the accelerated degradation caused by machine maintenance. Si *et al.* (2019) developed a triple-level maintenance strategy to obtain the optimal scheme. The maintenance model considered the maintenance capacity of teams of technicians and the imperfect PM action. However, the key issue is that this maintenance strategy is hierarchical, which may lead to the incomplete consideration of possible maintenance schemes.

To summarize, with the development of maintenance outsourcing, the technician routing problem based on group maintenance has been gradually studied. On the one hand, most of the previous studies suppose that the maintenance requirement of leasers is non-updated without considering the dynamic industrial context. On the other hand, even though some studies consider dynamic updates, these hierarchical maintenance strategies reduce the solution space, which directly affects the effectiveness of the final solution. However, parameter updating and holistic optimization can ensure the timeliness of O&M services and achieve long-term cost savings. To fulfill this research gap and further reduce the O&M cost, we utilize the dynamic failure rate of leased machines and lease parameters to construct the time-varying maintenance cost function. Based on the maintenance cost function of all machines, we develop a holistic maintenance strategy to determine the optimal maintenance timetable for leased machines, as well as the cost-effective service route of teams of technicians, so as to conduct timely and cost-effective PM actions.

3. Problem description

The MGTRP includes developing real-time systemic maintenance tasks based on machine degradation and assigning these tasks to existing teams of technicians such that timely and appropriate maintenance actions are performed to ensure normal production of the system. Concerning the long-term O&M service for multiple production systems, we need to make decisions about the maintenance grouping for each leased system and the service sequence for teams of technicians. The key to providing cost-effective and timely services is to dynamically assess a machine's degradation, identify optimal opportunities to dispatch a team of technicians, and perform PM actions along appropriate routes.

A MMPS is modeled as a directed graph, represented by $G = (\mathcal{N}, \mathcal{A})$ with the node set $\mathcal{N} = \{0, 1, 2, ..., n\}$ and the arc set $\mathcal{A} = \left\{(i,j) | i,j \in \mathcal{N}, i \neq j\right\}$. Vertex 0 stands for the maintenance center, which represents the departure and destination of each possible service route. The rest of $\mathcal{N}$, expressed as $\mathcal{I} = \{1, 2, ..., n\}$, represent n production systems that need to be serviced. Each system $i \in \mathcal{I}$ is composed of m_i machines in series. All the machines of multiple production systems are represented by the system nodes. The arcs contained in set $\mathcal{A}$ represent the possible service route among geographically distributed systems. To ensure the system's reliability, as well as reduce the unanticipated downtime, a set of teams of technicians $\mathcal{V} = \{1, 2, ..., v\}$ is dispatched to execute maintenance tasks dynamically. Appendix A lists the notation used throughout this article. First, the independent maintenance process is presented in Section 3.1 to introduce the process of obtaining the optimal PM interval for each leased machine. By pulling these PM intervals, the time-varying maintenance cost function of each machine is presented in Section 3.2. This function further captures future possibilities into the current maintenance decision by considering the impact of actual PM time on the subsequent maintenance process. These functions are used into the next subsection to obtain the best maintenance timetable for each machine from a global perspective. Finally, Section 3.3 describes the MGTRP with the routing and maintenance decisions, and then provides the corresponding optimization model with constraints.

3.1. Independent maintenance process

In the maintenance scheduling optimization of geographically distributed lessees, two types of maintenance actions, corrective minimal repair (CM) and imperfect PM, are performed to maintain the operating state of production systems. If a leased machine fails, it is necessary to repair it as soon as possible to bring the corresponding production system to an operating state. In this sense, CM actions are to return a failed machine to operation with its degradation state unchanged, which means that the failure rate after the repair operation is the same as before. In contrast, PM actions focus on reducing the possibility of unexpected failures and unanticipated downtime. After the imperfect PM action, the machines are restored to a better state, but start in an not-as-good-as-new condition at the next cycle. PM actions are scheduled by balancing the costs of PM routines and failure events.

We consider the outsourcing-service scenario that the lessor is responsible for the long-term O&M of n geographically distributed lessees (multi-machine production systems). Each machine $k \in \mathcal{M}$ is assumed to be operating except when there is a scheduled PM action or an unexpected failure. A PM interval is defined as the duration between two successive PM actions. If a leased machine fails during a PM interval, it undergoes a CM action to bring it back to an operational state. As we known, machines fail due to a gradual process of deterioration and aging during their lifetime. To ensure normal production and avoid system shutdown, the lessor needs to estimate the condition of machine degradation and then allocate teams of technicians from the maintenance center to perform timely and appropriate PM actions. We assume that the failure time of the machines follows a Weibull distribution, which has been widely used to describe the probability of failure occurrence in mechanical engineering. The failure rate $\lambda_{kh}(t)$ of machine k at the first PM cycle ($h = 1$) is expressed as follows:

$$\lambda_{kh}(t) = \frac{\beta_k}{\eta_k}\left(\frac{t}{\eta_k}\right)^{\beta_k - 1}, \quad h = 1, t \geq 0, \forall k = 1, 2, ..., m. \tag{1}$$

To reflect the internal maintenance effect and the external environment state on machine degradation, we consider both the lessor's maintenance effect factor and the lessee's environmental condition factor in the modeling of failure rates. The relationship between failure rates before and after the hth ($h \geq 1$) PM cycle is described as follows:

$$\lambda_{k(h+1)}(t) = \varepsilon_{kh}\lambda_{kh}\left(t + a_{kh}T'_{kh}\right), h \geq 1, t > T'_{kh}, \quad \forall k = 1, 2, ..., m. \tag{2}$$

where ε_{kh} is a parameter that captures the effect of the system's environment on the failure rate, and $\varepsilon_{kh} > 1$ indicates that the external environment leads to accelerated degradation. The environment factor can be estimated from historical degradation data. a_{kh} is the age reduction factor for an imperfect PM action, $0 < a_{kh} < 1$ indicates the imperfect PM action brings the machine to a better state, but not a brand-new condition. T'_{kh} is the updated length of the hth PM interval.

Based on the failure rate, a cost-oriented model is considered to schedule the optimal PM interval T^*_{kh} for sequential PM cycles. The objective of a cost-oriented model is to minimize the maintenance cost per unit time of machine k, as described by:

$$C_{kh}(T_{kh}) = \frac{C^p_{kh} + C^c_{kh}\int_0^{T_{kh}} \lambda_{kh}(t)dt}{T_{kh} + \left(T^p_{kh} + T^c_{kh}\int_0^{T_{kh}} \lambda_{kh}(t)dt\right)}, \tag{3}$$

where the numerator indicates the total maintenance cost (the sum of the PM cost and CM cost) in the current hth PM interval. C^p_{kh} and C^c_{kh} represent the cost of imperfect PM and CM actions on machine k, respectively. $\int_0^{T_{kh}} \lambda_{kh}(t)dt$ is the expected failure frequency of machine k within the time period $[0, T_{kh}]$. The denominator indicates the total duration of the PM interval. T^p_{kh} and T^c_{kh} represent the maintenance duration of imperfect PM and CM actions on machine k. By balancing the PM cost and CM cost, the optimal PM interval of machine k at cycle h, denoted T^*_{kh}, can be obtained by solving the following derivative function, $dC_{kh}(T_{kh})/dT_{kh}|_{T_{kh}=T^*_{kh}} = 0$.

When the optimal PM interval for each machine is determined, considering only their independent degradation, we can obtain the expected PM start time. For simplicity, we refer to this maintenance time as the independent PM time w_{kh} in subsequent research. However, it should be noted that the machines in each system are not independent and are interconnected. Therefore, the independent PM time with the minimal $C_{kh}(T^*_{kh})$ will no longer be the best O&M opportunity for the whole system. In other words, when systemic group maintenance is considered, the actual start time of PM actions (actual PM time) for each leased machine may be earlier or later than the independent PM time. In the next subsection, the deviation between the independent PM time and the actual PM time is modeled, so that the optimization model can reflect the maintenance costs corresponding to different actual PM times.

3.2. Time-varying maintenance cost computation

Considering the long-term O&M management of multiple lessees, the lease period of each lessee $i \in \mathcal{I}$ is expressed as $LP_i = \left[t^S_i, t^E_i\right]$, and the specific period data can be derived from the lease contract. Based on the optimal PM interval of leased machines, the independent PM time w_{kh} of machine k (belongs to lessee i) at the h th PM cycle can be calculated as follows:

$$w_{kh} = \begin{cases} t^S_i + T^*_{kh} & h = 1 \\ t^S_i + \sum_{h'=1}^{h-1} T'_{kh'} + \sum_{h'=1}^{h-1} T^p_{kh'} + T^*_{kh} & h \geq 2 \end{cases} \tag{4}$$

where t^S_i is the lease start time of lessee i, T^*_{kh} is the optimal PM interval obtained from the cost-oriented model. $T'_{kh'}$ represents the actual PM interval and $\sum_{h'=1}^{h-1} T'_{kh'}$ is the sum of the actual PM intervals of the previous $(h-1)$ cycles. Similarly, $T^p_{kh'}$ represents the system downtime for performing PM actions and $\sum_{h'=1}^{h-1} T^p_{kh'}$ is the cumulative downtime of machine k of the previous $(h-1)$ cycles.

From an economics point of view, when several PM actions are executed jointly, the total cost will be reduced, due to the decrease in system downtime and travel time. To quantify the impact of different actual PM times of the leased machine on the global maintenance schedule, we further propose the dynamic maintenance cost G_{kh} for machine k at the hth cycle. This function takes the actual PM time τ as an independent variable and estimates the expected maintenance cost by considering the trade-off between advanced maintenance and delayed maintenance. The maintenance cost function $G_{kh}(\tau)$ is expressed as follows:

$$G_{kh}(\tau) = C^p_{kh} + \frac{w_{kh} - \tau}{T^*_{kh}} \cdot C^p_{kh} - \left(\int_0^{w_{kh}} \lambda_{kh}(t)dt - \int_0^{\tau} \lambda_{kh}(t)dt\right) \cdot C^c_{kh} + \frac{(w_{kh} - \tau)^2}{t^E_i - t^S_i} \cdot D_k \tag{5}$$

The function consists of four parts as follows:

1. The first part C^p_{kh} is the cost of imperfectly maintaining machine k.
2. The second part $\frac{w_{kh}-\tau}{T^*_{kh}} \cdot C^p_{kh}$ captures the impact of PM interval changes on the number of PM actions. In particular, if a machine's PM action is advanced, which means the actual PM time τ is early than the independent PM time w_{kh} ($\tau < w_{kh}$), its current PM interval will be shortened. This will cause the fact that during the lease period, more PM actions will be needed and the lessor has to spend more cost on PM actions. Otherwise, if the PM action is postponed ($\tau > w_{kh}$), the number of PM actions within the lease period will be reduced. In other words, the cumulative cost of performing PM actions can be saved.
3. The third part $-(\int_0^{w_{kh}} \lambda_{kh}(t)dt - \int_0^{\tau} \lambda_{kh}(t)dt) \cdot C^c_{kh}$ captures the impact of PM interval changes on the expected failure frequency. On the one hand, if the PM action is advanced ($\tau < w_{kh}$), the shorter PM interval can

diminish the cumulative failure risk, which means that any additional expenditure on CM can be saved. On the other hand, if the PM action is postponed ($\tau > w_{kh}$), the unnecessary CM cost for unexpected failures increases. Therefore, it takes a negative value when the PM action is advanced and takes a positive value when the PM action is postponed.

4. The last part $\frac{(w_{kh}-\tau)^2}{t_i^E - t_i^S} \cdot D_k$ indicates how far the actual PM time deviates from the independent PM time. D_k indicates the importance coefficient of machine k, which can be derived from the lease contract and the machine importance measures (Lin *et al.*, 2016). Specifically, the greater the deviation, the larger is the value of this part. In other words, the farther the actual PM time τ is from the independent PM time w_{kh}, the greater the maintenance cost rate $C_{kh}(T_{kh})$.

By constructing the maintenance cost function $G_{kh}(\tau)$, we denote the impact of the actual PM start time for every leased machine on the subsequent maintenance process. We combine these maintenance cost functions and the decision variable τ_{ik}^v into the global optimization model in Section 3.3 to determine the optimal maintenance time point for each machine from a global perspective. The maintenance cost function of leased machines cleverly models future possibilities into the current maintenance decision. The implementation example of this maintenance cost function for a leased machine is presented in Appendix B.

3.3. Global optimization model

In this subsection, we present the mathematical formulation for the MGTRP. On the basis of the real-time maintenance cost function, the proposed strategy derives optimal schedules for the maintenance timetable of lessees' machines and the routing of the lessor's technician teams. Therefore, we incorporate maintenance actions along with (i) the maintenance capacity of each team in terms of how many machines can they maintain in one dispatch, and (ii) the travel distance between production systems and the maintenance center. The impact of PM actions on the operational condition of machines, as well as the production of systems, are captured through the decision variable, thus allowing the optimization model to be penalized when a system is interrupted, due to maintenance. Meanwhile, by setting the cost of dispatching each team of technicians, the optimization model adaptively determines the motivation for group maintenance.

In the maintenance cost function of each machine, we combine the binary variables (continuous variable τ and continuous variable ϕ) to make the machine-level maintenance decisions. x defines the routing decision for teams of technicians. Let F^v represent the deployment cost associated with dispatching a team of technicians. In other words, the lessor pays F^v for every team $v \in \mathcal{V}$ dispatched from the maintenance center. Moreover, this cost implicitly captures the maintenance grouping decision. The higher the F^v-value, the more aggressively will the optimization model l try to group PM actions as much as possible. There is often an essential cost associated with the required travel of the team of technicians and spare parts required to perform the repair. To reflect this cost, we model the travel cost by using travel distance d_{ij}, moving speed θ^v, and travel cost per hour C^v. For the series production system, once one machine is receiving PM action, the whole system will be shut down. To capture this dynamic, we impose a penalty cost to characterize the system downtime as a function of the machine maintenance decision. Let P_i denote the penalty per hour to quantify the impact of system shutdown on the solution. This cost also captures the maintenance grouping decision to reduce system downtime. By considering this penalty cost, the delicate balance between group maintenance of the same system and the timely maintenance action is kept, so that the optimization model dynamically determines the optimal scheme.

To extend the maintenance optimization to multiple production systems distributed in different geographical locations, the geographical distance between production systems and the maintenance center should be considered. Therefore, in addition to the consideration of system downtime, we also model the impact of adding travel time into the optimization model. To better clarify the long-term outsourcing maintenance service process, we develop a simple example and the corresponding time parameters are shown in Figure 1. The departure time point represents the time each team of technicians leaves the maintenance center. The arrival time point indicates the time point at which the technicians arrive at the location of the leasing organization and prepare to start related maintenance tasks. The travel time is the required period between the leasing organization and the maintenance center. And the machine maintenance time equals to the maximum PM duration of machines in the same system.

After describing variables and parameters, a complete solution of this optimization model can be represented by $s = (y, x, \phi, \tau)$. Let $TC_h(s)$ denotes the total cost of performing all PM actions under solution s at the hth cycle. To obtain an optimal maintenance schedule that could execute appropriate PM actions and minimize the total cost, we propose the following mixed-integer program;

$$\min TC_h(y,x,\phi,\tau) = \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{M}_i} y_{ik}^v \cdot G_{kh}\left(\tau_{ik}^v\right) + \sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{I}} x_{0j}^v \cdot F^v + \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}} x_{ij}^v \cdot \frac{d_{ij}}{\theta^v} \cdot C^v + \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{I}}\sum_{k\in\mathcal{M}_i} \max\left\{y_{ik}^v \cdot T_{kh}^p\right\} \cdot P_i \tag{6}$$

$$\text{s.t.}: \sum_{j\in\mathcal{I}} x_{0j}^v = \sum_{i\in\mathcal{I}} x_{i0}^v \le 1 \quad \forall v \in \mathcal{V} \tag{7}$$

$$\sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{N}} x_{ij}^v = \sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{N}} x_{ji}^v \quad \forall i \in \mathcal{I} \tag{8}$$

$$\sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{I}} x_{0j}^v \le l \tag{9}$$

$$\sum_{v\in\mathcal{V}} y_{ik}^v = 1 \quad \forall i \in \mathcal{I}, k \in \mathcal{M}_i \tag{10}$$

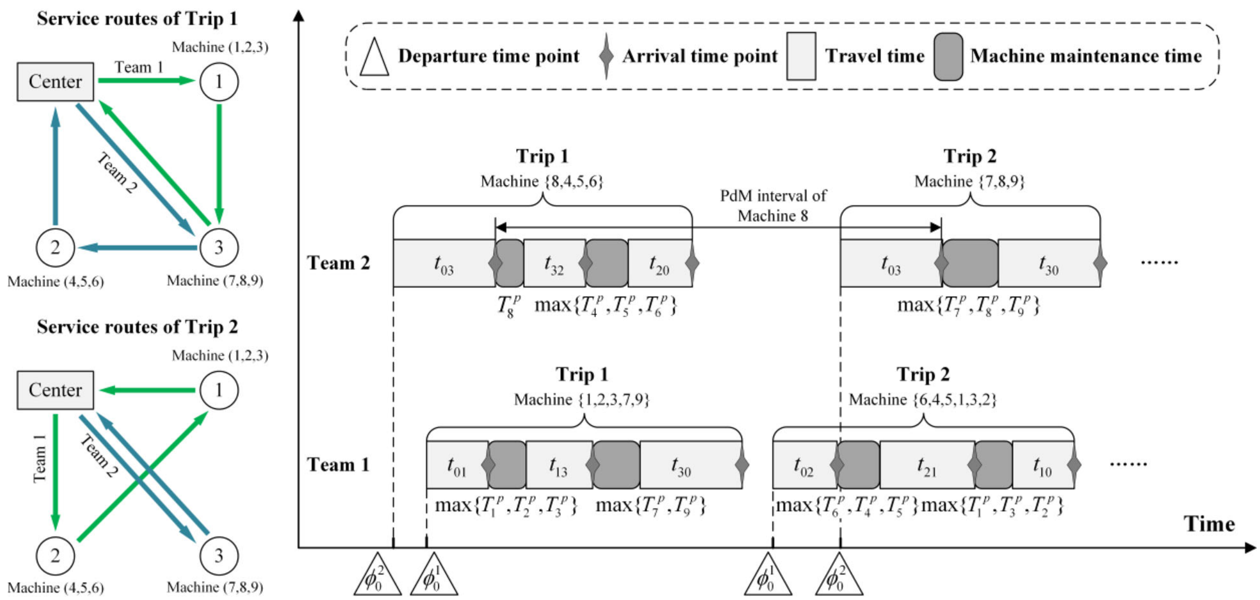


Figure 1. An example of maintenance grouping and technician routing.

$$\sum_{i\in\mathcal{J}}\sum_{k\in\mathcal{M}_i} y_{ik}^v \le q^v \quad \forall v\in\mathcal{V} \tag{11}$$

$$\tau_{jk}^v = x_{0j}^v \cdot y_{jk}^v \cdot \left[\phi_0^v + \frac{d_{0j}}{\theta^v}\right] \quad \forall v\in\mathcal{V}, j\in\mathcal{J}, k\in\mathcal{M}_j \tag{12}$$

$$\tau_{jk}^v = \sum_{i\in\mathcal{J}}\sum_{k'\in\mathcal{M}_i} x_{ij}^v \cdot \left[\tau_{ik'}^v + \max\left\{y_{ik'}^v \cdot T_{k'h}^p\right\} + \frac{d_{ij}}{\theta^v}\right] \quad \forall v\in\mathcal{V},$$
$$j\in\mathcal{J}, k\in\mathcal{M}_j, h\in\mathcal{H} \tag{13}$$

$$y_{jk}^v, x_{ij}^v \in \{0,1\} \quad \forall v\in\mathcal{V}, i,j\in\mathcal{N},\ k\in\mathcal{M}_i \tag{14}$$

$$\tau_{ik}^v > 0 \quad \forall v\in\mathcal{V}, i\in\mathcal{J},\ k\in\mathcal{M}_i \tag{15}$$

Objective function (6) minimizes the total cost $TC_h(s)$, which consists of four terms: maintenance cost, deployment cost, travel cost, and downtime penalty cost. Constraints (7) guarantee that each dispatched team of technicians must leave and finally return to the maintenance center. Constraints (8) state that any team of technicians that enters the system node should also depart from the same node. Constraints (9) aim to restrict the number of dispatched teams of technicians to be within the total number of existing teams of technicians. Constraints (10) ensure that the PM action of each leased machine is performed by exactly one team of technicians and is performed only once. Constraints (11) are maintenance capacity constraints, which limit the number of maintenance actions to be conducted by technician team v. Constraints (12) and (13) calculate the actual PM time of machine k in system j. If technician team v visit system j directly after leaving the maintenance center, the actual PM time $k\in\mathcal{M}_j$ is obtained from Equation (12). Otherwise, if technician team v visit system j after leaving system i rather than the maintenance center, the actual PM time $k\in\mathcal{M}_j$ is obtained from Equation (13). Finally, constraints (14) and (15) define the domain of variables in the model.

After optimizing the mixed-integer program that formulates the MGTRP, we obtain the optimal solution with the minimum total cost $TC(s^*)$. Then we can further arrange the global maintenance schedule, which includes the maintenance plan timetable of leased machines and the service route of required technicians. When the maintenance schedule is executed, the actual PM interval T'_{kh} of machine $k\in\mathcal{M}$ can be calculated. By using the rolling horizon, the failure rate $\lambda_{k(h+1)}(t)$ and the time-varying maintenance cost function $G_{k(h+1)}(\tau)$ will be re-evaluated and updated for the next $(h+1)$th cycle. This process continues until the end of the lease period, and the lessor can dynamically dispatch technicians to perform timely and appropriate PM actions for MMPSs. During the two consecutive PM actions (each PM interval), once an unexpected failure occurs, the CM action is carried out and the time axis of the corresponding machine is updated accordingly.

4. Solution algorithm

The technician routing problem obviously bears some resemblance to the classic Vehicle Routing Problem (VRP). The VRP typically aims to minimize the total travel cost of a number of vehicles to visit a given set of destinations. In light of the NP-hard nature of the VRP, it is unlikely that exact algorithms are fast enough to obtain the optimal solution. Given that MGTRP is an operational problem that needs to be solved frequently, solution times should not exceed a few minutes for realistic instances. Therefore, we hope to get a better maintenance schedule in a limited time.

To deal with the computational complexity, a novel hybrid metaheuristic algorithm is developed based on a Genetic Algorithm (GA) and an Iterated Local Search (ILS) algorithm. The idea of this hybridization is to develop an algorithm that is powerful in terms of diversification (global search) and intensification (local search) and intelligently learns information during the optimization process (Kraus *et al.*, 2020; Mosadegh *et al.*, 2020). The proposed algorithm should improve the computational efficiency and provide an

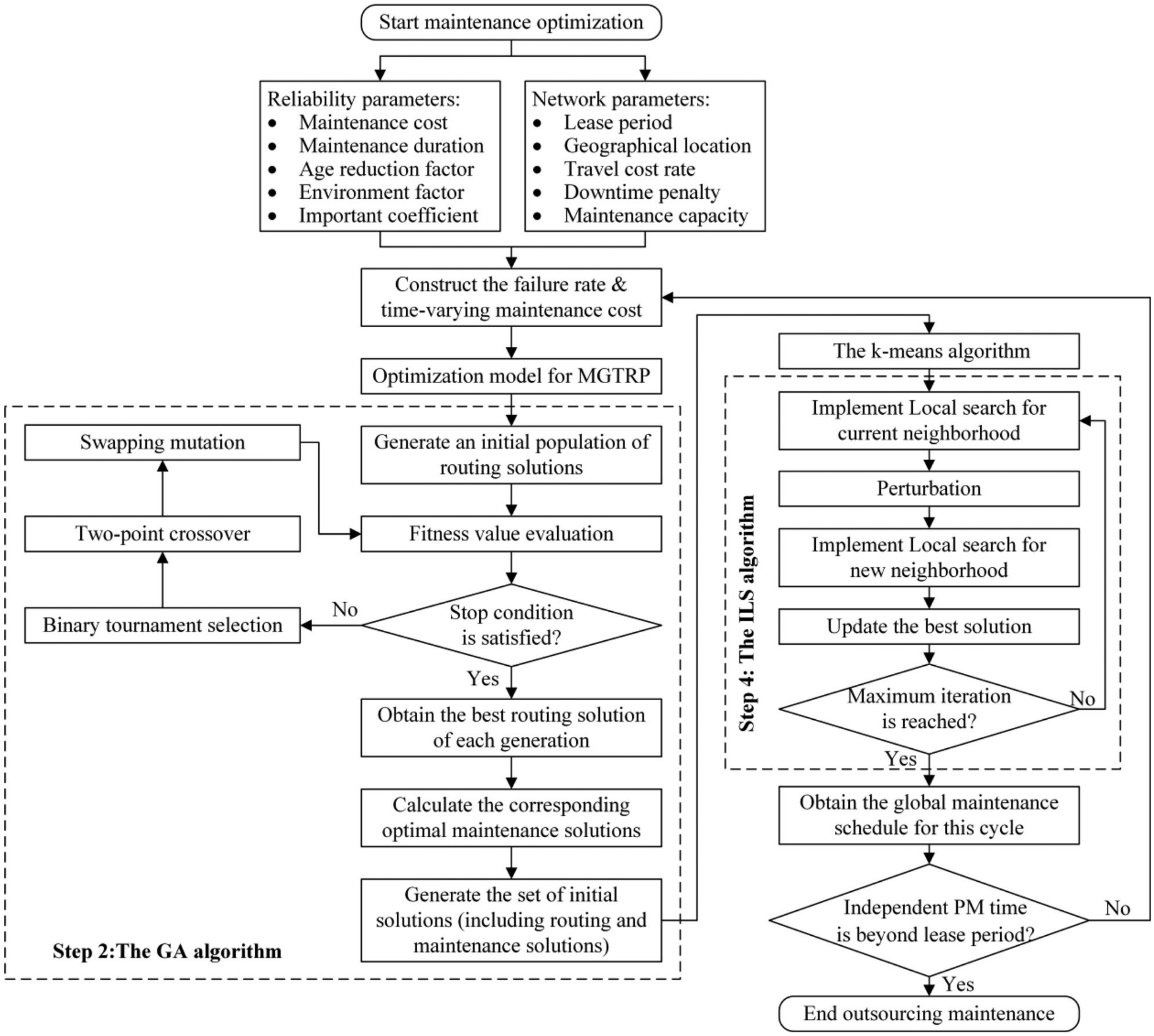


Figure 2. The flow chart of the GAKLS algorithm.

acceptable solution for solving the maintenance grouping and technician routing problem. The GA method has been widely utilized to solve optimization problems. The technique has achieved considerable success in a series of academic benchmark competitions as well as practical applications, and has been shown to be capable of yielding acceptable solutions. Moreover, ILS is a metaheuristic algorithm that is well known for its effectiveness in intensification and simplicity in practice. When a search is trapped in a local optimum, ILS helps the search to escape the trap without losing many of the good properties of the current solution (Lian *et al.*, 2016). In this research, GA searches the solution space and provides an initial set of feasible solutions. Then, the ILS algorithm is used to strengthen the solutions locally. For simplicity, the proposed algorithm is called GAKLS in this research.

To implement the GAKLS algorithm, the first essential issue is to appropriately encode the solution. More specifically, each solution consists of two parts: routing solution (y, x) and maintenance solution (ϕ, τ). The routing solution represents the machines allocated to each team of technicians and the order of visits. The maintenance solution indicates the actual PM time w_{kh} of each leased machine. Let $R(y, x)$ and $M(\phi, \tau)$ represent the routing and maintenance costs under solution s, respectively. Therefore, the total cost $TC_h(y, x, \phi, \tau)$ can be expressed as:

$$TC_h(y, x, \phi, \tau) = R(y, x) + M(\phi, \tau) \ . \tag{16}$$

In the routing solution, for each leased machine, the team of technicians is randomly selected in $[1, l]$ under maintenance capacity constraints. If the machine is marked as u, this means that the PM action of this machine is assigned to the team of technicians $u \in \mathcal{V}$. The objective function of routing solutions can be obtained from Equation (17), which aims to minimize the routing cost. Meanwhile, it can be noted that this route optimization problem is actually a problem that requires minimizing the deployment cost, travel cost, and downtime penalty cost, simultaneously. Therefore, we use the GA to solve the route optimization problem to obtain the initial set of feasible solutions:

Table 1. Maintenance parameters of the leased machine.

k	i	β_k	η_k	ε_{kh}	a_{kh}	T^p_{kh}(h)	T^c_{kh}(h)	C^p_{kh}($)	C^c_{kh}($)	D_k($/h)	T^*_{k1} (hours)
1	1	3.15	5600	1.052	0.025	20	66	6500	19,000	1140	3126
2		1.76	4300	1.036	0.016	18	74	3900	10,000	1400	2958
3		2.51	5500	1.023	0.018	16	48	6600	18,000	1460	3130
4	2	1.84	4200	1.015	0.023	25	38	5400	8500	1080	3607
5		1.72	6400	1.031	0.038	10	68	5600	28,000	1640	3044
6		2.75	5300	1.025	0.048	12	18	4000	6800	1280	3565
7	3	1.72	6400	1.037	0.038	10	68	5700	28,000	1480	3076
8		1.83	6100	1.044	0.036	8	22	4800	16,000	1240	3496
9		2.75	5300	1.025	0.049	12	18	4100	6800	1280	3597
10	4	1.84	4200	1.015	0.026	20	38	3400	7800	1420	2936
11		1.72	6400	1.035	0.037	18	68	4200	17,000	1420	3435
12		1.83	6100	1.041	0.036	20	22	5500	18,000	1160	3517
13	5	1.89	6300	1.037	0.021	14	68	4500	18,000	1220	3221
14		2.51	5500	1.021	0.035	10	48	6200	17,000	1430	3128
15		3.13	4600	1.018	0.029	16	40	4500	8000	1350	3009

$$\min R(y,x) = \sum_{v\in\mathcal{V}}\sum_{j\in\mathcal{J}} x^v_{0j}\cdot F^v + \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}} x^v_{ij}\cdot\frac{d_{ij}}{\theta^v}\cdot C^v + \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{J}}\sum_{k\in\mathcal{M}_i}\max\left\{y^v_{ik}\cdot T^p_{kh}\right\}\cdot P_i \tag{17}$$

In the process of solving the maintenance solution, we need to determine when each machine starts maintenance based on the service route obtained from the routing solution. Specifically, two different service routes with the same $R(y,x)$ can lead to very different actual PM times, and further result in different machine maintenance costs. For a given departure time ϕ^v_0 of the required team of technicians, the actual PM time τ^v_{ik} of machine $k\in\mathcal{M}_i$ can be calculated by Equation (12) and Equation (13). Therefore, for the given service route, the corresponding maintenance cost $M(\phi,\tau)$ of all PM actions can be transformed into a function with the departure time as an independent variable. Let $\Omega_v(\phi)$ denote the cumulative maintenance cost of machines that are maintained by technician team v, and the above-mentioned maintenance cost $M(\phi,\tau)$ is obtained as follows:

$$\min M(\phi,\tau) = \sum_{v\in\mathcal{V}}\sum_{i\in\mathcal{J}}\sum_{k\in\mathcal{M}_i} y^v_{ik}\cdot G_{kh}\left(\tau^v_{ik}\right) = \sum_{v\in\mathcal{V}}\Omega_v\left(\phi^v_0\right) \tag{18}$$

The flow chart of the proposed maintenance strategy is shown in Figure 2. GAKLS starts by generating a set of initial solutions using the GA. Then the k-means algorithm is used to select a set of representative solutions from the initial set. After that, the relevant solutions are improved by applying search operations such as *Local search* and *Perturbation*. The ILS algorithm is stopped when the maximum iteration number is reached. The specific procedure and settings of our proposed GAKLS algorithm for the maintenance grouping and technician routing problem are presented in Appendix C.

5. An illustrative example

In this section, we show the decision-making process of the proposed strategy in solving MGTRP. We also benchmark our maintenance strategy against some conventional policies to evaluate its cost-effectiveness. Consider a typical MMPS that containing five geographically distributed systems (each system consists of three machines in series) and one maintenance center. These machines cover various types, such as numeral control lathe, shaping machine, grinding machine, or drilling machine, etc.

Table 2. Travel distance between production systems and the maintenance center.

$i\in\mathcal{N}$	Center	1	2	3	4	5
Center	–	52	87	71	83	62
1	52	–	46	76	131	91
2	87	46	–	120	169	135
3	71	76	120	–	102	37
4	83	131	169	102	–	66
5	62	91	135	37	66	–

The detailed maintenance parameters of leased machines are evaluated by the lessor's reliability engineers and displayed in Table 1. In order to reflect the impact of early or delayed maintenance on machine reliability and distinguish the importance of different machines in a system, we set the total importance coefficient of each production system as 4000 $/h. In addition, in order to illustrate that the proposed strategy can dynamically obtain cost-effective maintenance schedules during the long-term lease period, we set a 2-year period for each production system ($LP_i=$ [0 h, 17,520 h], $i\in\mathcal{J}$).

For this example, the travel distance between production systems and the maintenance center is generated based on their Euclidean distances, as listed in Table 2. We define the moving speed θ^v of each technician team $v\in\mathcal{V}$ as 9 unit distance per hour, then the travel time can be calculated by d_{ij}/θ^v. The downtime cost rate P_i and the travel cost rate C^v are set to 300 $/h and 400 $/h, respectively. We consider that the lessor possesses five teams of technicians at the maintenance center. The deployment cost F^v for dispatching a team of technicians is $20,000, and the maintenance capacity of each technician team q^v is six machines per dispatch.

By solving the derivative function represented by Equation (3), the optimal PM interval of the first cycle T^*_{k1} is obtained and listed in Table 1. To reduce system downtime and travel costs, PM actions are performed into several groups. Then, the GAKLS algorithm is applied to solve MGTRP. The obtained maintenance schedule of the first cycle is shown in Table 3.

As shown in Table 3, to accomplish all PM actions in a timely and appropriate manner, the lessor needs to arrange three teams to service lessees. For example, starting from the maintenance center, team 1 first travels to lessee 5 and performs a PM action for machine 14, at 3030 h. Then, the team travels to lessee 4 and performs a PM action for machine 10, at 3048 h. After that, the team goes back to lessee 5 and performs PM actions for machines 15 and 13, at 3076 h. Finally, they return to the maintenance center at 3099 h. Moreover, it can be found that each lessee (production system) can be serviced by different teams at different time points. For example, machines 8 and 9 of lessee 3 are maintained by team 2 at 3541 h. Meanwhile, machine 7 of lessee 3 is maintained by team 3 at 3032 h. The change between the independent PM time point and the actual PM time point is clarified in Figure 3. It can be noticed that the

Table 3. Optimal maintenance schedule of the first cycle.

Team 1		Team 2		Team 3	
Machine	*Actual PM time (hours)*	*Machine*	*Actual PM time (hours)*	*Machine*	*Actual PM time (hours)*
14	3030	4	3502	7	3032
10	3048	6	3502	5	3056
15	3076	8	3541	2	3072
13	3076	9	3541	3	3072
		11	3565	1	3072
		12	3565		
Center	3099	Center	3595	Center	3098

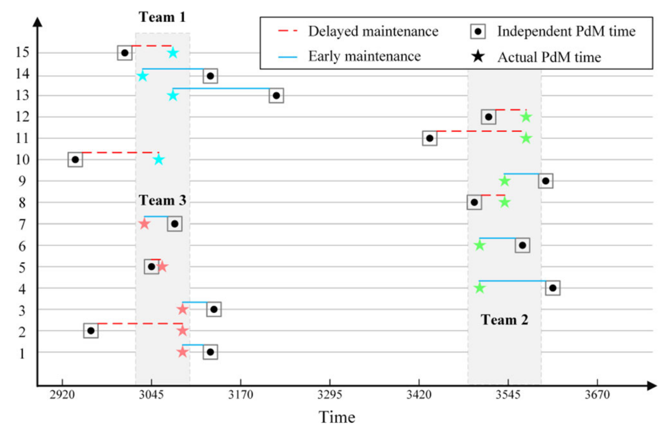


Figure 3. Schematic illustration of group maintenance among scattered systems.

optimal maintenance schedule prefers to combine the geographically contiguous and time adjacent machine maintenance into the same group, and then optimizes the service sequence.

After the maintenance optimization of the first cycle ($h = 1$), we re-evaluate the maintenance cost function of each machine using the new failure rate. Then we return to the first step and resolve the MGTRP to determine the global maintenance schedule for the next cycle. This decision-making process is executed in a rolling horizon mode to cover cost-effective O&M services within the lease period. The cyclic maintenance schedule and the corresponding total cost are shown in Figure 4.

The performance and cost metrics of these maintenance schedules are listed in Table 4. It can be noted that due to the impact of imperfect maintenance and environment on failure rates, the independent PM time of each machine becomes more dispersed. Therefore, the lessor needs to dispatch more teams of technicians to perform PM actions, even if the maintenance capacity is not fully utilized. These results also show that our proposed strategy can obtain the optimal maintenance schedule based on different machine conditions. Thus, the machine maintenance can be performed in a timely and appropriate manner, and the total cost can be reduced.

To illustrate the cost-effectiveness of our proposed strategy, we also benchmark it with three conventional strategies that are proposed to solve MGTRP. We ensure a fair comparison by using the same parameters and models for all strategies:

1. Maintenance Time Window (MTW) strategy: The first maintained machine of each production system provides an opportunity for the other machines. Then, each opportunity is utilized to group PM actions within the time window, and teams of technicians are allocated to perform group PM actions according to the best service route (Xia *et al.*, 2012). And the width of maintenance time windows is set to the optimal 350 hours.
2. Dynamic Maintenance Grouping and Routing (MGR) strategy: The PM interval of each machine is determined by minimizing its maintenance cost rate and is then used to arrange the individual PM dates. By pulling these individual PM dates of machines, the best grouping solution (a set of exclusive groups and the relevant service routes) is obtained by maximizing the total grouping economic profit (Nguyen *et al.*, 2019).
3. Triple-level Network Opportunistic Maintenance (NOM) strategy: The group PM set of each lessee is optimized by maximizing the leasing profit saving at each PM opportunity. After that, based on the maintenance requirements (group PM sets) of each lessee, teams of technicians are dispatched to perform these maintenance tasks along optimal service routes (Si *et al.*, 2019). The width of service time windows at the system level is set to the optimal 25 hours. The performance and cost metrics of the four maintenance strategies over the same lease period (17,520 hours) are presented in Figure 5.

Based on the comparative study, the advantages of our proposed strategy in dealing with the MGTRP can be summarized as follows:

1. We can intuitively see that compared with the other three strategies, our proposed strategy can effectively reduce the O&M cost and achieve long-term cost savings.
2. Different from the MTW strategy, our proposed strategy adaptively groups the PM actions of different systems to further decrease the travel cost and reduce unnecessary team dispatch. Compared with the MTW strategy, our strategy reduces the cumulative total cost by 30.1%.
3. Our strategy captures future possibilities into the current maintenance decision to quantify the impact of the actual PM time point on the subsequent maintenance process and achieve long-term O&M management.

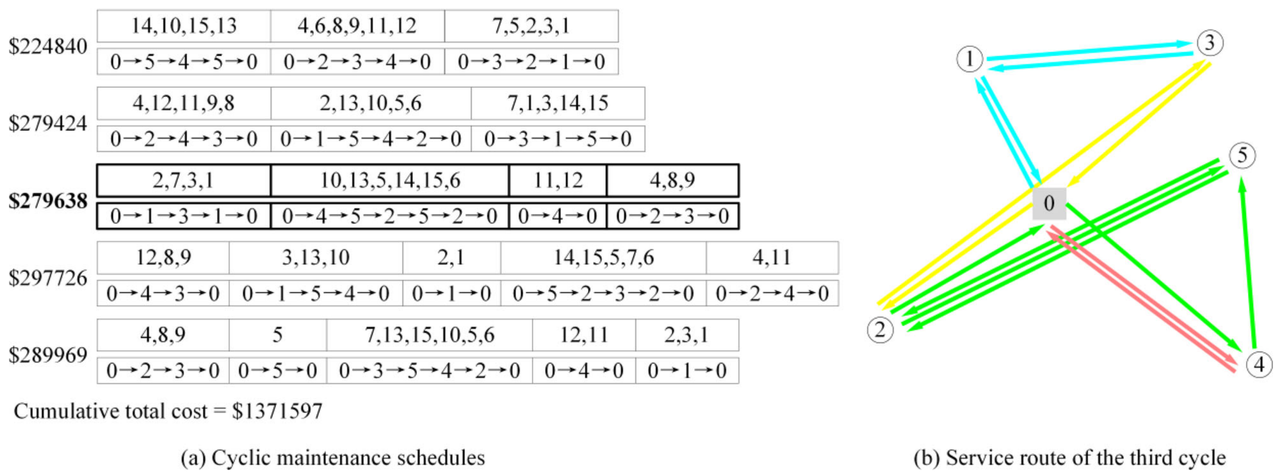


Figure 4. Real-time maintenance schedules within the lease period.

Table 4. The performance and cost metrics of cyclic maintenance schedules.

				Routing cost ($)		
Cycle	*Number of teams of technicians*	*Total cost ($)*	*Maintenance cost ($)*	*Deployment cost*	*Travel cost*	*Downtime penalty cost*
1	3	224,840	82,540	60,000	40,000	42,300
2	3	279,424	125,324	60,000	46,400	47,700
3	4	279,638	96,138	80,000	51,600	51,900
4	5	297,726	89,826	100,000	51,200	56,700
5	5	289,969	102,669	100,000	45,600	41,700

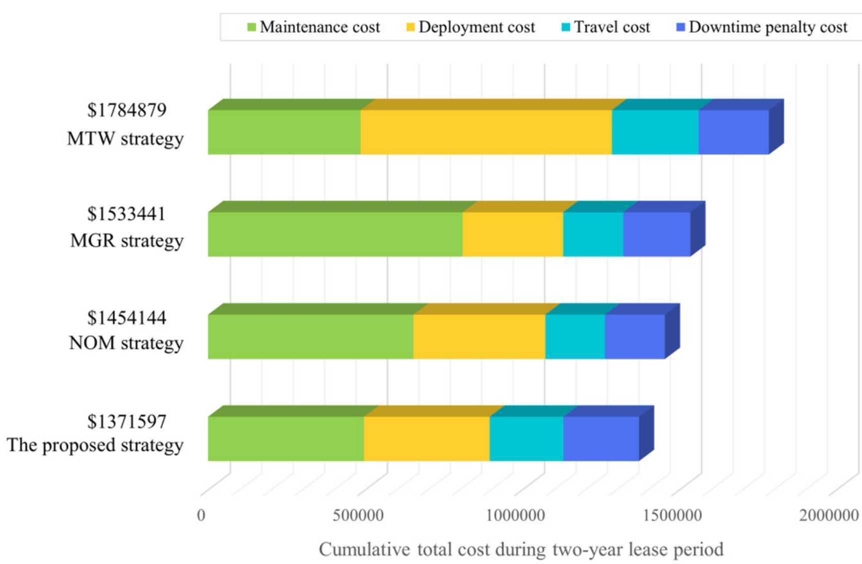


Figure 5. Cumulative total cost comparison among different strategies.

Obviously, compared with the MGR strategy, it decreases the maintenance cost from $810,325 to $496,497. In addition, by dynamically balancing the number of required technician teams and the timely maintenance of machines, our strategy decreases the cumulative total cost by 11.8%.

4. By considering both advanced maintenance and delayed maintenance for each machine, as well as dynamically searching for the optimal opportunity for each leased machine, our strategy expends the search space for possible solutions (maintenance schedules). Compared with the NOM strategy, it is intuitive to note that our strategy further reduces the cumulative total cost by 6.0%.

Furthermore, facing the maintenance scheduling optimization for MMPS, individual machine degradations, complex maintenance opportunities and network logistics optimization should be comprehensively considered. Therefore, we propose a holistic modeling approach to solve the MGTRP. For each leased machine, based on the dynamic failure rate observed by the OEM, we establish a time-varying maintenance cost function and capture future possibilities into the current maintenance decision-making process. Based on these maintenance costs, we further optimize several inter-related decisions: (i) the most suitable maintenance opportunity for each leased machine, (ii) cost-effective arrangements of teams of technicians to perform maintenance tasks, and (iii) optimal service routes to incorporate the required teams of technicians into a global optimization model. We use the GAKLS algorithm to solve this optimization model and obtain the global maintenance schedule.

In the general sense, our strategy can significantly achieve total cost savings, ensure service timeliness and further enable long-term O&M management. Different lessee geographical locations, machine degradation trends and PM durations will result in completely different global maintenance schedules. However, the mechanism of our proposed strategy can adapt to these changes and obtain adaptive maintenance and routing decisions. On the one hand, the impact of current maintenance decisions is captured through the time-varying maintenance cost function. This allows the global optimization model to balance the trade-off between advanced maintenance and delayed maintenance to determine the most appropriate PM time point for every machine. On the other hand, the global optimization model also dynamically compares total costs (including maintenance cost, deployment cost, travel cost and downtime penalty cost) and selects the solution with the lowest total cost at each PM cycle. This holistic modeling approach and sequential decision-making process guarantees long-term total cost savings, making this strategy more effective than conventional strategies (i.e., MTW, MGR and NOM). In summary, the proposed strategy performs best in dealing with the MGTRP, as it not only arranges the optimal maintenance opportunities for machines, but also purposefully groups PM actions among different systems to reduce system downtime and achieve service sequence optimization. Moreover, the proposed strategy can be extended to a sensor-driven maintenance strategy by replacing the generic failure rate in Equation (3) with a real-time failure rate.

6. Medium/large-sized numerical experiments

This section aims to conduct medium/large-sized numerical experiments to further examine the capability of the GAKLS approach and the proposed maintenance strategy to solve a realistic MGTRP. The data generation of maintenance parameters and network topology is presented in Appendix D. The computational performance of the GAKLS approach is demonstrated in Section 6.1, and. real-time maintenance schedules within the long-term lease period are presented in Section 6.2. A comprehensive sensitivity analysis is conducted in Appendix E.

6.1. Computational performance

In this subsection, the performance of the GAKLS algorithm is compared with three metaheuristic algorithms, namely variable neighborhood search (VNS), GA and simulated annealing (SA). All experiments are compiled in the Python 3 programming language executed on a Pentium 9 CPU with 2.30 GHz processor and 32 GB of RAM.

We consider the network topology described in Appendix D and generate five different variations by randomizing the maintenance parameters. The moving speed, downtime cost rate, travel cost rate, and deployment cost are set to the same as in Section 5. The maintenance capacity of each team of technicians is 10 machines. Meanwhile, to focus on the comparison of algorithm performance, we set a half-year leased period ($LP_i = [0\,\text{h}, 4380\,\text{h}]$) without considering multi-cycle optimization. It is well known that the quality of an algorithm is strongly influenced by its parameter settings. To get high-performance algorithms and ensure the accuracy of comparisons, appropriate tuning of algorithm parameters is carried out. In this experiment, the tuned algorithm parameters are listed as follows:

- VNS: The number of initial solutions $N_{init} = 20$, the number of iterations in total $Itr_{\max}^{VNS} = 110$, and the number of iterations in each neighborhood structure $Shake_{iter} = 6$.
- GA: The size of population $P_{size}^{GA} = 160$, the maximum number of iterations $Itr_{\max}^{GA} = 200$, the mutation rate $=$ 0.2, and the crossover rate $= 0.8$.
- SA: The initial annealing temperature $Te = 500$, the annealing rate $r = 0.95$, the minimal temperature $Te_{\min} = 0.01$, and number of solutions during each cycle $N_{cycle} = 100$.
- GAKLS: The size of population $P_{size}^{GA} = 160$, the maximum number of iterations $Itr_{\max}^{GA} = 200$, the mutation rate $= 0.2$, the crossover rate $= 0.8$, the number of clustering $k = 5$, the size of local search $P_{size}^{LS} = 50$, and the maximum number of perturbation $Itr_{\max}^{LS} = 30$.

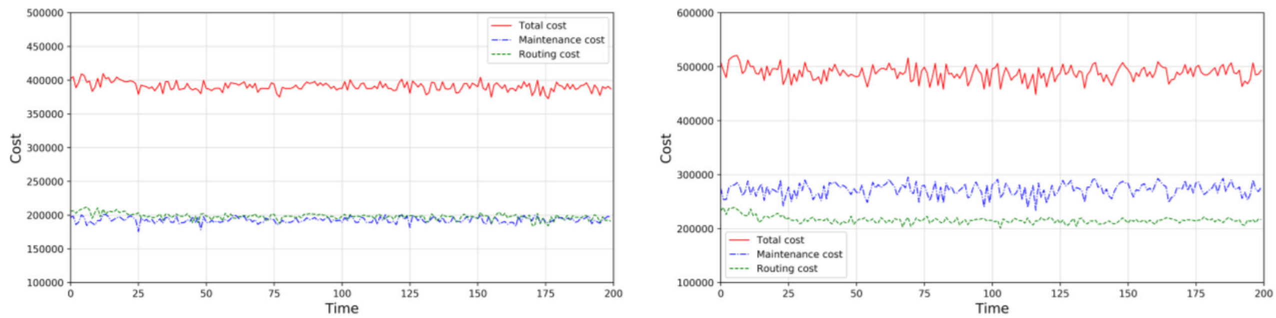
Table 5. Comparison among algorithms for the MGTRP.

No. \ $\overline{TC}$ ($)	*VNS*	*GA*	*SA*	*GAKLS*
1	416,367.5	401,240.2	380,040.8	**374,057.7**
2	403,869.3	387,623.2	364,456.8	**359,432.0**
3	412,718.1	398,515.9	371,187.1	**369,749.1**
4	400,111.7	382,369.6	369,816.6	**358,532.6**
5	425,123.6	407,164.0	382,448.8	**382,155.5**
Time(s)	[386,461]	[841,911]	[960,1224]	**[237,290]**

Table 5 reports the comparison between four algorithms. The bolded values are the results (total cost values and CPU-time) achieved by our proposed strategy. Each experiment is repeated 10 times with the same maintenance information, and the reported $\overline{TC}$-value is the mean value for the corresponding problem experiment. The user CPU-time (containing [min, max] values) contains the minimal and maximum computational duration (in seconds) for solving the corresponding MGTRP. The results show that our proposed GAKLS algorithm has a comparative advantage in terms of computational performance and computation time. The GAKLS algorithm can enables lessors to efficiently determine the number of teams of technicians for multi-location O&M services, and to leverage each maintenance team to implement timely and cost-effective maintenance schemes.

6.2. Real-time maintenance schedules within the long-term lease period

Apart from the algorithm comparison in Section 6.1, an adaptive maintenance decision process is conducted. To demonstrate the long-term effectiveness of the proposed



(a) Performance of solutions with the original importance coefficient

(b) Performance of solutions with the triple importance coefficient

Figure 6. The performance of the proposed GA solutions.

Table 6. Optimal maintenance schedule of the first cycle with different importance coefficients.

Original importance coefficient		*Triple importance coefficient*	
Total cost ($)	*Service routes of group maintenance*	*Total cost ($)*	*Service routes of group maintenance*
352,705	Team 1: [16,17,18,23,27,25,26,6,8,7] Team 2: [15,22,29,19,20,30,28,21,2,1] Team 3: [5,14,13,12,10,11,4,24,9,3]	405,995	Team 1: [13,15,1,22,30,28,19] Team 2: [18,4,5,21,25,8,7,9,6] Team 3: [3,20,16,17,14,24] Team 4: [10,26,11,12,27,29,23,2]

Table 7. The performance and cost metrics of solutions.

				Routing cost		
Solution	*Number of teams of technicians*	*Total cost ($)*	*Maintenance cost ($)*	*Deployment cost ($)*	*Travel cost ($)*	*Downtime penalty cost ($)*
1-1	3	352,705	191,305	60,000	24,000	77,400
1-2	3	372,473	186,373	60,000	32,800	93,300
1-3	3	392,871	208,071	60,000	36,000	88,800
1-4	4	442,406	222,606	80,000	42,000	97,800
1-5	4	461,136	247,136	80,000	35,600	98,400
1-6	5	485,434	244,334	100,000	37,600	103,500

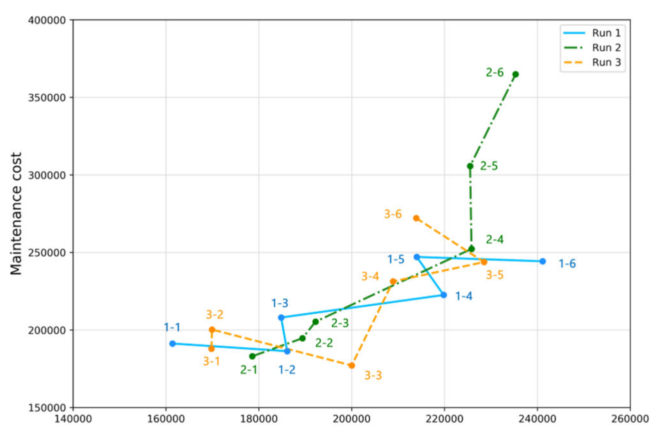


Figure 7. Performance of cyclic maintenance schedules of this example.

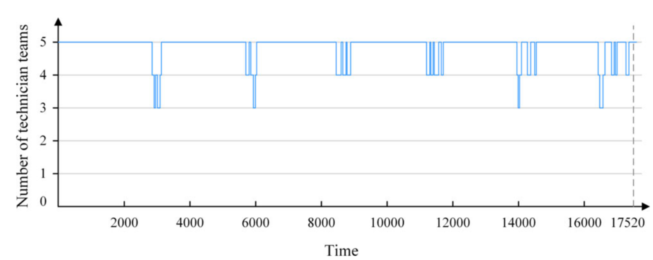


Figure 8. The number of teams of technicians in the maintenance center.

strategy in dealing with MGTRP, we set the 2-year lease period for every lessee. After randomly generating initial routing solutions, GA is applied to solve the technician routing problem and then find the optimal departure time of each team under a determined service route. The performance of the best solution in each generation is shown in Figure 6(a). It can be observed that the total cost of the current local optimal solution is $384,257, and the relationship between maintenance cost and routing cost is irregular.

After that, the k-means algorithm is employed to select k representative solutions from the initial set and provide inputs for the ILS algorithm. Eventually, the machines serviced by each team of technicians, the epoch of leaving the maintenance center, and the epoch of maintaining each system at the first PM cycle are shown in Table 6. It can be noted that the minimal total cost is $352,705 and the lessor needs to dispatch three teams to perform O&M services. To highlight the impact of the importance coefficient on maintenance schedules, we triple the importance coefficient of each machine. The corresponding performance of the best solution in each generation is shown in Figure 6(b), and the schedule with required technician teams is shown in Table 6. It can be observed that with the increase of the importance coefficient, the time-varying maintenance cost function will become tighter. Therefore, the lessor prefers to increase the number of teams of technicians to execute maintenance.

To reflect the performance of the GAKLS algorithm in terms of obtaining (near)-optimal solutions, we conduct three independent runs of the proposed algorithm. However, it should be noted that the solution procedure of the current cycle is affected by the optimal solution of the previous cycle. After we finish the maintenance planning of each cycle, we return to the first step and resolve the MGTRP with the updated parameters and models to generate the global maintenance schedule for the next cycle. This process is executed in rolling horizon mode to cover the 2-year lease period. The corresponding performance of cyclic maintenance schedules of three independent runs is shown in Figure 7.

To better explain the obtained solutions, we consider the solution of run 1 shown in Figure 7 as an example. The corresponding performance and cost metrics are shown in Table 7. The proposed strategy seeks to optimize the number of required technician teams and to balance the workload among teams. In addition, it also tries to plan the best service route and search for the optimal departure time of each team. As discussed in Section 1, a balanced maintenance schedule helps to ensure the expected production time of systems, as many systems age more quickly if they are under heavy use while in a degradation state. To gain a better intuitive understanding of what such an optimized schedule of technician teams looks like, Figure 8 shows the number of technician teams at the maintenance center during the lease period.

From Figure 8, it can be observed that the maximum number of teams of technicians required at the same time is two. This means that, even if the optimal solution of each cycle needs to dispatch teams of technicians three, four, or five times to perform all PM actions, the lessor only needs two teams for daily outsourcing maintenance. This analysis about the number of required teams of technicians can provide lessors with some managerial insights into technician teams and help them to optimize the daily use of technician resources. Meanwhile, a practical benefit of our proposed strategy is that it yields simple, but optimally structured decision rules that are easy to implement. It is generalizable and applicable to many other maintenance settings, which helps OEMs to perform timely and appropriate maintenance.

7. Conclusion

This article presents a service-oriented maintenance optimization strategy for integrating maintenance grouping and technician routing for a MMPS. The proposed strategy not only extends the group maintenance from a single system to multi-location multi-unit production systems, but also dynamically optimizes the corresponding service routes within the long-term lease period. By constructing a time-varying maintenance cost function and establishing a systematic maintenance optimization model, our proposed strategy can help lessors to determine an economical and practical maintenance scheme, as well as the best service route. Meanwhile, the influence of machine maintenance, travel time between lessees and the maintenance capacity of technician teams on O&M decision-making are explicitly considered.

Cumulative total cost reduction by applying the proposed strategy has been demonstrated in solving the MGTRP of MMPSs. In addition, the experimental results indicate that the global maintenance schedule can achieve remarkable cost-saving, optimize the use of technician teams, and adapt to a variety of different scenarios. The actual PM time of machines assists lessors to understand the trade-off between the ineffective use of machine lifetime caused by early maintenance and the increased failure risk due to delayed maintenance. Also, knowledge about the important parameters can help lessors to have better control over or provision of these parameters.

Further work will be on extending group maintenance with the consideration of other system structures, such as series-parallel system, reconfigurable system, etc. In addition the starting point and the ending point of technician teams should be from a maintenance center to multiple maintenance centers. In this situation, a workforce sharing problem needs to be researched based on cross-region maintenance optimization.

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