Technician Collaboration and Routing Optimization in Global Maintenance Scheduling for Multi-Center Service Networks

Guojin Si, Tangbin Xia, *Member, IEEE*, Kaigan Zhang, Dong Wang, *Member, IEEE*, Ershun Pan, and Lifeng Xi

***Abstract*—With the popularization of service-oriented manufacturing, the current operation & maintenance (O&M) has shifted from traditional in-house maintenance to proactive outsourcing maintenance. It is paramount for an original equipment manufacturer (OEM) to provide timely and cost-effective maintenance schemes to geographically distributed customer enterprises. Interestingly, transportation theories could be combined to facilitate multi-location O&M management. In this paper, a transportation-oriented cross-regional opportunistic maintenance (TCOM) policy is developed for solving O&M optimizations and planning real-time schemes for the multi-center service network. The optimization model of this TCOM policy addresses several inter-related decisions: (1) most suitable maintenance times for each leased machine, (2) cost-effective arrangements of technician teams to perform maintenance tasks, and (3) optimal service routes for required teams. We not only integrate maintenance grouping and technician routing, but also investigate the new issues arising from the collaborative sharing of technician teams belonging to different maintenance centers. Numerical examples show that this TCOM policy can achieve significant cost-saving in cross-regional maintenance grouping and multi-location routing optimization for OEMs.**

***Note to Practitioners*—This paper is motivated by the critical problem of computing an optimal maintenance policy for the multi-center service network of geographically distributed production systems to achieve a timely and cost-effective O&M management. We consider individual machine degradations, complex maintenance opportunities and network logistics optimization to establish a global maintenance scheme for the multi-center service network. The existing approaches are to schedule the preventive maintenance (PM) for a single machine or multi-unit leased system, which is unilateral and cannot be applied to multi-location production systems. Although the network opportunistic maintenance policy has been proposed in the literature for maintenance grouping and technician routing problem, it still does not consider the limited workforce resource and the collaborative sharing of technician teams from different maintenance centers. To fill this literature gap, in this paper, we develop the TCOM policy to determine the optimal maintenance timetable for leased machines, as well as the cost-effective service route of technician teams belonging to multiple maintenance centers, so as to conduct timely and cost-effective PM on multi-location production systems. Compared with the conventional maintenance policy, our adaptive policy greatly reduces the total outsourcing maintenance cost in long-term O&M services.**

***Index Terms*—Maintenance, technician routing, multi-center service network, collaborative sharing, clustering iterated local search.**

I. Introduction

With the service-oriented manufacturing has been widely applied, the scale of lessee enterprises has consecutively expanded, which has led to the globalization of maintenance outsourcing [1]–[3]. In terms of maintenance outsourcing, a series of attractive benefits can be reached for both partners. For customer enterprises as the lessees, because of the sophistication and diversification of machines, equipment leasing helps to reduce in-house maintenance expenses and acquire specialized maintenance skills. For an original equipment manufacturer (OEM) as the lessor, maintenance services provide a new profitable spot and raise an opportunity to enhance client loyalty. Under this background, the lessor ensures the reliable operation and maintenance (O&M) services of geographically distributed lessees by constructing a service network and dispatching technician teams to provide real-time maintenance [4].

Maintenance is not a stand-alone activity, but interacts with many other activities (such as production planning, technician management, and execution route optimization, etc.) in real industry. The independent maintenance of each manufacturing enterprise leads to the incomplete utilization of available maintenance resources. To improve technician

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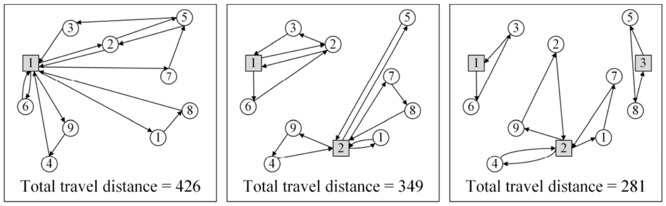


(a) One maintenance center (b) Two maintenance centers (c) Three maintenance centers

Fig. 1. The decrease in total travel distance with the increase in the number of maintenance centers.

efficiency and reduce the frequency of system downtime, it is essential to consider inter-machine dependencies to combine maintenance activities reasonably [5]–[8]. Moreover, the continuous increment of manufacturing enterprises (the lessees) makes it extremely difficult to quickly respond and dispatch maintenance resources. Therefore, besides the above benefits, this transformation also exponentially increases the complexity of maintenance decision-making, urging lessors to investigate some new frameworks to execute timely maintenance actions for a large-scale multi-location network. The most challenging aspect is to integrate individual machine degradations, complex maintenance opportunities, and network logistics optimization to obtain a cost-effective global maintenance scheme.

To face this problem, some lessors divide the service network into multiple regions, and establish regional maintenance centers to concern O&M services in parallel [9]–[11]. Typically, technician teams are distributed in different maintenance centers within the service network. And the geographic location of each maintenance center is determined by minimizing the total travel distance according to the research of location routing problems. Upon a proactive maintenance task or an unexpected failure, the central technician teams with required spare parts are dispatched to perform maintenance actions for lessee enterprises. By developing maintenance methods within each region, resources can be better integrated to provide more efficient service responses. Fig. 1 can better clarify the issue. It shows that as the number of maintenance centers increases, the total travel distance decreases dramatically. However, it is essential to observe that due to the dynamic and inherent stochasticity of machine degradations, this local framework is only suitable for short-term periodic maintenance planning. For the long-term O&M service, it is necessary to consider the collaborative sharing of technician teams to meet real-time maintenance requirements and achieve cost savings.

Meanwhile, advances in sensor technology and wireless communication play a vital role in enabling the Industrial Internet of Things (IIoT) [12]. The estimation of machine degradation is one of the most pivotal IIoT applications [13]. Modern technologies, such as Industry 4.0 and cyber-physical systems, can improve the capability of failure monitoring and the accuracy of condition-based preventive maintenance (PM). By executing remote diagnostics, the lessor can immediately dispatch technician teams to perform PM actions, rather than wasting valuable time on diagnosis activities. However, there is no systematic maintenance policy to utilize degradation information from leased machines to establish an O&M framework for a multi-center service network (MCSN). In this paper, we propose global maintenance scheduling with technician collaboration and routing optimization. Its goal is to jointly determine (1) the collaborative allocation of technician teams to multiple lessees, (2) service routes used to perform the maintenance activities, and (3) maintenance timetables (the actual maintenance start time) of machines. Therefore, a transportation-oriented cross-regional opportunistic maintenance (TCOM) policy is developed, which dynamically address maintenance grouping and technician routing problem.

Maintenance scheduling has been gradually studied in the literature of service-oriented manufacturing mode. Most of the existing research mainly focuses on a single leased machine [14]–[16]. Besides, a few papers involve multi-unit series systems, which assume a typical failure distribution (typically Weibull) to represent machinery failure risk [17]. Jaturonnatee *et al*. [18] first developed the preventive maintenance policy for a leased machine, in which the penalty cost from the lease contract was considered. Xia *et al.* [19] grouped preventive maintenance actions of the multi-unit series system dynamically by using the downtime opportunity. Due to the lack of topology path optimization and technician capability allocation, these in-house maintenance policies cannot be directly applied to the service network. More recently, the improvement of logistics management capability has prompted scholars to study the maintenance scheduling for the entire networked infrastructure [20]. To obtain the practical maintenance timetables and service routes, it is necessary to propose the maintenance policies for geographically distributed lessees [21], [22]. Díaz-Ramírez *et al*. [23], Camci [24], and Irawan *et al*. [25] performed the maintenance scheduling optimization for geographically distributed machines while assuming only one technician team is available, and each machine could be maintained only once. López-Santana *et al*. [26] extended the problem to consider the condition that each machine can be maintained more than once, and multiple technician teams can be dispatched. The above models considered the systems constituted of isolated machines, but they cannot handle the maintenance of the real-world service network topology. Nguyen *et al*. [27] studied the maintenance scheduling optimization for multi-unit series systems with distributed network structures. Si *et al*. [28] and Xia *et al.* [29] divided the problem into multiple levels and obtained the global maintenance schemes for the leasehold service network cycle by cycle. However, these studies focused primarily on a single center and assumed an unlimited number of teams is kept.

To the best of my knowledge, the maintenance scheduling problem has not been appropriately dealt with for the multi-center service network. Therefore, to fulfill this research gap, we develop the TCOM policy to determine the optimal maintenance timetable for leased machines, the cost-effective service route of technician teams, and collaborative sharing decisions of existing technician teams, so as to conduct timely and cost-effective PM for the MMSN. See Table I for contribution of different authors. By optimizing the maintenance scheduling of multi-center multi-lessee network holistically, the maintenance resources of multiple maintenance centers can

TABLE I
CONTRIBUTION OF DIFFERENT AUTHORS

Maintenance policy	Research level	Authors	Machine preventive maintenance	System opportunistic maintenance	Networked maintenance scheduling	Multi-center resource coordination
In-house maintenance	Machine level	Jaturonnatee et al. (2006) [17]	√			
	Factory level	Xia et al. (2017) [18]	√	√		
		Chang et al. (2019) [16]	√	√		
Multi-factory maintenance	Network level	Díaz-Ramírez et al. (2014) [22]			√	
		Camci (2015) [23]	√		√	
		López-Santana et al. (2016) [25]	√		√	
		Irawan et al. (2017) [24]	√		√	
		Nguyen et al. (2019) [26]	√	√	√	
		Si et al. (2019) [27]	√	√	√	
		Xia et al. (2021) [28]	√	√	√	
		This paper	√	√	√	√

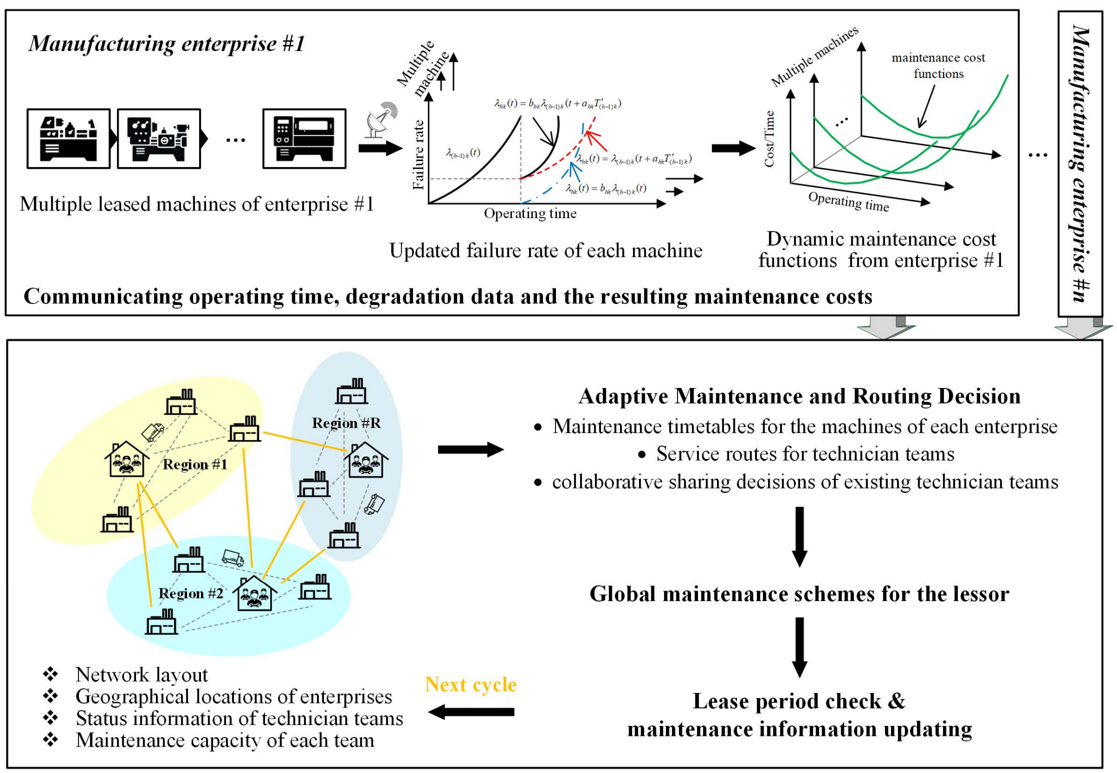


Fig. 2. Proposed global maintenance scheduling framework.

be balanced and the service efficiency of technicians can be improved. Fig. 2 illustrates the decision-making framework of the proposed TCOM policy. Individual machine degradations, complex maintenance opportunities, and network logistics optimization are integrated to provide real-time outsourcing maintenance schemes.

There are three significant contributions made by this research. Firstly, our proposed TCOM policy improves the applicability in modeling and solving the maintenance grouping and technician routing problem for multi-center service networks. Secondly, we optimize the collaborative sharing of technician teams from different maintenance centers to obtain cross-regional maintenance schedules. Thirdly, we incorporate updated maintenance cost functions, system downtime, and the maintenance capacity of technician teams into a dynamic optimization model. Especially, the global maintenance scheme is obtained in real-time by pursuing the minimum total outsourcing maintenance cost. Moreover, a clustering iterated local search algorithm (CILS) is proposed to ensure the efficiency and accuracy of maintenance scheduling decisions.

The remainder is organized as follows. Section II proposes the mathematical model to describe the multi-center maintenance scheduling problem. Section III presents a novel solution approach to solve the optimization model. Section IV presents the experiments performed to illustrate the advantages of the TCOM policy and the CILS algorithm. Finally, we provide concluding remarks in Section V.

II. Problem Description and Formulation

A. Problem Description

In this paper, we consider a complex multi-center service network consisting of L manufacturing enterprises (lessees) and C maintenance centers. Each lessee has M_i leased machines arranged serially and operates stably unless there are scheduled maintenance and unexpected failures. In the maintenance scheduling of multi-location lessees, we consider two types of maintenance actions: corrective minimal repair (CM) and imperfect preventive maintenance (PM). The PM plan (the optimal PM interval) of each machine is obtained through the cost-oriented model. If a leased machine fails during a PM interval, it undergoes a CM action to bring it back to an operational state. The lessor establishes multiple maintenance centers and dynamically dispatch technician teams to provide outsourcing maintenance services for these geographically distributed lessees. To ensure normal production and avoid system shutdown, the lessor needs to estimate the level of machine degradation and then allocate technician teams from different maintenance centers to perform timely PM actions. Therefore, a comprehensive maintenance scheduling problem is proposed, which not only needs to arrange the maintenance schedule of leased machines but also needs to determine the service route of existing technician teams. More importantly, the collaborative scheduling of technician teams belonging to different maintenance centers needs to be studied to achieve technician sharing and reduce the total outsourcing maintenance cost.

The MCSN is defined on $\mathcal{G} = (\mathcal{N}, \mathcal{A})$. The node-set $\mathcal{N} = \mathcal{N}_c \cup \mathcal{N}_l$ consists of maintenance center depots $\mathcal{N}_c = \{1, 2, \ldots, C\}$, and lessee nodes $\mathcal{N}_l = \{1, 2, \ldots, L\}$. Every node $i \in N$ represents the geographical location (including abscissa and ordinate) of lessees and maintenance centers. The set of arcs $\mathcal{A} = \{(i, j)|i, j \in \mathcal{N}, i \neq j\}$ represents the possible service routes between lessees and multiple maintenance centers. And each service route starts and ends at the same maintenance center. Let $\mathcal{V}_r = \{1, 2, \ldots, V_r\}$ be the set of technician teams located at maintenance center $r \in \mathcal{N}_c$, so that the complete set of technician teams is given by $\mathcal{V} = \bigcup_{r\in\mathcal{N}_c} \mathcal{V}_r$. The technician teams from different maintenance centers are dispatched to perform PM actions in the right time, aiming to reduce unnecessary shutdown by monitoring machine health.

This paper proposes the TCOM policy to dynamically obtain global maintenance schemes of multi-center service networks. It not only jointly examines group maintenance and routing of technician teams, but also considers the new issue arising from the collaborative sharing of technician teams belonging to different maintenance centers. In addition, the impact of group maintenance on operating conditions, as well as the impact of technician collaboration, are captured through additional variables, thus allowing the optimization model to be penalized when the production system of lessees is shut down and the technician team is shared. Its mechanism with cross-regional collaborative sharing and global O&M optimization can significantly ensure cost reduction, service timeliness and network robustness.

B. Mathematical Formulation

1) Predicting Maintenance Costs for Leased Machines: As widely done in the literature, the scholars build the maintenance cost rate $c_{hk}(T_{hk})$ as shown in Eq. (16) which aims to minimize the maintenance cost per unit time. As this maintenance cost rate shows a decreasing trend followed by an increasing trend, the optimal PM interval T_{hk}^* for each machine can be obtained by solving the following derivative function $dc_{hk}(T_{hk})\big/dT_{hk} = 0$ [14]–[16], [18], [19]. Generally, the corresponding time point based on the optimal PM interval is called the individual PM time point (denoted by t_{hk}^*). However, for multi-center maintenance scheduling problems, the individual PM time point is no longer the best O&M opportunity for the entire manufacturing system [25]–[30]. Therefore, we quantify the impact of different PM maintenance time points on system operation by building the maintenance cost function $U_{hk}\left(\tau_{ik}^{rv}\right)$ and considering time variables τ_{ik}^{rv} to determine the actual PM time point of each leased machine. The maintenance cost function $U_{hk}\left(\tau_{ik}^{rv}\right)$ of machine k at hth PM cycle is expressed as follows:

$$t_{hk}^* = \begin{cases} T_{hk}^* & h = 1 \\ \sum\limits_{h'=1}^{h-1} T'_{h'k} + \sum\limits_{h'=1}^{h-1} T_{h'k}^P + T_{hk}^* & h \geq 2 \end{cases} \tag{1}$$

$$U_{hk}\left(\tau_{ik}^{rv}\right) = \frac{\left(\tau_{ik}^{rv} - t_{hk}^*\right)^2}{LP_i} \cdot c_k^{tp} \cdot I_k \tag{2}$$

where $T'_{h'k}$ represents the actual PM interval and $T_{h'k}^P$ is the duration of a PM action. LP_i is the lease period of lessee i, $\frac{\left(\tau_{ik}^{rv} - t_{hk}^*\right)^2}{LP_i}$ is proposed to quantify the extent to which the actual PM time point τ_{ik}^{rv} deviates from the individual PM time point t_{hk}^* during the lease period. Specifically, $U_{hk}\left(\tau_{ik}^{rv}\right)$ will increase quadratically as τ_{ik}^{rv} gradually moves away from t_{hk}^*. c_k^{tp} is the time punishment cost rate for machine k. And I_k is the importance coefficient of machine k. By setting different importance coefficients, the priority of machines is represented. The lessor can prioritize the maintenance of high-priority machines and ensure that repaired machine is in acceptable mechanical condition.

Moreover, we combine these maintenance cost functions $U_{hk}\left(\tau_{ik}^{rv}\right)$ and the decision variable τ_{ik}^{rv} into the optimization model described in the next section to further search the optimal maintenance opportunity of each leased machine from a global perspective. By systematically optimizing the machine maintenance timetable, global maintenance schemes balance insufficient maintenance and over-maintenance.

2) Optimizing Global Schemes for Service Networks: Then, to model the consideration that each technician team can maintain limited machines in once dispatch, we set the maintenance capacity of technician team $v \in \mathcal{V}_r$ as q^{rv}. That is, the maximum number of machines that can be maintained by each technician team is denoted. Let F^{rv} represent the deployment cost associated with dispatching a technician team from its maintenance center. Moreover, this cost implicitly captures maintenance grouping decisions. The higher F^{rv} is, the more aggressive the TCOM policy will try to combine PM actions together.

Once several PM actions of the same lessee are performed at the same time, the lessee will stop production during the service period. This essentially creates system downtime until these maintenance tasks are completed. Therefore, let P_i denote the penalty per hour to quantify the impact of system shutdowns on the solution. T_{hk}^{P} represent the duration of a preventive maintenance action for machine k. By considering the downtime penalty cost, the impact of group maintenance on multi-unit systems can be reflected. Also, the technician team may provide O&M services for lessee enterprises that do not belong to their service regions. On the one hand, maintenance resource sharing can dynamically balance regional resources and improve service efficiency. On the other hand, it also raises the risk of insufficient resources for local maintenance activities. To reflect this duality, let R^{rv} denote the penalty cost due to the collaborative sharing of technician teams.

To describe the TCOM policy, we introduce the following decision variables. α, y and x together define the routing decision for technician teams: 1) Binary variable $\alpha_{ik}^{rv}=1$ when machine k of lessee i is undergoing preventive maintenance by technician team $v \in \mathcal{V}_r$ at time epoch τ_{ik}^{rv}, and 0 otherwise; 2) Binary variable $y^{rv}=1$ if technician team $v \in \mathcal{V}_r$ is dispatching to perform the relevant O&M services, and 0 otherwise; 3) Binary variable $x_{ij}^{rv}=1$ when technician team $v \in \mathcal{V}_r$ is travel from lessee i to lessee j, and 0 otherwise. Meanwhile, ϕ and τ together define the machine maintenance decision: 1) Variable ϕ^{rv} is the departure time of technician team $v \in V_r$ from its corresponding maintenance center; 2) Variable τ_{ik}^{rv} is the arrival time of technician team $v \in \mathcal{V}_r$ to perform the relevant PM action for machine k of lessee i. In addition, the arrival time can be calculated from the departure time of each technician team. γ defines the collaborative sharing condition. Binary variable $\gamma_{ik}^{rv}=1$ if the PM actions of machine k in lessee i are performed by technician team $v \in \mathcal{V}_r$ from other maintenance centers, and 0 otherwise.

Then, a complete solution can be represented by the tuple $\boldsymbol{s}=(\alpha, y, x, \phi, \tau, \gamma)$. Let $TC_h(\boldsymbol{s})$ represent the total outsourcing maintenance cost under solution $\boldsymbol{s}$ at the hth PM cycle.

$$\begin{aligned}\min TC_h(\boldsymbol{s}) = {} & \underbrace{\sum_{r\in\mathcal{N}_c v\in v_r}\sum_{i\in\mathcal{N}_l}\sum_{k\in\mathcal{M}_i}\alpha_{ik}^{rv}\cdot U_{hk}\left(\tau_{ik}^{rv}\right)}_{\text{(i) machine maintenance cost}} \\ & + \underbrace{\sum_{r\in\mathcal{N}_c}\sum_{v\in v_r} y^{rv}\cdot F^{rv}}_{\text{(ii) deployment cost}} \\ & + \underbrace{\sum_{r\in\mathcal{N}_c}\sum_{v\in\mathcal{V}_r}\sum_{j\in\mathcal{N}}^{r_{ij}} x_{ij}^{rv}\cdot C^{rv}\cdot D_{ij}/\theta^{rv}}_{\text{(iii) travel cost}} \\ & + \underbrace{\sum_{r\in\mathcal{N}_c}\sum_{v\in v_r}\sum_{i\in\mathcal{N}_l}\sum_{k\in\mathcal{M}_i}\max\left\{\alpha_{ik}^{rv}\cdot T_{hk}^{P}\right\}\cdot P_i}_{\text{(iv) downtime penalty}} \\ & + \underbrace{\sum_{r\in\mathcal{N}_c}\sum_{v\in V_r}\sum_{i\in\mathcal{N}_l}\sum_{k\in\mathcal{M}_i}^{rv}\gamma_{ik}^{rv}\cdot R^{rv}}_{\text{(v) coordination penalty cost}}\end{aligned} \tag{3}$$

$$\sum_{j\in\mathcal{N}_l} x_{dj}^{rv} = \sum_{i\in\mathcal{N}_l} x_{id}^{rv} \le 1 \quad \forall r\in\mathcal{N}_c,\ v\in\mathcal{V}_r,\ d\in\mathcal{N}_c \tag{4}$$

$$\sum_{r\in\mathcal{N}_c}\sum_{v\in\mathcal{V}_r}\sum_{j\in\mathcal{N}_l} x_{ij}^{rv} = \sum_{r\in\mathcal{N}_c}\sum_{v\in\mathcal{V}_r}\sum_{j\in\mathcal{N}_l} x_{ji}^{rv} \quad \forall i\in\mathcal{N}_l \tag{5}$$

$$\sum_{i\in\mathcal{N}_c}\sum_{j\in\mathcal{N}_l} x_{ij}^{rv} \le y^{rv} \quad \forall r\in\mathcal{N}_c,\ v\in\mathcal{V}_r \tag{6}$$

$$\sum_{v\in\mathcal{V}_r} y^{rv} \le V_r \quad \forall r\in\mathcal{N}_c \tag{7}$$

$$\sum_{r\in\mathcal{N}_c}\sum_{v\in\mathcal{V}_r} \alpha_{ik}^{rv} = 1 \quad \forall i\in\mathcal{N}_l,\ k\in\mathcal{M}_i \tag{8}$$

$$\sum_{i\in\mathcal{N}_l}\sum_{k\in\mathcal{M}_i} \alpha_{ik}^{rv} \le q^{rv} \quad \forall r\in\mathcal{N}_c,\ v\in\mathcal{V}_r \tag{9}$$

$$\sum_{r\in\{b\}}\sum_{v\in\mathcal{V}_r} \alpha_{ik}^{rv} + \sum_{r'\in\mathcal{N}_c/\{b\}}\sum_{v'\in\mathcal{V}_r} \gamma_{ik}^{r'v'} = 1 \quad \forall i\in\mathcal{N}_l,\ k\in\mathcal{M}_i \tag{10}$$

$$\tau_{jk}^{rv} = \sum_{i'\in\mathcal{N}_c} x_{i'j}^{rv}\cdot\left[\phi^{rv} + D_{ij}/\theta^{rv}\right]$$
$$\forall r\in\mathcal{N}_c,\quad v\in\mathcal{V}_r,\ j\in\mathcal{N}_l,\ k\in\mathcal{M}_j \tag{11}$$

$$\tau_{jk}^{rv} = \sum_{i\in\mathcal{N}_l}\sum_{k\in\mathcal{M}_i} x_{ij}^{rv}\cdot\left[\tau_{ik}^{rv} + \max\left\{\alpha_{ik}^{rv}\cdot T_{hk}^{P}\right\} + D_{ij}/\theta^{rv}\right]$$
$$\forall r\in\mathcal{N}_c,\quad v\in\mathcal{V}_r,\ j\in\mathcal{N},\ k\in\mathcal{M}_j \tag{12}$$

$$\alpha_{ik}^{rv}, y^{rv}, x_{ij}^{rv}, \gamma_{ik}^{rv} \in \{0,1\}$$
$$\forall r\in\mathcal{N}_c,\quad v\in\mathcal{V}_r,\ i,j\in\mathcal{N},\ k\in\mathcal{M} \tag{13}$$

$$\phi^{rv}, \tau_{ik}^{rv} > 0 \quad \forall r\in\mathcal{N}_c, v\in\mathcal{V}_r, i\in\mathcal{N} \tag{14}$$

The objective function (3) minimizes the total outsourcing maintenance cost required to provide preventive maintenance to geographically distributed lessees: 1) The first term of the objective represents the machine maintenance cost. 2) The second term captures the deployment cost, which is paid for dispatching technician teams from their maintenance centers to multiple lessees. 3) The third term represents the travel cost of each assigned technician team. 4) The fourth term indicates the downtime penalty cost, which is related to the actual machine shutdown caused by group maintenance of the same system. And 5) the last term reflects the coordination penalty cost of technician team sharing.

Constraints (4) guarantee that each technician team must depart and finally arrive at the same maintenance center. Constraints (5) state that any technician team that enters the lessee node should also depart from the same node. Constraints (6) indicate that in case each technician team is used, then its service route should start from the maintenance center. Meanwhile, constraints (6) also indicate that each technician team can leave the maintenance center only once at each PM cycle. Constraints (7) aim to restrict the number of dispatched technician teams within the total number of technician teams in the corresponding region. Constraints (8) guarantee that each PM action needs to be performed only once at each cycle. Constraints (9) emphasize that the number of maintained machines by the technician team is less than its maintenance capacity. Constraints (10) state that the PM action of each leased machine is either carried out by the local technician team or the technician team from other

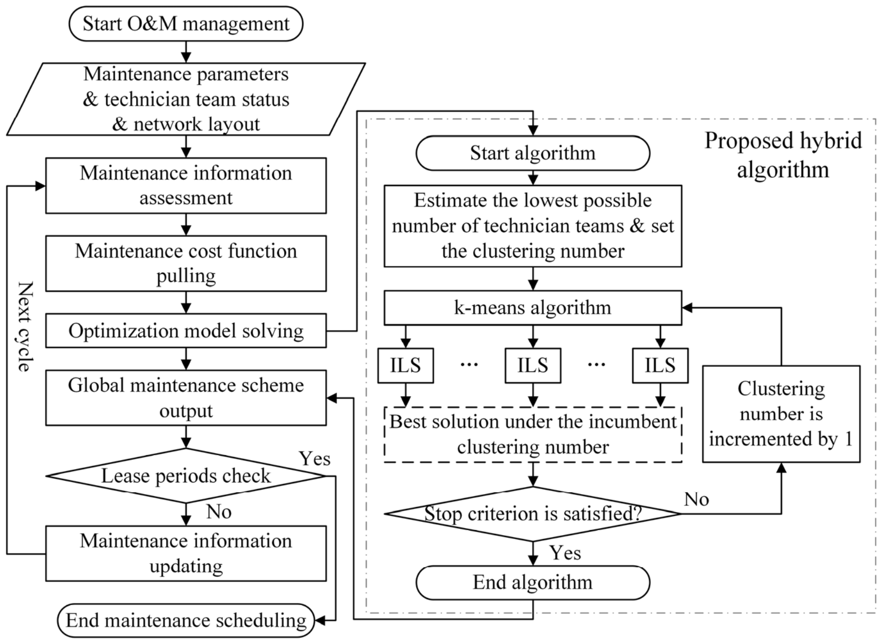


Fig. 3. Decision-making process of the proposed TCOM policy.

maintenance centers. Constraints (11) represent the arrival time of the technician team at lessee directly from maintenance centers. Constraints (12) also calculate the arrival time of the technician team at lessee directly from other lessees. Finally, constraints (13) and (14) define the domain of decision variables. After optimizing the mixed-integer program, we obtain the global scheme with the minimum $TC_h(\boldsymbol{s})$ at the current hth PM cycle. Then we resolve the optimization model with the updated maintenance information to determine the global maintenance scheme for the next $(h+1)$th cycle. And during each PM cycle, once an unexpected failure occurs, the CM action is carried out and the time axis of the corresponding machine is updated accordingly.

III. Solution Method

The main goal of this section is to develop a solution approach to solve the multi-center maintenance scheduling problem. Towards this goal, a novel hybrid metaheuristic algorithm called CILS algorithm is developed based on the k-means clustering algorithm and the iterated local search (ILS) algorithm. The idea of our proposed hybridization is to develop an algorithm that is powerful in terms of diversification (global search) and intensification (local search) during the optimization process [31], [32].

Moreover, Fig. 3 depicts the decision-making process of the proposed TCOM policy. Based on maintenance parameters and maintenance cost function, the optimization model as listed in Eq. (3)-(14) can be constructed. Then CILS algorithm is processed to solve this optimization model. Firstly, we estimate the lowest possible number of required teams and set the clustering number as described in Section 3.4. Then k-means is used to combine the geographically contiguous and time adjacent machine maintenance into the same group to reduce search scope and generate a set of initial solutions, as shown in Section 3.2. After that, ILS is used to strengthen the solutions locally in Section 3.3. When the stop criterion is satisfied, we output the best solution to further generate the global maintenance scheme at the current PM cycle.

A. Solution Representation

The solution vector representation should be as compact as possible, while having the complete expression of a solution to the maintenance scheduling optimization. A complete solution (global maintenance scheme) $\boldsymbol{s} = (\alpha, y, x, \phi, \tau, \gamma)$ can be regarded as consisting of two parts: routing solution (α, y, x, γ) and maintenance solution (ϕ, τ). Each routing solution represents the leased machines allocated to each technician team and the order of their visits. To appropriately encode a routing solution, we use two vectors: machine vector $\boldsymbol{m} = (m_1, m_2, \ldots, m_N)$ and team vector $\boldsymbol{v} = (v_1, v_2, \ldots, v_N)$. $m_k (k = 1, 2, \ldots, N)$ denotes the kth machine to be visited and maintained. $v_k (k = 1, 2, \ldots, N)$ denotes the technician team visiting the kth machine, and responsible for the corresponding PM action.

One important issue to be noted is that the representation should not represent infeasible routing solutions. If a routing solution violates a certain number of constraints, an extra penalty is added to its objective function. This penalty decreases the chance of that routing solution to participate in the reproduction procedures in subsequent steps. For the purpose of illustration, an example is described in Fig. 4.

As shown in Fig. 4(a), the solution indicates that team 1 first travels to lessee 2 and performs PM actions for machines 4, 6 and 5. Then, team 1 travels to lessee 4 and conducts PM actions for machines 10, 11 and 12. After that, team 1 continues to perform the PM action for machine 2. Finally, they return to maintenance center 1 after completing all maintenance tasks. Therefore, the tuple constituted by two vectors ($\boldsymbol{m}$ and $\boldsymbol{v}$) contains the complete information of a routing solution.

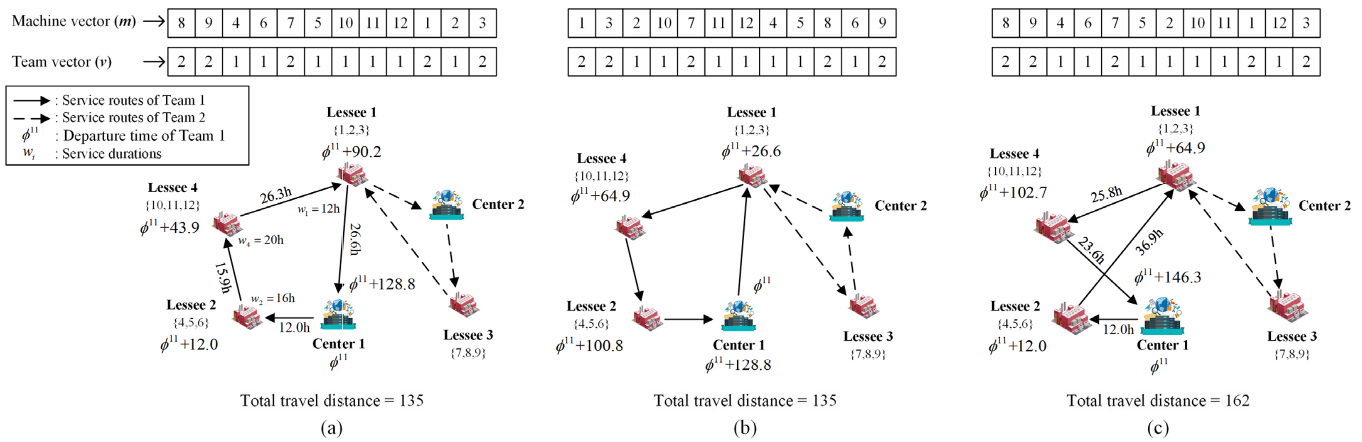


Fig. 4. The example of solution representation.

After describing the information about all routing decisions (i.e., the group maintenance scheme and the corresponding service route of each required team), we need to propose a representation to express the maintenance solution. It should be noted that, in Fig. 4(a) and Fig. 4(b), two different service routes with the same routing cost can lead to different arrival times, in other words, different actual PM time points. In addition, with the same departure time of two technician teams from their maintenance centers, the arrival times at each lessee and the total travel distance of technician teams depend on the selected service route (see the example in Fig. 4(a) and Fig. 4(c)). Therefore, each maintenance solution indicates the departure time of each technician team and the actual PM time point of each leased machine. Meanwhile, for the given departure time and routing decision of the required technician team, the actual PM time point of the machine that maintained by the corresponding team can be calculated by Eq. (11) and (12). Therefore, each maintenance solution representation contains information about the departure time ϕ^{rv} of technician teams.

B. k-Means Clustering Algorithm

In our TCOM policy, the global maintenance scheme is obtained by minimizing the TC. Meanwhile, the TC is closely related to the service route and actual PM time point. As far as cost minimization is concerned, the optimal solution tends to integrate geographically adjacent machines with similar degradation trends into a group. Therefore, k-means is used to classify all leased machines into different clusters to reduce search scope and ensure the quality of initial solutions [33].

As shown in Fig. 5, each node represents a leased machine, which has three-dimensional information, including abscissa value (X-axis), ordinate value (Y-axis) and individual PM time point (Z-axis). The number of clusters k represents the number of required technician teams, and the nodes in the same cluster mean the machines maintained by the same team. Based on clustering results, we further determine the starting center of each technician team. By projecting the clustering centers to X-Y plane, the theoretical geographical location of clustering centers is obtained. And the nearest maintenance center is

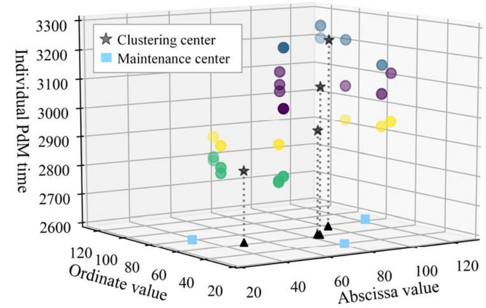


Fig. 5. An example for k-means algorithm.

selected as the starting point for the corresponding technician team. After classifying all machines, we obtain a set of well-behaved initial solutions. Then, the ILS is used to locally intensify each initial solution to obtain better performance.

C. Iterated Local Search Algorithm

The ILS algorithm has been widely utilized to solve optimization problems, and has been shown that it can escape the trap of local optimum without losing many of the good properties [34]. To implement the ILS, we start with the initial solution generated by k-means algorithm and perform the localSearch(.) function to search its neighborhood with the hope to find better solutions. Note that, only feasible solutions can be accepted in our solution approach. After performing localSearch(s_{cur}), the better solution s^*_{cur} obtained in the history can be updated.

After that, the ILS algorithm performs Perturbation(s^*_{cur}). Through this random perturbation, solution s^*_{cur} can be perturbed to another place in the solution space. For performing Perturbation(.) function, it should not be too much severe that acts as the random restart, but should be effective enough that kicks out the solution s^*_{cur} from the local minimum. Accordingly, a set of numbers in the team vector of the solution representation are selected (usually 15%-30% of solution size) and their values are replaced with valid numbers under the maintenance capacity constraint.

Next, localSearch(s'_{cur}) is applied again to obtain a new local optimal solution s'^*_{cur}. And acceptSolution($s^*_{\text{cur}}, s'^*_{\text{cur}}$) is employed to check whether the new local optimal solution $s_{\text{cur}}^{'*}$ is better than the previous local optimal solution s_{cur}^{*}. in other words, $TC_h(s_{\text{cur}}^{'*}) < TC_h(s_{\text{cur}}^{*})$. In particular, the acceptSolution(.) function only accepts a better solution. Therefore, the best solution obtained in the history s_{best} can be updated during the termination criteria. Since the performance of ILS is greatly affected by the localSearch(.) function, the design and implementation of local search operator is very important. Meanwhile, it is impossible to search all the neighboring solutions of a given intermediate solution s_{cur}. Therefore, intraswap and interswap operators are applied on the solution representation, and the solution with the highest improvement in the objective function is reported as the new local optimal solution. Specifically, we swap the 10% of possible changes for each solution to ensure the performance of neighborhood structures. The intraswap operator randomly selects two different stations (leased machines) from one route and then swaps them. Different from intraswap, the interswap randomly selects two different stations from two service routes. And these main procedures continue until the termination criteria is reached.

D. Hybridization Mechanism

This subsection proposes the hybridization of the k-means and ILS algorithms to provide an efficient solution approach in terms of both diversification and intensification. The solution procedure starts with estimating the lowest possible number of technician teams required for solution, and proceeds with solving the problem based on this estimation. The above estimation is obtained based on the number of leased machines m and the maintenance capacity q^{rv}, as $v_{\text{low}} = \lceil m / \sum_{v\in\mathcal{V}_r} q^{rv} \rceil$.

Based on the estimation of v_{low}, we set the clustering number $\mathbb{k}\,(v_{\text{low}} \rightarrow \mathbb{k})$. Then, k-means diversely searches the solution space and provides the initial set of solutions. The next step is the local intensification by ILS. During the process of performing ILS, we first execute the corresponding operators (perturbation and local search) on each routing solution, and then optimize the maintenance solution (the departure time of each technician team) by minimizing the maintenance cost $f_h^2(\phi, \tau)$. The best routing solution under the same routing cost and travel distance is saved for the next neighborhood structures.

At the end of ILS algorithm, the best solution s_{best} under the incumbent clustering number is retained. And the termination criteria used in our approach is based on the number of existing technician teams v. When the termination criteria is not reached, the clustering number will be incremented by 1 and the main loop will be continued to find the new s_{best}. The solution approach stops after iteration counter of the main loop reaches the predetermined value. Meanwhile, the optimal solution s^* among these global optimum solutions under different clustering numbers is accepted.

E. Update and Rolling Horizon

The global maintenance scheme (including maintenance timetable and service route) of the current cycle can be obtained from the optimal solution s^*. After maintenance scheduling of the current cycle, we take note of the duration of each group maintenance, update the rolling horizon of each machine, and reevaluate the maintenance cost function using the updated failure rate. Then, we resolve the optimization problem with the updated maintenance information to determine the optimal maintenance scheme for the next cycle. Meanwhile, when faced with unexpected situations, we return to the first step and resolve the mixed-integer optimization model of the TCOM policy to provide adaptive maintenance and routing decisions.

IV. Numerical Experiments

In this section, the applicability of the TCOM policy and the CILS algorithm are validated. We first clearly illustrate the proposed TCOM policy and its decision-making process. Afterwards, a comparative study is presented to demonstrate the performance of the TCOM policy in solving the maintenance scheduling optimization for the multi-center service network. Afterward, a comprehensive sensitivity analysis is conducted. Finally, the advantage of the CILS algorithm is demonstrated by comparing with other algorithms.

A. An Illustrative Example

We consider an illustration scenario where the lessor has three maintenance centers ($C = 3$) and six technician teams ($V = 6$) that responsible for the O&M of nine lessee enterprises ($L = 9$). Each lessee enterprise leases three leased machines working in series. For this network, we consider a two-year TCOM programming ($LP_i = 17520$h). The original lifetime distribution of machine $k \in \mathcal{M}$ follows a Weibull distribution with the scale parameter η_k and the shape parameter β_k. The influence of imperfect PM and environmental conditions is further considered through model factors, as done by Xia *et al.* [6]. Therefore, the failure rate $\lambda_{hk}(t)$ of machine k between successive PM cycles is shown by (15). And the generic maintenance cost rate $c_{hk}(T_{hk})$ is shown by (16), which aims to integrate the failure rate, maintenance costs and maintenance durations to obtain the optimal PM interval for each machine.

$$\lambda_{hk}(t) = \begin{cases} (\beta_k/\eta_k)(t/\eta_k)^{\beta_k-1} & h = 1 \\ b_{hk}\lambda_{(h-1)k}\left(t + a_{hk}T'_{(h-1)k}\right) & h \geq 2 \end{cases} \tag{15}$$

$$c_{hk}(T_{hk}) = \frac{C_{hk}^P + C_{hk}^C \int_0^{T_{hk}} \lambda_{hk}(t)dt}{T_{hk} + T_{hk}^P + T_{hk}^C \int_0^{T_{hk}} \lambda_{hk}(t)dt} \tag{16}$$

For applying the TCOM policy, we employed the discrete uniform distribution to generate the following maintenance parameters for each machine: $\beta_k \sim U_d[1.70, 3.20]$; $\eta_k \sim U_d[5000, 6500]$; $a_{hk} \sim U_d[1.015, 1.055]$; $b_{hk} \sim U_d[0.015, 0.050]$; $T_k^P \sim U_d[8, 20]$; $T_k^C \sim U_d[18, 80]$; $C_k^P \sim U_d[3500, 6500]$; $C_k^C \sim U_d[5000, 30000]$; $c_k^{tp} I_k \sim U_d[9000, 15000]$. Accordingly, $U_{hk}(t)$ could be estimated. Then, the optimization model can capture the trade-off to derive optimal maintenance schemes from a global perspective. The detailed maintenance parameters are listed in Appendix A.

TABLE II
TRAVEL TIME BETWEEN EACH PAIR OF NODES

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	r_1	r_2	r_3
i_1	-	29	23	30	15	10	34	21	35	11	22	37
i_2		-	11	49	37	37	15	26	34	18	46	25
i_3			-	40	28	30	11	16	24	13	37	18
i_4				-	15	23	45	24	28	36	11	39
i_5					-	10	36	16	27	22	9	34
i_6						-	40	23	35	20	13	40
i_7							-	21	22	24	44	11
i_8								-	14	18	24	18
i_9									-	31	33	13
r_1										-	30	30
r_2											-	42
r_3												-

TABLE III
GLOBAL MAINTENANCE SCHEME OF FIRST TCOM PROGRAMMING CYCLE

Team 1		Team 2		Team 3		Team 4	
Mach.	τ_{ik}^{rv}	Mach.	τ_{ik}^{rv}	Mach.	τ_{ik}^{rv}	Mach.	τ_{ik}^{rv}
18	2982	13	3141	9	2820	8	2815
3	3017	14	3141	21	2839	4	2836
5	3060	6	3203	20	2839	27	2880
16	3109	1	3240	25	2883	17	2925
24	3140	12	3268	26	2883	2	2945
23	3140	11	3268	19	2921	7	2993
22	3140	10	3268	15	2977		
Center1	3183	Center2	3291	Center3	3027	Center1	3018

By pulling the updated maintenance cost function of all leased machines, TCOM dynamically optimizes maintenance timetables, as well as service routes to proactively conduct maintenance actions of the multi-center service network. The travel time between lessees and maintenance centers is listed in Table II. The travel cost rate C^{rv} is set to \$200/h. And the deployment cost F^{rv} for dispatching technician teams and required spare parts from maintenance centers is set to \$200,000/time.

Performing PM actions will affect the operational condition of systems. Once a machine is scheduled to be maintained, a pressing issue for lessee enterprises is to ensure that the machine is restored as soon as possible. Thus, we set the downtime penalty cost rate P_i^{rv} as 300 \$/h. The coordination penalty is set to \$2000 per machine. The maintenance capacity of each technician team is set to 7 machine/time. And the lowest possible number of technician teams v_{low} is calculated as 4. By applying the CILS algorithm, the global maintenance scheme of the first cycle is shown in Table III.

The service arrangements, including the arrival time points of visiting each machine to conduct relevant PM actions are listed in Table III. After finishing the decision-making process for the first cycle ($h = 1$), we update the maintenance cost function of every machine and reevaluate the status information of existing technician teams. Then, we resolve the optimization problem with the updated maintenance information to determine the global maintenance scheme for the second cycle ($h = 2$). By using a rolling horizon, the individual PM time point t_{2k}^* of each leased machine is updated based on arrival times τ_i^{rv}, maintenance durations and actual PM intervals of the first cycle T_{1k}^*, as shown in Eq. (1).

TABLE IV
COST PERFORMANCE OF SEQUENTIAL TCOM PROGRAMMING CYCLES

	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
TC_h	1,063,062	1,272,960	1,338,468	1,582,624	2,515,071
i	29,662	39,760	114,468	148,624	1,069,271
ii	800,000	1,000,000	1,000,000	1,200,000	1,200,000
iii	107,000	98,800	98,800	108,200	123,200
iv	104,400	104,400	97,200	97,800	96,600
v	22,000	30,000	28,000	28,000	26,000

By using a rolling horizon analytics framework to process the proposed TCOM policy, we generate global maintenance schemes of sequential cycles during the lease period. Table IV presents the cost performance for this case. The cost performance first reports the total outsourcing maintenance cost and then breaks it down to its components including (i) machine maintenance cost, (ii) deployment cost, (iii) travel cost, (iv) the penalties associated with machine downtime and (v) team coordination. As the individual PM time point of each machine is gradually dispersed, TCOM policy minimizes the total cost by increasing the number of required technician teams. This process is executed on a rolling horizon to provide efficient outsourcing maintenance services during the lease period.

To summarize, for the global OEM responsible for the maintenance scheduling of the multi-center multi-lessee service network, our proposed TCOM policy can cyclically provide the global maintenance scheme with the minimal total cost. Based on these global maintenance schemes, the OEM can arrange technician teams from different maintenance centers to perform timely and cost-effective PM for multi-location lessees. The consideration of resource sharing can ensure the response speed of O&M services and improve the use efficiency of technicians.

B. Policies Comparison

To evaluate the cost-effectiveness, we benchmark TCOM policy with three conventional policies that are widely used in industry. We ensure a fair comparison by using the same parameters and basic models for all maintenance policies:

1) Periodic Preventive Maintenance (PPM) Policy: The machines are scheduled to be maintained preventively only at periodic times $nT (n = 1, 2, \ldots, N)$ over the lease period. T represents the constant time interval between two successive PM actions. And technician teams are dispatched from their maintenance centers to perform regional maintenance tasks.

2) Sequential Group Maintenance (SGM) Policy: To decrease repeat assignment and frequent shutdown, it uses the maintenance opportunity arisen by the early PM action to groups the PM actions of all machines in the same system. And technician teams follow the fixed route (from the maintenance center to each lessee without routing optimization) to execute these group maintenance tasks.

3) Local Preventive Maintenance (LPM) Policy: Technician teams only focus on the outsourcing maintenance service of lessees in the same maintenance region. By jointly optimizing

TABLE V
COST PERFORMANCE OF DIFFERENT MAINTENANCE POLICIES

	PPM	SGM	LPM	TCOM
TC_h	29,246,164	21,752,000	8,734,547	**7,772,185**
i	962,164	12,105,000	1,734,547	1,401,785
ii	27,000,000	9,000,000	6,000,000	5,200,000
iii	702,000	386,000	480,600	536,000
iv	582,000	261,000	518,400	500,400
v	0	0	0	134,000

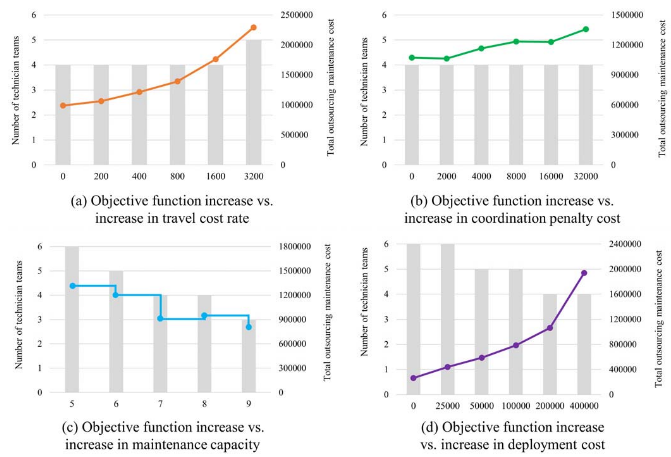
the maintenance grouping and technician routing, the local maintenance schemes are obtained without considering the cross-regional technician sharing. By applying the above maintenance policies, the lessor that responsible for multi-location lessee enterprises can obtain cyclic maintenance schedules for each policy. Table V exhibits the cumulative total outsourcing maintenance cost of four maintenance policies.

Based on the comparative study, the advantages of the TCOM policy can be summarized as follows: Firstly, compared with the other policies, TCOM decreases deployment costs since it fully utilizes the maintenance capacity of technician teams and considers the collaborative scheduling of technician teams in different maintenance centers. By decreasing the number of technician teams, TCOM helps lessors make more efficient use of maintenance resources, resulting in more accurate staffing of maintenance centers. Secondly, TCOM identifies the dynamic health statues of machines and optimize maintenance timetables from a global perspective, thereby avoiding insufficient maintenance and over-maintenance of all leased machines. Obviously, compared to the SGM policy, TCOM decreases the machine maintenance cost from \$12,105,000 to \$1,401,785 by combining PM actions of different systems. Thirdly, compared with the LPM policy, TCOM reduces \$332,762 by further considering the cross-regional maintenance scheduling.

In the general sense, our policy can significantly reduce the total cost, ensure service timeliness and further utilize maintenance resources. Different lessee geographical locations, machine degradation trends and preventive maintenance durations will result in completely different schemes. However, the mechanism of our TCOM policy can adapt to these changes and obtain an adaptive maintenance and routing decision. On the one hand, the consideration of $U_{hk}\left(\tau_{ik}^{rv}\right)$ allows the 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, by purposefully groups PM actions among scattered lessees to reduce system downtime and optimal service sequence, the global optimization model dynamically compares $TC_h(\boldsymbol{s})$ and selects the solution with the lowest cost. Moreover, the consideration of resources sharing among different maintenance centers decrease the repeated dispatch of technician teams and ensure personnel utilization efficiency.

C. Sensitivity Analysis

Apart from the cost comparison, the sensitivity analysis is also conducted. We present four case studies to highlight the performance in different scenarios. Then on the base of these, we propose some managerial insights for these parameters which make solutions highly sensitive. This knowledge about important parameters can help OEM to optimize network configuration and improve O&M service levels.



(a) Objective function increase vs. increase in travel cost rate

(b) Objective function increase vs. increase in coordination penalty cost

(c) Objective function increase vs. increase in maintenance capacity

(d) Objective function increase vs. increase in deployment cost

Fig. 6. Objective function sensitivity versus important parameters.

In all the following analyses, the sensitivity of the objective functions is calculated based on a deterministic scenario. From Section 4.1, we note that as O&M service hours increase, the TCOM policy increases the number of required technician teams to minimize the TC-value. Therefore, to focus on the sensitivity analysis and clearly observe the changes in the number of required technician teams due to parameter changes, we consider the single-cycle optimization. Figure 6 consolidates the sensitivity analysis of the number of technician teams and the objective function (TC-value).

Fig. 6(a) represents the sensitivity of the objective function to an increase in the travel cost rate. As a direct consequence, we observe that the total outsourcing maintenance cost shows an increasing pattern. Moreover, when the travel cost rate rises to \$3200/h, TCOM prefers to add a technician team to conduct multi-location PM actions. This means that if travel costs are too high, the lessor can consider increasing the number of technician teams to ensure multi-center O&M services.

Fig. 6(b) illustrates the sensitivity of the functions to the increase in the coordination penalty cost. As we expected, we note that the TCOM policy re-optimizes maintenance schedules and corresponding service routes to avoid increasing the number of required technician teams. Therefore, the lessor can focus on intra-regional maintenance plans as the unit coordination penalty cost increases.

Fig. 6(c) investigates the effect of increasing maintenance capacities on objective function values. We observe that as the maintenance capacity of every technician team increases, TCOM makes more of an effort to limit the number of technician teams to satisfy the maintenance requirement of lessees. In multi-location O&M services, the lessor can set the maintenance capacity of every technician team according to the number of leased machines and the actual situation.

Fig. 6(d) focuses on the sensitivity of the objective function to the change of the deployment cost. We note that the total outsourcing maintenance cost shows an increasing pattern. Further, this trend means that the number of technician teams becomes increasingly important and dominant as

TABLE VI
COMPARISON AMONG FOUR ALGORITHMS FOR MULTI-CENTER PROBLEMS

No. \ TC	GA	ILS	GA-ILS	CILS
1	1,395,644	1,375,707	1,295,762	**1,188,518**
2	1,450,502	1,401,377	1,272,382	**1,200,860**
3	1,423,542	1,424,480	1,304,002	**1,203,646**
4	1,441,867	1,418,465	1,299,329	**1,201,613**
5	1,417,033	1,384,662	1,297,217	**1,202,353**
Time(s)	[260,287]	[411,451]	[244,274]	[192,205]

their associated deployment cost rises. From a management perspective, as the deployment cost increases, the lessor needs to reduce the use of technician teams to achieve cost savings.

D. Comparison Performance

The performance of the CILS algorithm is compared with three metaheuristic algorithms, namely genetic algorithm (GA), iterated local search algorithm (ILS), and a hybrid algorithm based on genetic algorithm and iterated local search algorithm (GA-ILS). And all experiments are compiled in Python 3 programming language executed on a Pentium 7 CPU with 3.00 GHz processor and 16 GB of RAM. Meanwhile, we use the same geographic location information as Section 4.1 and use the same discrete uniform distribution to generate the maintenance parameters for the leased machine at each experiment. Similarly, to avoid the impact of the maintenance schemes of the previous cycle on the current PM cycle, we also consider the single-cycle maintenance scheduling of multi-center service network.

The performance of the proposed CILS algorithm with those of GA, ILS and GA-ILS is compared through the aforementioned scenario with different maintenance parameters. It is generally known that the quality of an algorithm is significantly influenced by the setting of its algorithm parameters. To get the high-performance algorithm, proper tuning of its parameters is carried out by using response surface methodology (RSM). After conducting RSM, tuned parameters of the CILS, GA, ILS and GA-ILS algorithms are considered as follows:

- **GA**: the size of population $P_{size} = 160$; the maximum number of iterations $Itr_{max}^{GA} = 200$; selection operator = binary tournament; mutation operator = swap operator; crossover operator = one-point crossover; mutation rat = 0.2; crossover rate = 0.8.
- **ILS**: the number of initial solutions $P_{initialsize} = 20$; the size of iterations in total $Itr_{size}^{LS} = 50$; the maximum number of iterations in each neighborhood structure $Itr_{max}^{NS} = 50$; selection operator = random selection.
- **GA-ILS**: $P_{size}^{GA} = 160$; $Itr_{max}^{GA} = 200$; selection operator = binary tournament; mutation operator = swap operator; crossover operator = one-point crossover; mutation rat = 0.2; crossover rate = 0.8, $Itr_{size}^{LS} = 200$; $Itr_{max}^{NS} = 150$.
- **CILS**: $P_{initialsize} = 30$; $Itr_{size}^{LS} = 50$; $Itr_{max}^{NS} = 30$; selection operator = based on clusters from k-means.

Table VI reports the comparison between four algorithms. We consider 5 experiments, and each experiment is repeated 10 times with the same maintenance parameters. The reported TC-value is the mean value for the corresponding problem experiment. The user CPU-time (containing [min, max] value) contains the minimal and maximum computational durations (in seconds) for solving the corresponding multi-center problems. The results show that the superior performance of the proposed CILS algorithm in comparison with GA, ILS, and GA-ILS algorithms. Specifically, for different multi-center maintenance scheduling problems, CILS all has better solutions and speed than the other three algorithms.

V. CONCLUSION

This paper develops a transportation-oriented cross-regional opportunistic maintenance (TCOM) policy for multi-center service networks, which jointly optimizes the maintenance grouping and technician routing problems. To provide a holistic maintenance scheme for geographically distributed lessees, the optimization model comprehensively integrates the maintenance cost function, the service route of technician teams, constraints of maintenance capacity, and economic penalties associated with conducting maintenance actions. By integrating the technician collaboration and routing optimization, the proposed TCOM policy can meet dynamic maintenance requirements and achieve total cost savings in global maintenance scheduling for multi-center networks.

Other than reliability characteristics from degradation information, the maintenance cost function of each leased machine is used to determine optimal and practical maintenance timetables. Furthermore, by sharing the technician team from different maintenance centers, not only the flexibility of O&M management is improved, but also the maintenance capacity of technician teams is fully utilized. In addition, the increased flexibility results in less system downtime and improves the lessor's ability to cope with extreme scenarios encountered in daily O&M management. Finally, the illustrative example and extensive experiment results show that the TCOM policy and the CILS algorithm can achieve significant improvements in dealing with multi-center maintenance scheduling problems.

Future extensions of this research will focus on investigating the impact of technicians with different skills, and then quantifying the trade-off between total cost and network reliability. Besides, the obstacles in industrial application of the TCOM policy in real O&M environments with stochastic failures should also be overcome.

NOTATIONS

Sets and Indices

- $\mathcal{M}_i$ Set of leased machines for lessee i (index $k \in \mathcal{M}_i = \{1, 2, \ldots, M_i\}$)
- $\mathcal{N}_c$ Set of maintenance centers (index $r \in \mathcal{N}_c = \{1, 2, \ldots, C\}$)
- $\mathcal{N}_l$ Set of lessee enterprises (indices $i, j \in \mathcal{N}_l = \{1, 2, \ldots, L\}$)
- $\mathcal{V}_r$ Set of technician teams located at maintenance center r (index $v \in \mathcal{V}_r = \{1, 2, \ldots, V_r\}$)
- $\mathcal{H}$ Set of preventive maintenance cycles (index $h \in \mathcal{H}$)

Parameters

$\lambda_{hk}(t)$	Failure rate of machine k at hth cycle
$c_{hk}(T_{hk})$	Maintenance cost rate of machine k during hth cycle
t^*_{hk}	Individual PM time point of hth cycle for machine k
T^*_{hk}	Optimal PM interval of machine k at hth cycle
$T'_{h'k}$	Actual PM interval of machine k at hth cycle
$U_{hk}(t)$	Maintenance cost function of hth cycle for machine k
LP_i	Lease period of lessee i
c^{tp}_k	Time punishment cost rate for machine k
I_k	Importance coefficient of machine k
$F^{r\upsilon}$	Deployment cost of maintenance resources for technician team $\upsilon \in \mathcal{V}_r$
$C^{r\upsilon}$	Travel cost per unit time of technician team $\upsilon \in \mathcal{V}_r$
D_{ij}	Travel distance between lessee i and j
$\theta^{r\upsilon}$	Moving speed of technician team $\upsilon \in \mathcal{V}_r$
P_i	Unit downtime penalty cost of lessee i
$R^{r\upsilon}$	Coordination penalty cost of technician team $\upsilon \in \mathcal{V}_r$
$q^{r\upsilon}$	Maintenance capacity of technician team $\upsilon \in \mathcal{V}_r$
b_{hk}	Environmental factor of machine k at hth cycle
a_{hk}	Age reduction factor of machine k at hth cycle
C^P_{hk}	Cost of a preventive maintenance for machine k at hth cycle
C^C_{hk}	Cost of a corrective minimal repair for machine k at hth cycle
T^P_{hk}	Duration of a preventive maintenance for machine k at hth cycle
T^C_{hk}	Duration of a corrective minimal repair for machine k at hth cycle

Decision Variables

$\alpha^{r\upsilon}_{ik}$	Binary variable: 1, if machine k of lessee i is undergoing preventive maintenance by technician team $\upsilon \in \mathcal{V}_r$ at time $\tau^{r\upsilon}_{ik}$; 0, otherwise
$y^{r\upsilon}$	Binary variable: 1, if technician team $\upsilon \in \mathcal{V}_r$ is dispatching to perform relevant O&M services; 0, otherwise
$x^{r\upsilon}_{ij}$	Binary variable: 1, if technician team $\upsilon \in \mathcal{V}_r$ is travel from lessee i to lessee j; 0, otherwise
$\gamma^{r\upsilon}_{ik}$	Binary variable: 1, if preventive maintenance actions of machine k in lessee i are performed by the technician team $\upsilon \in \mathcal{V}_r$ from other maintenance centers; 0, otherwise
$\phi^{r\upsilon}$	Continuous variable: departure time point of technician team υ from its corresponding maintenance center
$\tau^{r\upsilon}_{ik}$	Continuous variable: arrival time point of technician team $\upsilon \in \mathcal{V}_r$ to perform PM action for machine k of lessee i

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