Progressive Opportunistic Maintenance Policies for Service-Outsourcing Network With Prognostic Updating and Dynamical Optimization

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

***Abstract*—Increasing machine investments and expensive operations and maintenance (O&M) costs have made manufacturing system leasing and maintenance service outsourcing gaining a momentum. Leading original equipment manufacturers, as lessors, have focused on providing cost-effective maintenance schemes to serve their client-enterprises (lessees) all over the world. However, individual equipment degradations, complex system structures, and global network layout bring challenges for the real-time decision-making. This article comprehensively develops a service-outsourcing progressive opportunistic maintenance methodology for a global service-outsourcing network with prognostic updating and dynamical optimization. At the equipment layer, an automated prognostic model is utilized to characterize and update the individual path of each leased equipment's degradation signals. At the local layer, an opportunistic maintenance policy is developed for balancing production capacity and optimizing maintenance decisions of each system with even series-parallel structure. At the global layer, a routing optimization policy is proposed for the service-outsourcing network by integrating service time windows and multiple geographical locations to optimize the service route of required maintenance teams and the service start time of each group set. Finally, this hierarchical methodology has been verified in a multilocation service-outsourcing network. Its mechanism with real-time prognostic updating and dynamical O&M optimization can significantly ensure cost reduction, service timeliness and network robustness.**

***Index Terms*—Dynamical multilayer optimization, maintenance, progressive opportunistic maintenance, sensor-driven prognostic updating, service-outsourcing network.**

Manuscript received November 27, 2020; revised March 21, 2021; accepted April 16, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 51875359 and Grant 51975355, in part by the Natural Science Foundation of Shanghai Grant 20ZR1428600, and in part by the Ministry of Education-China Mobile Research Foundation under Grant CMHQ-JS-201900003. This article was recommended for publication by Associate Editor S. Li. *(Corresponding author: Guojin Si.)*

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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TR.2021.3074506.

Digital Object Identifier 10.1109/TR.2021.3074506

NOMENCLATURE

Decision variable

$\Omega(ijk, e_{i,h})$	Integer variable: 2, if the normal production of machine k is halting to maintain the system's capacity balance; 1, if the PdM action of machine k in procedure j is advanced at $e_{i,h}$ with positive LPS(s); and 0, if the PdM action of machine k in procedure j is not advanced with non-positive LPS(s).
$\Omega(ij^*k, e_{i,h})$	Binary variable: 1, if the PdM action of machine k in procedure j^* is advanced at $e_{i,h}$ with positive LPS(p); 0, otherwise.
$x_{ii'm,u}$	Binary variable: 1, if maintenance team $m \in \mathcal{M}$ travels from lessees i to i' at the u th cycle; 0, otherwise.
$z_{im,u}$	Continuous variable: actual service start time of lessee i when performed by maintenance team $m \in \mathcal{M}$ at the current uth global-layer cycle.

Parameters

π	Number of sets whose TTFs are greater than or equal to τ.
σ	Scale parameter of the degradation function.
$\xi^b_{ijk,r}$	Functional principal component (FPC) score in MFPCA.
$c^p_{i'}$	Late penalty cost for starting maintenance of lessee i' later than the time window.
$c^w_{ii'}$	Waiting cost between nodes i to i'.
C^C_{ijk}	Capacity punishment cost of machine k.
C^P_{ijk}, C^R_{ijk}	Cost of a PdM action and a minimal repair for machine k.
$Cp^{\text{remain}}_{i,h}$	Remaining capacity of client-enterprise i at hth local-layer cycle.
Cp_i	Overall capacity of client-enterprise i.
$\mathrm{GP}_{i,h}$	Group PdM set of client-enterprise i at hth local-layer cycle.
$\mathrm{LPA^M_{ijk,h}}$	Failure control addition of machine k at hth local-layer cycle.
$\mathrm{LPA}^R_{ijk,h}$	Machine rent addition of machine k at hth local-layer cycle.
$\mathrm{LPA}^C_{ijk,h}$	Capacity punishment reduction of machine k at hth local-layer cycle.

$\mathrm{LPA}^{D}_{ijk,h}$	Accelerating depreciation reduction of machine k at hth local-layer cycle.
$LPA^{P}_{ijk,h}$	Frequent maintenance reduction of machine k at hth local-layer cycle.
$\mathrm{LPS}(p)_{ijk,h}$	Leasing profit savings for parallel subsystems at hth local-layer cycle.
$\mathrm{LPS}(p)_{ijk,h}$	Leasing profit savings for series subsystems at hth local-layer cycle.
$T^{*}_{ijk,d}$	Optimal PdM interval of machine k at dth equipment-layer cycle.
T^{P}_{ijk}, T^{R}_{ijk}	Durations of a PdM action and a minimal repair for machine k.
TSC_u	Total service-outsourcing cost at uth global-layer cycle.
V^{S}_{ijk}, V^{E}_{ijk}	Original and residual values for machine k at leasing starting and ending.
α_0	Intercept of equipment-layer LLS regression model.
β_0	Substitutional intercept of LLS regression model after simplification.
β_b	Relevant regression coefficient of LLS regression model after simplification.
$\alpha(t)$	Coefficient function of equipment-layer LLS regression model.
δ_{ijk}	Depreciation rate of machine k.
$\gamma_{ij,h}$	Number of machines with positive $\mathrm{LPS}(s)$-value in procedure j $(j \neq j^*)$.
κ_{ijk}	Rent rate of machine k.
$\lambda_{ijk,d}(t)$	Real-time hazard rate of machine k at dth equipment-layer cycle.
$\omega_{ij,h}$	Maximum halting equipment quantity of procedure j $(j \neq j^*)$.
$\omega_{ij^*,h}$	Number of machines with positive $\mathrm{LPS}(p)$-value (early PdM) in procedure j^* of the triggering machine $E_{ij^*k^*}$.
$\psi_{ij,h}$	Minimum equipment quantity of procedure j $(j \neq j^*)$.
$\psi_{ij^*,h}$	Number of other machines (*in situ* PdM) in procedure j^*.
$\varepsilon_{ijk,r}$	Sensor error of the degradation function for machine k.
$\varepsilon_{ijk,s}$	Random noise of LLS regression model after simplification.
c_m	Maintenance team's dispatch cost of team m.
$c_{ii'}$	Transportation cost between nodes i and i'.
$c_{ijk,d}(t)$	Maintenance cost rate of machine k at dth equipment-layer cycle.
$e_{i,h}$	Opportunity moment of client-enterprise i at hth local-layer cycle.
E_{ijk}	Machine k belongs to procedure j of client-enterprise (lessee) i.
L_i	Lease period of client-enterprise i.
Q_m	Capacity of maintenance team m.
R_u	Optimal service routes of maintenance teams at u th global-layer cycle.
$s_{ijk,r,p}(t)$	Degradation signal from pth sensor of set $r$for machine k.
$s_{ijk,r}(t)$	Degradation signal from the whole P sensors for machine k.
$T'_{ijk,d}$	Actual PdM interval of machine k at dth equipment-layer cycle.
$t_{ii'}$	Transportation time between nodes i and i'.
$t_{ijk,h}$	PdM moment of machine k at h th local-layer cycle.
$y_{ijk,d}$	Predicted TTF of real-time sensor information for machine k at dth equipment-layer cycle.
$y_{ijk,r}$	TTF of a degradation set $r \in \mathcal{H}_k$ from the historical dataset of machine k.

Sets

$\mathcal{E}$	Set of equipment-layer cycles (index $d \in \mathcal{E} = \{12,\ldots,E\}$).
$\mathcal{G}$	Set of global-layer cycles (index $u \in \mathcal{G} = \{12,\ldots,G\}$).
$\mathcal{I}$	Set of client-enterprises (series-parallel systems) (index $i, i' \in \mathcal{I} = \{12,\ldots,N\}$).
$\mathcal{L}$	Set of local-layer cycles (index $h \in \mathcal{L} = \{12,\ldots,L\}$).
$\mathcal{M}$	Set of maintenance teams (index $m \in \mathcal{M} = \{12,\ldots,M\}$).
$\mathcal{H}_k$	Historical dataset of machine k(index $r \in \mathcal{H}_k = \{12,\ldots,H_k\}$).
$\mathcal{V}$	Set of nodes (client-enterprises and the maintenance central) (index $i, i' \in \mathcal{V} = \{01,\ldots,N\}$).

I. Introduction

WITH The global manufacturing competition, many leading original equipment manufacturers (OEMs) have focused on product leasing and maintenance services all over the world [1]. This leasing trend provides product-service value-added and competitive advantages for both partners [2]. For client-enterprises as lessees, it helps to avoid high upfront investments, save in-house maintenance expenses and obtain specialized maintenance supports from the OEM with significant knowledge accumulated on equipment. For OEMs as lessors, the market share and customer loyalty can be increased, while the income of outsourcing maintenance services has become the new profit growth spot. For example, Rolls Royce provides repair services for its plane engines in the ways of power-by-the-hour. Siemens dispatches maintenance workforce to repair equipment for global factory customers. However, for a service-outsourcing network, individual degradations of various equipment, series-parallel structures of leased systems, and geographical layouts of multiple locations bring challenges to the operation and maintenance (O&M) decision-making for such a large-scale community.

Failures of equipment result from the gradual accumulations of damage with aging, referred as their individual degradations [3]. To capture and avoid risks associated with failures, it is essential to model the degradation processes more accurately at the equipment layer [4]. There is a large amount of literature on degradation modeling, while most maintenance policies are developed on the base of population-specific reliability characteristics. It captures general failure behaviors of a category of equipment without considering unit specific information. In contrast with traditional methods, we use sensor-driven degradation signals (e.g., vibration, pressure, etc.) for health prognosis, which estimates the time-to-failure (TTF) distribution of each equipment. In addition, historical degradation data collected by the OEM is harvested for further data mining and health prognosis. Essentially, based on continuously monitored signals and historical data mining, leased machines are viewed as a collaborative community. We intertwine general population-specific reliability characteristics with the degradation properties of individual equipment.

With manufacturing system leasing widely applied in the industry, more and more attentions have been paid to outsourcing maintenance [5]. Most of the existing policies have focused on the decision-making problem for a single leased machine [6]–[8]. It is because system structures bring the challenges from structural, stochastic, economic and resource dependencies [9], let alone the more complicated multilocation network. Thus, to address the intractable computational complexity, we present the conception of progressive opportunistic maintenance and primarily focus on the real-time service requirements of each location at the local layer. The core distinction being that various machines in the system require different predictive maintenance (PdM) intervals due to individual degradations. Hence, it gives rise to a setting that can benefit significantly from grouping PdM actions together. For handling series-parallel structures, the decision-making is divided as the procedure layer (for each working procedure consisting of parallel machines) and the system layer (for the whole system consisting of series procedures). The production capacity balancing is integrated through working procedures to output profit-maximum outsourcing PdM requirements.

For a leading OEM, its global service-outsourcing network usually covers client-enterprises in multiple locations. The most challenging aspect of our methodology is to integrate individual machine degradations, grouped PdM requirements and multiple geographical locations at the global layer. Global service optimizations require a comprehensive arrangement of PdM requirements (different time points, PdM durations, geographical locations, etc.) and the route maintenance teams [10]. Thus, maintenance scheduling has become more interesting, since it is likely to benefit from dynamically optimizing the service order of multi-location PdM sets, and therefore limit the number of maintenance teams' visits to these client-enterprises. To do so, based on real-time requirements from the local layer and the directed graph from the network layout, we propose a global-layer routing policy to obtain the route of each maintenance team, the actual start time of each PdM action, as well as the total service-outsourcing cost. Other than the static schemes from overall network models, dynamical optimizations within this progressive methodology help to achieve quick responses to random requirements.

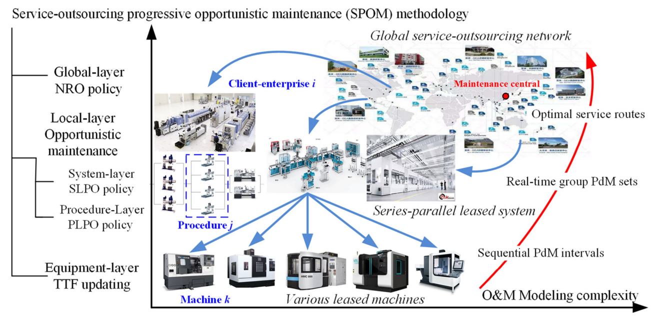


Fig. 1. Progressive opportunistic maintenance decision-making framework.

The aim of this paper is to develop a service-outsourcing progressive opportunistic maintenance (SPOM) methodology to support dynamical O&M decisions for a global network. Fig. 1 shows this decision-making framework. Individual machine degradations, complex system structures, and global network layout are integrated to provide real-time O&M schemes. The mechanism of this hierarchical SPOM methodology is interactively designed as follows.

1) For each leased machine, based on continuously monitored signals and historical degradation data from the OEM, we propose an automated prognostic model by utilizing a functional (log)-location-scale (LLS) regression method to represent degradation processes and accurately predict TTF distributions. Sequentially outputted PdM intervals based on real-time updated TTF distributions will arise equipment-layer opportunities in the corresponding leased system.
2) For each series-parallel system, we define the first machine reaches its PdM interval as the triggering one, bringing a maintenance opportunity: For other machines in this procedure, the impact of each machine's halting on the production capacity will be quantified, thus a parallel-structure leasing profit optimization (PLPO) policy is developed to economically combine PdM actions within this procedure. We also compute other procedures' maximum halting machine quantities to ensure the production capacity balancing for the system-layer programming. In the multiprocedure system, we identify the opportunities of performing PdM actions in advance for the nonrepair machines connected in series with the triggering machine. To do so, a serial-structure leasing profit optimization (SLPO) policy is proposed by dynamically calculating the leasing profit additions (LPAs) and reductions for each PdM adjustment. Outputted group PdM sets will be the local-layer requirements for the whole network.
3) For the global service-outsourcing network, by pulling real-time group PdM sets from multi-location client-enterprises, we develop a network routing optimization (NRO) policy by considering the travel time between lessees' multiple locations and the OEM's maintenance central. Available maintenance teams are arranged to cover the location with PdM requirements within their corresponding service time windows. PdM intervals of

each machine and service requirements of each location are dynamically updated. Thereby, NRO programming is performed again with sequentially updated information and opportunities, which are triggered by the local layer as the global-layer inputs. This layer-by-layer progressive mechanism ensures the cost reduction and the service timeliness.

The remainder of this article is organized as follows: In Section II, we present the relevant literature on O&M scheduling. In Section III, the equipment-layer automated prognostic model is presented. In Section IV, the procedure-layer PLPO policy and the system-layer SLPO policy are proposed. In Section IV, the global-layer NRO policy is developed. We present a case study based on real-world degradation data and verify the effectiveness of the hierarchical SPOM methodology in Section V. Finally, Section VI concludes this article.

II. Review Related Work

Maintenance optimization, as a major issue in industry, has been researched extensively in the literature. Most existing studies on maintenance policies focus on scheduling suitable maintenance intervals, time points and schemes [11], [12]. Generally, failure-based corrective maintenance (CM), time-based preventive maintenance (PM) and condition-based PdM are used to ensure normal operations of equipment. CM action, also called minimal repair, is performed to return a failed machine to operation with its degradation state unchanged. In contract, PM action is preventively performed at the end of an interval to avoid unnecessary failures. PM intervals are normally scheduled based on population-specific reliability characteristics with failure time distributions (weibull, exponential, poisson, etc.). In contrast, by using sensor technologies, machine specific degradation signals (e.g., increased vibration, crack propagation, or temperature changes) can help to accurately predict TTF. Bertling *et al*. [13] proposed a reliability-based maintenance policy by combining experience from statistics and practical knowledge of component failures and maintenance measures. Chen *et al*. [14] expanded the common specific degradation modeling by using Tweedie exponential dispersion processes. Fang *et al*. [15] developed a semiparametric approach to predict remaining lifetime with missing data. Gebraeel *et al*. [16] developed a Bayesian updating method that using real-time condition monitoring information to update the stochastic parameters of exponential degradation models. Elwany *et al*. [17] proposed a modeling framework that characterizes the path of degradation signals to forecast the machine evolution. In this article, we combine the prognostic models in [18] with a cost rate model to provide real-time PdM intervals of each leased machine at the equipment layer.

Conventional maintenance policies focus on in-house maintenance where enterprises and maintenance teams are on the same side. With machinery leasing widely applied, client-enterprises have been encouraged to rely more on the OEM to provide maintenance services. Current literature on outsourcing maintenance mode focuses on a single leased machine, while few papers involve complex leased systems. However, recent leased machinery is often not a single machine but instead a complex multiunit system. Thus, it is necessary to analyze the impacts of system structure, the opportunities of group maintenance and the savings of crew dispatches. Xia *et al*. [19] proposed an opportunistic maintenance policy for series system by optimizing the leasing profit saving (LPS). Chang *et al.* [20] presented a grouping execution policy for series system by maximizing service cost saving and availability improvement degree. However, due to the lack of production capacity balancing, these policies cannot be directly applied to handle series-parallel structures. Meanwhile, these systemic policies cannot identify service opportunities for service-outsourcing networks at a higher layer.

Recently, with the industry globalization, O&M scheduling for multi-factory problem has been studied in the literature. Chung *et al.* [21] presented a genetic algorithm approach for multifactory production networks to keep the system's reliability in a defined acceptable level. Goel and Meisel [22] introduced a combined routing and scheduling problem for periodic maintenance operations in electricity networks. Gharaei and Jolai [23] proposed a programming formulation for a multiagent scheduling problem to achieve Pareto solutions in a multifactory supply chain. Mazidi *et al.* [24] addressed the generation maintenance scheduling problem for deregulated power system. However, these event-based studies are mainly focused on the implementation and route planning of already given maintenance tasks. Such policies cannot be well extended to modern factories, where maintenance scheduling is highly correlated with dynamic degradation prediction.

In order to obtain the realistic maintenance schemes, it is necessary to further consider the maintenance optimization of each leased machine based on its degradation analytics. Camci [25] studied the maintenance scheduling of geographically distributed machines with failure probability predictions, assuming that only one team is available and each machine is maintained once. Lopez-Santana *et al*. [26] extended this problem to further consider that each scattered machine can be maintained multiple times, and multiple teams are waiting to be dispatched. Rashidnejad *et al.* [27] proposed a PM policy for geographically distributed machines by minimizing the total cost and maximizing the availability. Nguyen *et al*. [28] extended the PM optimization to multilocation multiunit production systems. Jia and Zhang [29] studied maintenance planning and technician routing problem for a network infrastructure by minimizing the incurred cost and maximizing its reliability. To the best of our knowledge, there is no maintenance methodology that incorporates sensor-driven prognostic technologies into the multilocation opportunistic maintenance problem. Other important factors, such as the leased systems' efficiency and multiple maintenance teams' dispatching should also be integrated into a progressive O&M framework. The benefit of such integration is that it provides a comprehensive solution for real-time prognostic updating of each machine and dynamical O&M optimizations of global service-outsourcing network.

As mentioned in Section I, our multilayer SPOM methodology establishes the linkage among the equipment-layer degradation prognosis, the local-layer maintenance adjustments and the global-layer routing optimizations. For each leased machine, we replace the population-specific lifetime distributions with sensor-driven TTF prognostic updating. For each leased system, the series-parallel structure and production capacity balancing are analyzed to utilize PdM opportunities. For the multilocation network, geographical location distances, and maintenance team dispatching are integrated with real-time service requirements to obtain cost-effective maintenance schemes. Along the line of this article, the opportunities arise from complex degradation, economic and logistic interdependencies between machines, systems and the whole network, thus it remains critical to integrate these factors into service decisions. This hierarchical SPOM methodology not only extends the current concept of opportunistic maintenance, but also helps to promote the machinery leasing and maintenance outsourcing all around the world.

III. Equipment-Layer Automated Prognostic Model With TTF Updating

We consider a global service-outsourcing network containing geographically distributed client-enterprises whereby each leased system is composed of various machines. For achieving the global O&M service dynamically, it is necessary to utilize sensor-driven prognostic techniques to provide real- time health conditions of leased machines. In the equipment layer, two types of maintenance actions described in the literature are considered: PdM and minimal repair. We leverage on the real-time sensor information to reflect the degradation process and accurately predict the TTF distribution. Moreover, TTFs are assumed to follow an affirmatory LLS distribution, which can be estimated from the corresponding historical degradation dataset.

For a leased machine E_{ijk} (machine k belongs to procedure j of client-enterprise i), we utilize the historical dataset $\mathcal{H}_k$ that consists of the degradation data from H sets. Each set possesses the hazard information during a PdM interval and monitors the degradation by $P(P \geq 1)$ sensors. We define the TTF distribution of set r ($r \in \mathcal{H}_k$) as $y_{ijk,r}$, and denote the degradation signal from pth sensor of set $r$by $s_{ijk,r,p}(t)$. Then, we build the following LLS regression model to represent the relationship between TTF distributions and degradation signals

$$y_{ijk,r} = \alpha_o + \int_0^{\tau} \alpha(t)^T s_{ijk,r}(t)\, dt + \sigma\varepsilon_{ijk,r} \tag{1}$$

where α_o is the intercept, $s_{ijk,r}(t)$ is degradation signal from the whole P sensors, and $\alpha(t)$ is the coefficient function. $\alpha_o + \int_0^{\tau} \alpha(t)^T s_{ijk,r}(t)dt$ is the location parameter, and σ is the scale parameter of the degradation function. $\varepsilon_{ijk,r}$ captures the sensor error and the inherent stochasticity of degradation processes with a standard LLS density $\omega(\varepsilon)$. Moreover, function ω has different formulations under different LLS distributions. For instance, $\omega(x) = 1/(\sqrt{2\pi})\exp(-x^2/2)$ for a normal distribution. $\omega(x) = 1/(x\sqrt{2\pi})\exp(-(\ln x)^2/2)$ for a lognormal distribution. $\omega(x) = \exp(x - \exp(x))$ for a smallest extreme value (SEV) distribution and $\omega(x) = \exp(x - \exp(x))/x$ for a Weibull distribution.

In our automated prognostic model, to describe the degradation process feasibly and simply, we decompose degradation signals by using the multivariate functional principal component analysis (MFPCA) in [5]. Therefore, the LLS regression model after simplification and approximation can be expressed as follows:

$$y_{ijk,r} = \beta_0 + \sum_{b=1}^{B} \beta_b \xi_{ijk,r}^b + \sigma\varepsilon_{ijk,r} \tag{2}$$

where β_0 is the substitutional intercept. $\xi_{ijk,r}^b$ is the functional principal component (FPC) score in MFPCA, β_b is the relevant regression coefficient, and B represents the principal component number selected by representative selection criteria.

The proposed prognostic model uses the MFPCA to extract degradation features from various sensor information. For updating the TTF distribution precisely, both the historical degradation from the lessor and the real-time condition data from the lessees should possess in the same time domain. We update the TTF at the time τ and establish degradation observations on the domain $[0, \tau]$. Moreover, we denote the truncated degradation signal in historical dataset $\mathcal{H}_k$ as $\{s_{ijk,r}(t)\}_{r=1}^{\pi}$, where π is the number of sets whose TTFs are greater than or equal to τ. After that, the FPC-score $\xi_{ijk,r}^b$ are calculated dynamically by solving $\xi_{ijk,r}^b = \int_0^{\tau} (s_{ijk,r}(t) - \hat{\mu}(t))^T \hat{\varphi}^b(t)dt$. Here $\hat{\mu}(t)$ is the mean function and $\{\hat{\varphi}^b(t)\}_{b=1}^B$ is the eigen-function. Based on the FPC-score $\hat{\xi}_{ijk,r}^b$ and the TTF $y_{ijk,r}$, we build the following (log)-likelihood function to bring an estimate on regression parameters $\hat{\beta}_0, \hat{\beta}_b, \hat{\sigma}$:

$$\hat{\beta}_0, \hat{\beta}_b,\ \hat{\sigma} = \arg\min_{\beta_0,\beta_b,\sigma} \mathfrak{l}(\beta_0, \beta_b, \sigma)\,. \tag{3}$$

If $y_{ijk,r}$ follows a location-scale distribution (normal distribution and SEV distribution), the likelihood function is

$$\begin{aligned}&\mathfrak{l}\ (\beta_0, \beta_b, \sigma)\\ &\quad = -n\ln\sigma + \sum_{r=1}^{\pi} \ln\omega \frac{y_{ijk,r} - \beta_0 - \sum_{b=1}^{B} \beta_b \xi_{ijk,r}^b}{\sigma}.\end{aligned} \tag{4}$$

If the TTF $y_{ijk,r}$ follows a log-location-scale distribution (lognormal distribution and Weibull distribution), the log-likelihood function is

$$\begin{aligned}\mathfrak{l}(\beta_0, \beta_b, \sigma) = &-n\ln(\sigma y_{ijk,r})\\ &+ \sum_{r=1}^{\pi} \ln\omega \frac{\ln(y_{ijk,r}) - \beta_0 - \sum_{b=1}^{B} \beta_b \xi_{ijk,r}^b}{\sigma}.\end{aligned} \tag{5}$$

Simultaneously, the appropriate TTF distribution for each machine is obtained by applying the Bayesian information criterion (BIC). We calculate the BIC-value under each LLS distribution and choose the distribution with the smallest value

$$\text{BIC} = -2\mathfrak{l}(\hat{\beta}_0, \hat{\beta}_b, \hat{\sigma}) + (B+2)\log\pi. \tag{6}$$

Then, we estimate the FPC-score $\hat{\xi}_{ijk,d}^b$ of the current degradation signal. Based on $\hat{\xi}_{ijk,d}^b$, $\hat{\beta}_0$, $\hat{\beta}_b$ and $\hat{\sigma}$, the probability density function $\Pr(\ \hat{y}_{ijk,d} = t)$ and the cumulative density function $\Pr(\hat{y}_{ijk,d} < t)$ of the current sensor information $y_{ijk,d}$ can be obtained. Consequently, the real-time hazard rate of machine k at dth equipment-layer cycle is updated as follow

$$\lambda_{ijk,d}(t) = \frac{\Pr\left(y_{ijk,d} = t\right)}{1 - \Pr\left(y_{ijk,d} < t\right)}. \tag{7}$$

Moreover, the hazard rate and maintenance parameters (maintenance costs and durations) are translated into a maintenance cost function, which captures the tradeoff between the early maintenance and the risk associated with the unexpected failure. The maintenance cost rate $c_{ijk,d}(t)$ of machine k at dth equipment-layer cycle is expressed as follows:

$$c_{ijk,d}(t) = \frac{C_{ijk}^P + C_{ijk}^R \int_0^{T_{ijk,d}} \lambda_{ijk,d}(t)\, dt}{T_{ijk,d} + \left(T_{ijk}^P + T_{ijk}^R \int_0^{T_{ijk,d}} \lambda_{ijk,d}(t)\, dt\right)} \tag{8}$$

where C_{ijk}^P and C_{ijk}^R are the costs of a PdM action and a minimal repair, respectively. T_{ijk}^P and T_{ijk}^R are the duration of a PdM action and a minimal repair, respectively. The optimal PdM interval $T_{ijk,d}^*$ of machine k is derived by solving the derivative function $dc_{ijk,d}/d\,T_{ijk,d} = 0$. Ultimately, these PdM intervals are integrated into the local-layer maintenance adjustment.

IV. Local-Layer Opportunistic Maintenance Policy With Capacity Balancing

By pulling equipment-layer PdM intervals, we schedule group maintenance opportunities within a series-parallel system with multiple procedures. For the series-parallel system of each client-enterprise, the first machine reaches its PdM interval can be defined as the triggering one that brings a maintenance opportunity. At the local layer, an opportunistic maintenance policy is designed to analyze the LPSs to combine PdM actions of machines. By opportunistically advancing several PdM actions to group execution, it can efficiently avoid unnecessary workforce dispatch, ensure production capacity balance, and achieve overall profit maximization.

To achieve the lease-oriented opportunistic maintenance for the complex series-parallel structure, the local-layer decision-making is subdivided into the procedure layer and the system layer. Facing each maintenance opportunity, we first quantify the impact of machine shutdown on the production capacity of the same procedure. A PLPO policy helps to combine PdM actions at the procedure layer economically. Then the maximum halting machine quantities of other procedures and the LPSs of remaining nonrepair machines are dynamically computed. After that, the SLPO policy integrates leasing profit and capacity balancing to output profit-maximum maintenance schemes at the system layer.

To comprehensively reflect the impact of advancing a PdM action, both the corresponding LPAs and leasing profit reductions (LPR) are formulated. Thus, for parallel subsystems, the real-time LPS of a leased machine E_{ijk} (machine k belongs to procedure j of client-enterprise i) at the hth local-layer cycle can be denoted by

$$\begin{aligned}
\mathrm{LPS}(p)_{ijk,h} &= \mathrm{LPA}_{ijk,h}^R + \mathrm{LPA}_{ijk,h}^M - \mathrm{LPR}_{ijk,h}^P \\
&\quad - \mathrm{LPR}_{ijk,h}^D - \mathrm{LPR}_{ijk,h}^C \\
&= T_{ijk}^P\, \kappa_{ijk} + \left(\int_0^{T_{ijk,d}^*} \lambda_{ijk,d}(t)\, dt \right.\\
&\quad \left. - \int_0^{T'_{ijk,d}} \lambda_{ijk,d}(t)\, dt\right) C_{ijk}^R \\
&\quad - \frac{t_{ijk,h} - e_{i,h}}{T'_{ijk,d}} C_{ijk}^P - \delta_{ijk} \frac{t_{ijk,h} - e_{i,h}}{L_i} \\
&\quad \times \left(V_{ijk}^S - V_{ijk}^E\right) - T_{ijk}^P C_{ijk}^C
\end{aligned} \tag{9}$$

where LPA consists of the machine rent addition $\mathrm{LPA}_{ijk,h}^R$ (which means the PdM advancement makes the unnecessary downtime of PdM duration become additional operation duration and brings leasing rent) and the failure control addition $\mathrm{LPA}_{ijk,h}^M$ (which reflects that the shortened original PdM interval reduces the failure possibility). Meanwhile, LPR includes the frequent maintenance reduction $\mathrm{LPR}_{ijk,h}^P$ (which shows PdM advancements will lead to more PdM actions for increased cycles), the accelerating depreciation reduction $\mathrm{LPR}_{ijk,h}^D$ (which is consistent with the fact that frequent PdM actions accelerate the disvalue of the leased machine), and the capacity punishment reduction $\mathrm{LPR}_{ijk,h}^C$ (for parallel structure, the PdM action of a parallel machine with the triggering one would inevitably bring a decrease in the system productivity).

Thereby, in the PLPO programming, start from the local-layer cycle $h = 1$, the PdM moment $t_{ijk,h}$ from equipment-layer outputs are assigned to the local-layer opportunity moment $e_{i,h}$. And the leased machine $E_{ij^*k^*}$ with the minimal $e_{i,h}$-value is defined as the triggering one. Then LPS of other non-repair machines of the same procedure are computed to support PdM adjustments. If $\mathrm{LPS}(p) > 0$, an Early PdM action will be taken. Otherwise, *in situ* PdM will be the choice. Here, the variable $\Omega(ij^*k, e_{i,h})$ indicates whether to advance other PdM actions to be performed together with $E_{ij^*k^*}$. And we use $\omega_{ij^*,h}$ and $\psi_{ij^*,h}$ to count the machines performed Early PdM actions and arranged In-situ PdM choices in this procedure j^* at $e_{i,h}$, respectively,

$$\Omega\left(ij^*k, e_{i,h}\right) = \begin{cases} 1 & \mathrm{LPS}(p)_{ij^*k,h} > 0 \\ 0 & \mathrm{LPS}(p)_{ij^*k,h} \le 0 \end{cases} \tag{10}$$

$$\omega_{ij^*,h} = \sum_{k=1}^{K_{ij^*}} \Omega\left(ij^*k, e_{i,h}\right), \psi_{ij^*,h} = K_{ij^*} - \omega_{ij^*,h}. \tag{11}$$

It is doubtless that every procedure is supposed to have the equal overall capacity Cp_i. Therefore, for this parallel subsystem, the remaining capacity is formulated as

$$Cp_{i,h}^{\mathrm{remain}} = \left(\frac{\psi_{ij^*,h}}{K_{ij^*}}\right) Cp_{i.} \tag{12}$$

To maintain the system's capacity balance, we further calculate the minimum machine quantity $\psi_{ij,h}$ and the maximum halting machine quantity $\omega_{ij,h}$ for other procedures

$$\psi_{ij,h} = \frac{Cp_{i,h}^{\mathrm{remain}}}{Cp_i / K_{ij}},\ \ \omega_{ij,h} = K_{ij} - \psi_{ij,h}\ \left(j \neq j^*\right). \tag{13}$$

Then, SLPO scheduling for series subsystems finds a group of machines that can produce the profit surplus. The real-time LPS for the series subsystem can be calculated as

$$\begin{aligned}\mathrm{LPS}(s)_{ijk,h} &= \mathrm{LPA}^{R}_{ijk,h}+\mathrm{LPA}^{M}_{ijk,h}-\mathrm{LPR}^{P}_{ijk,h}-\mathrm{LPR}^{D}_{ijk,h}\\ &= T^{P}_{ijk}\,\kappa_{ijk}+\left(\int_0^{T^{*}_{ijk,d}}\lambda_{ijk,d}\left(t\right)dt\right.\\ &\qquad\left.-\int_0^{T'_{ijk,d}}\lambda_{ijk,d}\left(t\right)dt\right)C^{R}_{ijk}\\ &\quad-\frac{t_{ijk,h}-e_{i,h}}{T'_{ijk,d}}C^{P}_{ijk}-\delta_{ijk}\frac{t_{ijk,h}-e_{i,h}}{L_i}\\ &\quad\times\left(V^{S}_{ijk}-V^{E}_{ijk}\right).\end{aligned}\tag{14}$$

Once $\mathrm{LPS}(s)_{ijk,h}>0$, it exists a profit surplus if $E_{ijk}(j\neq j^{*})$ is performed an early-PdM at $e_{i,h}$. Besides, capacity balancing outputs from the procedure layer should be considered to develop the optimum PdM adjustment

$$\Omega\left(ijk,e_{i,h}\right)=\begin{cases}1 & \mathrm{LPS}(s)_{ijk,h}>0\\ 0 & \mathrm{LPS}(s)_{ijk,h}\leq 0\end{cases}\quad(j\neq j^{*})\tag{15}$$

$$\gamma_{ij,h}=\sum_{k=1}^{K_{ij}}\Omega\left(ijk,e_{i,h}\right)\left(j\neq j^{*}\right).\tag{16}$$

On the one hand, if $\gamma_{ij,h}\leq\omega_{ij,h}$, the machines' PdM actions with $\mathrm{LPS}(s)>0$ are performed in advance with the triggering machine $E_{ij^{*}k^{*}}$. And recognize $(\omega_{ij,h}-\gamma_{ij,h})$ machines with the higher $\mathrm{LPS}(s)$-values among remaining machines to halt in the PdM actions (Assign these halting machines with $\Omega\left(ijk,e_{i,h}\right)=2$), when other $\psi_{ij,h}$ machines remain operational. On the other hand, if $\gamma_{ij,h}>\omega_{ij,h}$, classify all machines with $\mathrm{LPS}(s)>0$ in the downward sequence, choose the $\omega_{ij,h}$ machines with higher $\mathrm{LPS}(s)$-values and execute Early-PdM actions together with $E_{ij^{*}k^{*}}$ in group PdM sets $\mathrm{GP}_{i,h}$, whereas other $\psi_{ij,h}$ machines would keep working.

By comparing the number of machines with the positive profit saving ($\gamma_{ij,h}$) and the maximum halting quantity ($\omega_{ij,h}$), we arrange the local-layer maintenance grouping and adjustment. For series-parallel leased systems, we obtain PLPO decisions $\Omega(ij^{*}k,e_{i,h})$ and SLPO decisions $\Omega(ijk,e_{i,h})$ for machine E_{ijk} at each local-layer opportunity moment $e_{i,h}$. Based on these local-layer decisions and auxiliary analysis, we generate the profit-maximum group PdM set $\mathrm{GP}_{i,h}$ at each opportunity moment. Then, group PdM sets $\mathrm{GP}_{i,h}$ (include the Early-PdM machines and the triggering machine) and the corresponding opportunity moments $e_{i,h}$ will be used as inputs to the global-layer routing optimization.

V. Global-Layer Routing Optimization Policy With Service Window

To expend sensor-driven opportunistic maintenance to a service-outsourcing network, the global-layer NRO policy integrates the travel time between lessees' multiple locations and the lessor's maintenance central. For providing efficient O&M service to globally distributed lessees (client-enterprises), the lessor needs to efficiently dispatch multiple maintenance teams. In addition, the lessor also has to arrange the maintenance requirements for each maintenance team, and the sequence in which these group PM sets must be performed.

The service-outsourcing network is described as a directed complete graph $G=(\mathcal{V},\mathcal{A})$ with a node-set $\mathcal{V}=\{0,1,2,\ldots,N\}$ and an arc set $\mathcal{A}=\{(i,i'|i,i'\in\mathcal{V},i\neq i')\}$. The subset of $\mathcal{V}$, denoted by $\mathcal{I}\subseteq\mathcal{V}$, represents N lessees to be served. To provide O&M services timely and economically, a set of maintenance teams $\mathcal{M}=\{12,\ldots,M\}$ is dynamically dispatched to service multi-location lessees. They conduct group PdM actions within the corresponding service time-window under the optimum service route. Each series-parallel system starts the corresponding maintenance after the earliest time of its time window. And each service route originates and ends at the maintenance central.

At each global-layer cycle, there are many lessees waiting for O&M services. The lessor acquires the maintenance requirement and opportunity moment of each series-parallel system from the local layer. Then, NRO policy utilizes these local-layer outputs and routing parameters (transportation cost, dispatch cost, and maintenance capacity) to derive both the route of maintenance teams and the service start time of every group PdM set. The specific data flow of the proposed multi-layer SPOM methodology is shown in Fig. 2.

From the equipment-layer degradation prognosis and the local-layer maintenance adjustment, we obtain the group PdM sets $\mathrm{GP}_{i,h}$ and the corresponding opportunity moments $e_{i,h}$ from multilocation lessees cyclically. To facilitate the global maintenance routing, we extend an opportunity moment $e_{i,h}$ to a service time window $[t^{s}_{i,u},t^{e}_{i,u}]$ while keeping the local-layer decisions unchanged. The lower bound $t^{s}_{i,u}$ equal to the opportunity moment $e_{i,h}$ minus the width of the time window w_i, as $t^{s}_{i,u}=e_{i,h}-w_i$. The upper bound $t^{e}_{i,u}$ equal to the opportunity moment $e_{i,h}$, as $t^{e}_{i,u}=e_{i,h}$. Then we define the number of machines in group PdM set as the demand of maintenance capacity ($\mathrm{GP}_{i,h}\rightarrow s_{i,u}$). Based on the above auxiliary parameters, we arrange the sensor-driven maintenance requirements at uth global-layer cycle.

For each maintenance requirement of lessee $i\in\mathcal{I}$, it includes a service time window $[t^{s}_{i,u},t^{e}_{i,u}]$, a demand for maintenance capacity $s_{i,u}$, and a service-outsourcing duration $T^{\max}_{i,u}$ at uth global-layer cycle. To satisfy real-time maintenance requirements and decrease the routing cost effectually, existing maintenance teams $\mathcal{M}=\{12,\ldots,M\}$ are dynamically dispatched from the maintenance central until the end of lease periods. Then, we model the global-layer routing optimization with two decision variables (binary variables $x_{ii'm,u}$ and time variables $z_{im,u}$). And the objective function is to minimize the total service-outsourcing cost TSC_u subject to the constraints covering logistics path planning and maintenance resource limitation. The global-layer routing optimization is modeled as follows:

$$\begin{aligned}\min TSC_u &= \sum_{i\in\mathcal{V}}\sum_{i'\in\mathcal{V}}\sum_{m\in\mathcal{M}}\sum_{u\in\mathcal{U}}c_{ii'}t_{ii'}x_{ii'm,u}\\ &+\sum_{i\in\mathcal{I}}\sum_{i'\in\mathcal{V}}\sum_{m\in\mathcal{M}}\sum_{u\in\mathcal{U}}c^{w}_{ii'}\left[z_{i'm,u}-\left(z_{im,u}+T^{\max}_{i,u}\right.\right.\end{aligned}$$

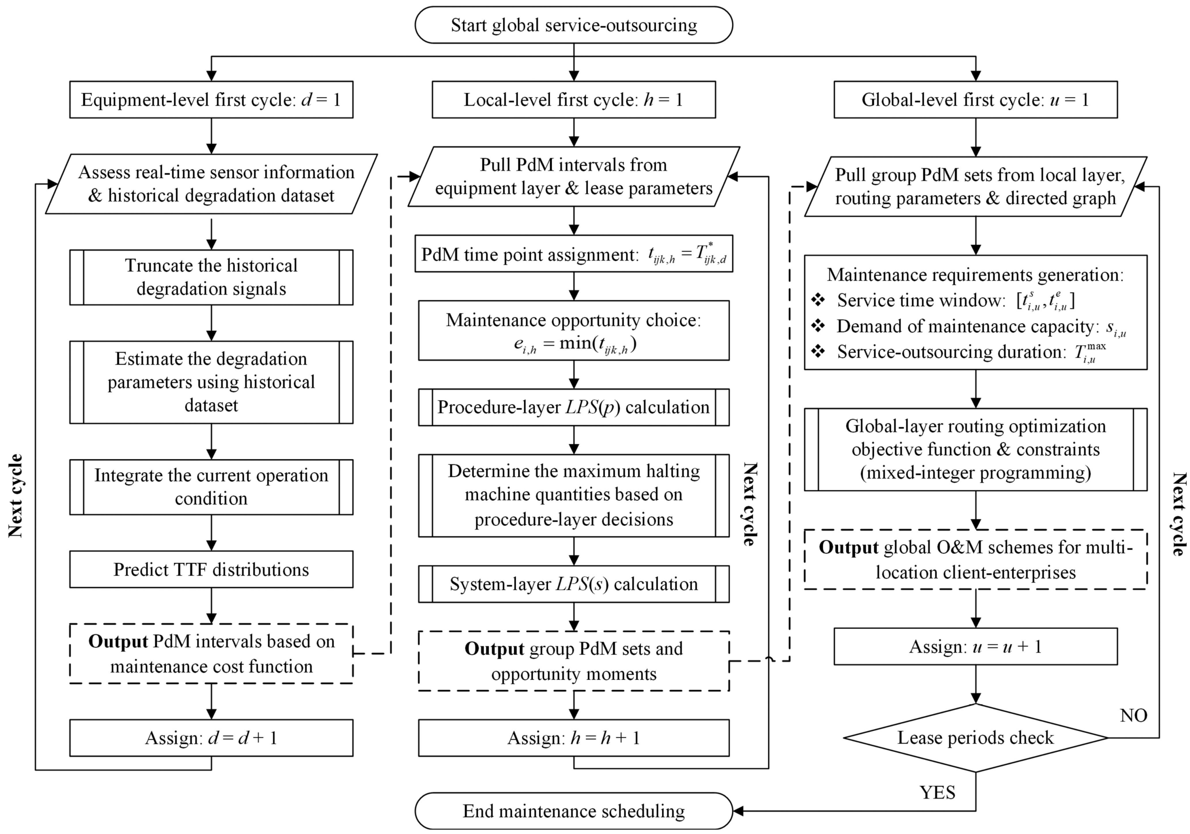


Fig. 2. Data flow of multilayer SPOM methodology.

$$+ \ t_{ii'})]^{+} x_{ii'm,u}$$

$$+ \sum_{i' \in \mathcal{I}} \sum_{m \in \mathcal{M}} \sum_{u \in \mathcal{U}} c_m x_{0i'm,u}$$

$$+ \sum_{i \in \mathcal{V}} \sum_{i' \in \mathcal{I}} \sum_{m \in \mathcal{M}} \sum_{u \in \mathcal{U}} c^p_{i'} x_{ii'm,u} \left[z_{i'm,u} - t^e_{i,u} \right]^{+} \tag{17}$$

$$\sum_{i' \in \mathcal{V}} \sum_{m \in \mathcal{M}} x_{ii'm,u} = 1 \ \forall i \in \mathcal{V}, \ u \in \mathcal{U} \tag{18}$$

$$\sum_{i \in \mathcal{V}} x_{ii'm,u} - \sum_{a \in \mathcal{V}} x_{i'am,u} = 0 \ \forall i' \in \mathcal{I}, m \in \mathcal{M}, \ u \in \mathcal{U} \tag{19}$$

$$\sum_{i \in \mathcal{I}} x_{0im,u} = 1 \ \forall m \in \mathcal{M}, \ u \in \mathcal{U} \tag{20}$$

$$\sum_{i \in \mathcal{I}} x_{i0m,u} = 1 \ \forall m \in \mathcal{M}, \ u \in \mathcal{U} \tag{21}$$

$$\sum_{i \in \mathcal{I}} \sum_{i' \in \mathcal{V}} s_{i,u} x_{ii'm,u} \leq q_m \ \forall m \in \mathcal{M}, \ u \in \mathcal{U} \tag{22}$$

$$z_{im,u} \geq t^s_{i,u} \ \forall i \in \mathcal{I}, m \in \mathcal{M}, \ u \in \mathcal{U} \tag{23}$$

$$x_{ii'm,u} \in \{01\} \ \forall i, i' \in \mathcal{V}, m \in \mathcal{M}, \ u \in \mathcal{U}. \tag{24}$$

In the objective function (17), the first term represents the transportation cost between multiple lessees and the maintenance central. The second term represents the cost of maintenance teams waiting outside the service time windows, where $[\cdot]^+$ indicates $\max(\cdot, 0)$. The third term captures the dispatch cost of maintenance teams, which is paid for the deployment of spare parts, repair tools and technicians from the maintenance central to multiple lessees. The final term is the late penalty cost based on the number of hours later than the upper bound of time windows.

Meanwhile, constraints (18) guarantee that each group PdM set is assigned to one maintenance team once. Constraints (19) require that after one maintenance team arrives at lessee i' and completes PdM, this team has to leave to another destination. Constraints (20) and (21) ensure that every maintenance team must leave and finally arrive at the maintenance central. Constraints (22) represent the maintenance capacity limitations, which ensure the maintenance capacity of each team can cover the number of leased machines to be maintained. Constraints (23) prohibit any maintenance team from starting the sensor-driven PdM action before the lower bound of time windows. Finally, constraints (24) impose the binary condition on decision variables. By solving the optimization model of NRO policy, the optimum service route of teams can be obtained.

VI. Case Study

In this section, we utilize degradation signals of the leased machines within a multilocation service-outsourcing network

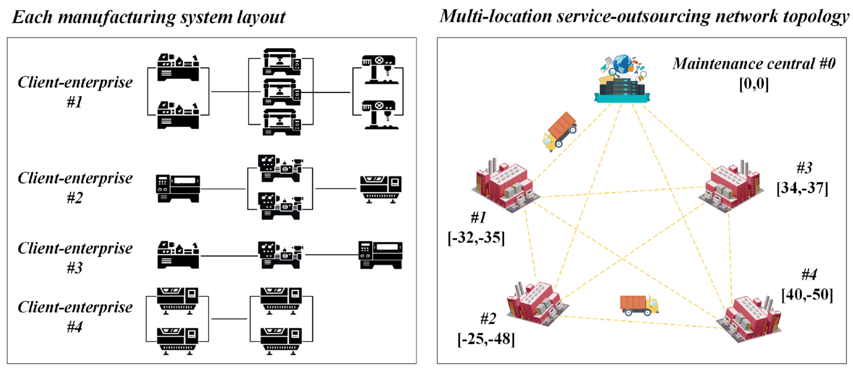


Fig. 3. Multilocation service-outsourcing network layout.

TABLE I
BIC VALUES UNDER DIFFERENT LLS DISTRIBUTIONS FOR EQUIPMENT

k	Normal	Lognormal	SEV	Weibull	k	Normal	Lognormal	SEV	Weibull
1	1668.72	**1658.03**	1699.66	1670.06	10	1056.75	1060.14	**1053.72**	1055.17
2	**1400.98**	1402.99	1425.97	1408.07	11	**1639.83**	1649.40	1653.65	1641.92
3	1577.22	1581.21	1592.05	**1573.55**	12	1061.77	1070.25	**1019.35**	1020.54
4	**1331.05**	1338.71	1340.96	1333.99	13	1375.21	**1374.89**	1396.11	1382.46
5	1455.63	**1434.79**	1513.56	1481.01	14	1744.32	1742.73	1787.83	**1734.76**
6	1639.88	1651.28	1672.20	**1630.77**	15	1623.11	**1598.44**	1673.54	1633.98
7	1577.06	**1571.85**	1608.44	1583.00	16	**1386.61**	1387.97	1410.24	1397.35
8	**1439.26**	1444.88	1462.13	1447.40	17	924.177	926.623	**908.280**	918.197
9	1429.89	**1428.13**	1462.19	1439.54	18	1668.18	**1649.88**	1714.60	1671.21

to verify the effectiveness of this multilayer SPOM methodology. In the equipment layer, real-world sensor signals and the historical degradation signals are used to demonstrate the automated prognostic model. In the local layer, we focus on the leased system of a client-enterprise (lessee) and show how the profit savings and the capacity balance jointly optimize the group maintenance schedule. In the global layer, based on real-time requirements of each enterprise, we schedule optimum service routes of maintenance teams during a long-term lease period. Finally, a comparative study is presented to illustrate the advantages of SPOM methodology.

Leased manufacturing systems of client-enterprises at different locations can be subdivided into multiple procedures that operate sequentially to produce. Each procedure can be composed of a single leased machine, or several individual ones in parallel. We consider an illustration scenario where the OEM (lessor) has multiple maintenance teams for the outsourcing maintenance service of 18 machines scattered across 4 client-enterprises. The specific network topology is shown in Fig. 3, and the vectors between any pair of nodes represent the possible service routes.

A. Predicting PdM Intervals by Real-Time Sensor Data

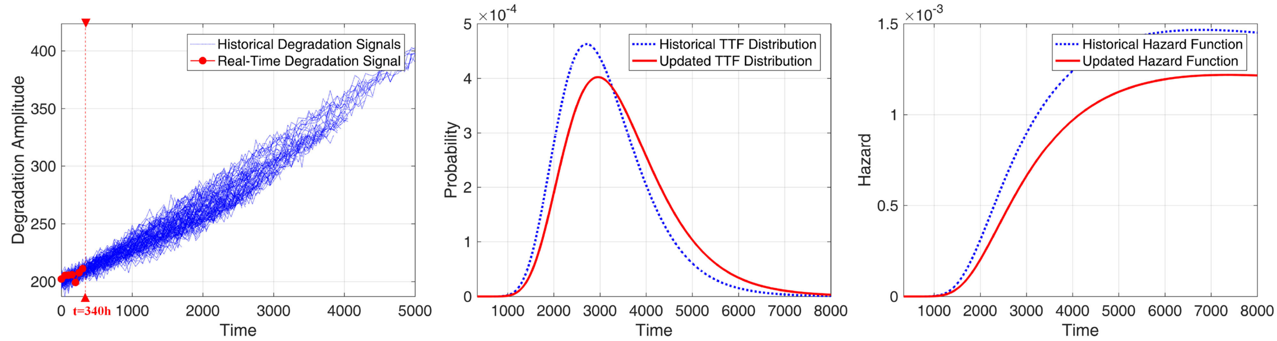
To emulate degradation occurring on each machine, we use real-life degradation data acquired from numerical control device. Besides, we arrange dedicated sensors to monitor the vibration signals of essential components. For the equipment-layer real-time prognosis, we collect 100 sets of historical degradation signals for each machine. Each set possesses the hazard information during a PdM interval, which represents the duration of two adjacent PdM activities. We assume the TTF distribution follows one of typical LLS distributions (including normal distribution, lognormal distribution, smallest extreme value distribution, and Weibull distribution). Based on historical failure signals and online sensor data, the LLS distribution of each machine is matched by evaluating BIC. As given in Table I, the most appropriate distribution is determined with the minimum BIC-value.

Based on the determined LLS distribution, the corresponding regression model is established according to (2). Moreover, the TTF prediction starts from 100 h and continuously updates every 48 h to reflect the real-time machine condition. As a motivating example, Fig. 4 shows the updated TTF distribution and the corresponding hazard rate of machine 1 after 340 h of operation.

With the updated hazard rate from the automated prognostic model, the maintenance cost rate of each leased machine is formulated to capture the tradeoff between early maintenance and the risk of unexpected failures due to delayed maintenance. During a lease period of 448 days (10752 h), equipment-layer PdM intervals of machine 1 is exhibited in Fig. 5.

B. Grouping PdM Actions by Leasing Profit Optimization

By dynamically pulling equipment-layer PdM intervals, different maintenance actions are scheduled to be performed in groups to avoid frequent downtime and save maintenance costs. The first machine reaches its PdM time points (as the triggering one) brings a maintenance opportunity. The local-layer policy



(a) (b) (c)

Fig. 4. Updated TTF distribution (b) and hazard rate (c) based on degradation signals (a).

TABLE II
MAINTENANCE AND LEASE PARAMETERS OF LEASED MACHINES

i	j	k	T^P_{ijk}	T^R_{ijk}	C^P_{ijk}	T^R_{ijk}	κ_{ijk}	δ_{ijk}	V^S_{ijk}	V^E_{ijk}	C^C_{ijk}
1	1	1	20	66	6500	18000	20	0.22	670000	560000	18
		2	25	74	8000	20000	14	0.15	500000	440000	18
	2	3	10	38	3400	8800	16	0.13	960000	910000	12
		4	12	68	9600	28000	10	0.14	730000	700000	12
		5	14	48	6000	17000	16	0.16	430000	390000	12
	3	6	15	30	4000	10000	20	0.28	600000	530000	18
		7	10	22	2800	9000	12	0.11	700000	620000	18
2	4	8	8	18	4000	6800	18	0.22	830000	760000	22
	5	9	15	55	8800	23000	8	0.12	350000	310000	11
		10	21	65	6400	19000	14	0.11	700000	660000	11
	6	11	24	74	8100	12000	18	0.15	960000	860000	22
3	7	12	11	37	3300	28000	16	0.13	520000	400000	13
	8	13	13	69	9400	25000	10	0.12	400000	350000	13
	9	14	14	46	6200	19000	20	0.22	860000	700000	13
4	10	15	15	31	3300	9900	18	0.16	330000	250000	10
		16	12	23	8500	25000	20	0.22	460000	390000	10
	11	17	9	19	4100	30000	22	0.28	600000	550000	10
		18	14	34	2600	9000	18	0.16	820000	760000	10

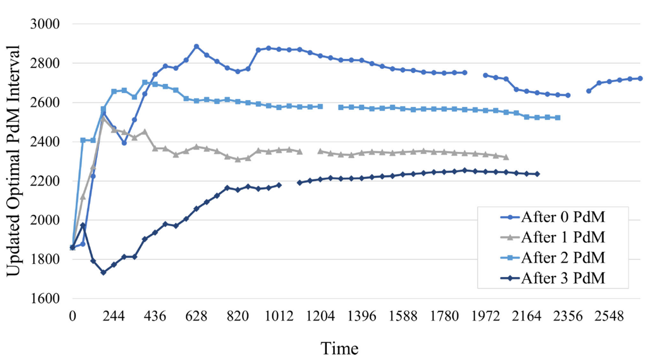


Fig. 5. Updated PdM intervals within the lease period.

fully utilizes every opportunity to combine PdM actions for the leased system with production capacity balancing and leasing profit optimization. Maintenance parameters estimated by OEM engineers and lease parameters from lease contracts given in Table II are involved.

As shown in Fig. 3, client-enterprise #1 leases a triple-procedure manufacturing system of an engine part. This leased system consists of seven machines with individual degradations, while machines in these three procedures are lathe machines, milling machines and drilling machines, respectively. Table III illustrates the decision-making at the first cycle ($h = 1$). More concretely, assign the equipment-layer PdM intervals $T^*_{ijk,d}$ to the local-layer PdM time points $t_{ijk,h}$ for opportunistic maintenance. Machine 5 is scheduled to be the first triggering one with a shutdown opportunity. Define its PdM time point $t_{ijk,h} =$ 1891h as the local-layer grouping execution time $e_{i,h}$. Then, preform PLPO policy for the other machines in the same procedure according to Eq. (9). $\mathrm{LPS}(p)_{113} =$ \$98 indicates the Early PdM of machine 3 results in extra income. Thus, machine 3 is brought forward to the grouping set GP_{11} and performed PdM together. After determining the remaining machine quantity with PdM actions are implemented in procedure 1, the

TABLE III
LOCAL-LAYER PROGRAMMING OF CLIENT-ENTERPRISE $i = 1$ AT THE FIRST CYCLE

j	k	$T^*_{ijk,d}$	$t_{ijk,h}$	$e_{i,h}$	$LPS(p)_{ijk,h}$	$LPS(s)_{ijk,h}$	$\Omega(ijk, e_{i,h})$	$\omega_{ij,h}$	$\gamma_{ij,h}$
1	1	2752	2752			-2540	0	1	1
	2	1938	1938			549	1		
2	3	1976	1976		98		1	2	2
	4	2468	2468	1891	-157		0		
	5	1891	1891		---	---	PdM		
3	6	2814	2814			-1493	0	1	1
	7	2284	2284			152	1		

TABLE IV
LOCAL-LAYER PROGRAMMING OF CLIENT-ENTERPRISE $i = 4$ AT THE FIRST CYCLE

j	k	$T^*_{ijk,d}$	$t_{ijk,h}$	$e_{i,h}$	$LPS(p)_{ijk,h}$	$LPS(s)_{ijk,h}$	$\Omega(ijk, e_{i,h})$	$\omega_{ij,h}$	$\gamma_{ij,h}$
10	15	2097	2097	2097	---	---	PdM	1	1
	16	3035	3035		-1615		0		
11	17	2934	2934			-1476	0	0	1
	18	2862	2862			-1372	2		

maximum quantity of halting machines of other procedures is computed to maintain the balance of capacity. For the machines of other procedures, perform SLPO policy according to (14). Thus, machines 2 and 7 are also advanced with positive LPS-values. Moreover, $\omega_{ij,h} = \gamma_{ij,h}$, which means other machines with negative LPS-values remain operational to keep the system capacity.

For another client-enterprise #4, as depicted in Fig. 3, it consists of 4 CNC machines that evenly distributed in 2 procedures to machining the engine turbine blade. Similar local-layer programming would be sequentially executed at each opportunity, and the decision-making at the first cycle is given in Table IV. Machine 15 becomes the triggering one. According to the results, only machine 15 in procedure 10 is maintained here. For production balancing, only machine 18 with the larger LPS-value of procedure 11 is chosen to halt $(\Omega\left((i = 4, j = 11, k = 18), e_{41}\right) = 2)$.

Based on local-layer programming for each client- enterprise, the service demands of the whole service- outsourcing network are further organized. Arrange leased machines with $\Omega\left(ijk, e_{i,h}\right) = 1$ in the respective grouping $\mathrm{GP}_{i,h}$, and count the number of machines in $\mathrm{GP}_{i,h}$ to determine the demands of the maintenance capacity $s_{i,u}$. Meanwhile, the service duration of each group set $T^{\max}_{i,u}$ equals to the maximum durations for combined PdM actions. The time point of each maintenance opportunity $e_{i,h}$ is expended to the service time-window $[t^s_{i,u}, t^e_{i,u}]$ to suppose the global-layer optimization. In particular, the lower bound $t^s_{i,u}$ equals to $e_{i,h}$, and the upper bound $t^e_{i,u}$ latter than $e_{i,h}$ under the width of the time window as 24 hours. Maintenance requirements of this service-outsourcing network at the first local-layer cycle ($h = 1$) are gathered in Table V.

TABLE V
MAINTENANCE REQUIREMENTS AT THE FIRST LOCAL-LAYER CYCLE

$i \in \mathcal{I}$	$GP_{i,h}$	$s_{i,u}$	$t^s_{i,u}$	$t^e_{i,u}$	$T^{max}_{i,u}$
1	{2,3,5,7}	4	1891	1915	25
2	{10}	1	1824	1848	21
3	{12,13}	2	2163	2187	13
4	{15}	1	2097	2121	15

C. Optimizing Global Schemes by Service Time Window

The global-layer NRO policy is designed for multiple maintenance teams by minimizing the total service-outsourcing cost to obtain the optimum service routes dynamically. The transportation cost rate $c_{ii'}$, the waiting cost rate $c^w_{ii'}$ and the late penalty cost rate $c^p_{i'}$ are set to \$150, \$50, and \$30 p.u. time, respectively. Besides, the dispatch cost c_m for sending a maintenance team from the maintenance central is \$10000, and the maintenance capacity of each maintenance team Q_m is 6 machines/time. Based on the service demands of the first cycle given in Table V, to satisfy requests of all distributed client-enterprises, the OEM (lessor) arranges two maintenance teams to ensure O&M management. It can be noticed in Table VI that both maintenance teams start and end at the maintenance central, one team serves client-enterprises #2, #1 and another team serves #4, #3 successively. The total service-outsourcing cost of these optimal service routes is $\mathrm{TSC}_1 = \$60700$.

After the decision-making above for the global-layer cycle, we take note of the maintained and operational machines, update the rolling horizon of each scattered machine, and reevaluate the degradation properties using the new sensor data. Sequentially, we turn to resolve the hierarchical optimization problem to determine the updated outsourcing maintenance schemes for the next cycle. This process is executed in a rolling horizon mode to cover the effective service-outsourcing within the lease period. Furthermore, the whole case is carried on U cycles with real-time equipment degradation signals. Table VI gives the outsourcing maintenance schemes during the lease period. Based on the optimized service routes and departure time point of each required team, the OEM can arrange the corresponding team to perform O&M services for multilocation lessees. After that, our SPOM

TABLE VI
OUTSOURCING MAINTENANCE SCHEMES OF SEQUENTIAL GLOBAL-LAYER CYCLES

u	$GP_{i,h}$	$z_{im,u}$ $i=1$	$i=2$	$i=3$	$i=4$	R_u	TSC_u
1	{2,3,5,7}{10}{12,13}{15}	1891	1824	2163	2097	[0→2→1→0][0→4→3→0]	60700
2	{4}{8,9,11}{14}{16,18}	2385	2726	2811	2471	[0→1→4→0][0→2→3→0]	73820
3	{1,6}{10,11}{12,13}{17}	2737	4345	4271	2663	[0→4→1→0][0→3→2→0]	73100
4	{2,3,5}{8}{14}{15}	3874	5068	5869	3996	[0→1→4→0][0→2→0][0→3→0]	91000
5	{1,4,6,7}{9}{12,13}{16,17,18}	4893	6014	6090	4747	[0→2→3→0][0→1→0][0→4→0]	90090
6	{2,3,5}{8,10,11}{12,13}{15}	6137	6635	8198	6725	[0→2→4→0][0→1→0][0→3→0]	88830
7	{1,4,6,7}{8,9,10,11}{14}{16,17,18}	7243	8730	8655	7410	[0→3→2→0][0→1→0][0→4→0]	89010
8	{2,3,5}{10}{12,13}{15}	8294	10467	10236	8616	[0→1→4→0][0→3→2→0]	92100
9	{1,4,6,7}{16,18}	9499	---	---	9968	[0→1→4→0]	53900
10	{2,3,5}{15,17}	10378	---	---	10477	[0→1→4→0]	51130

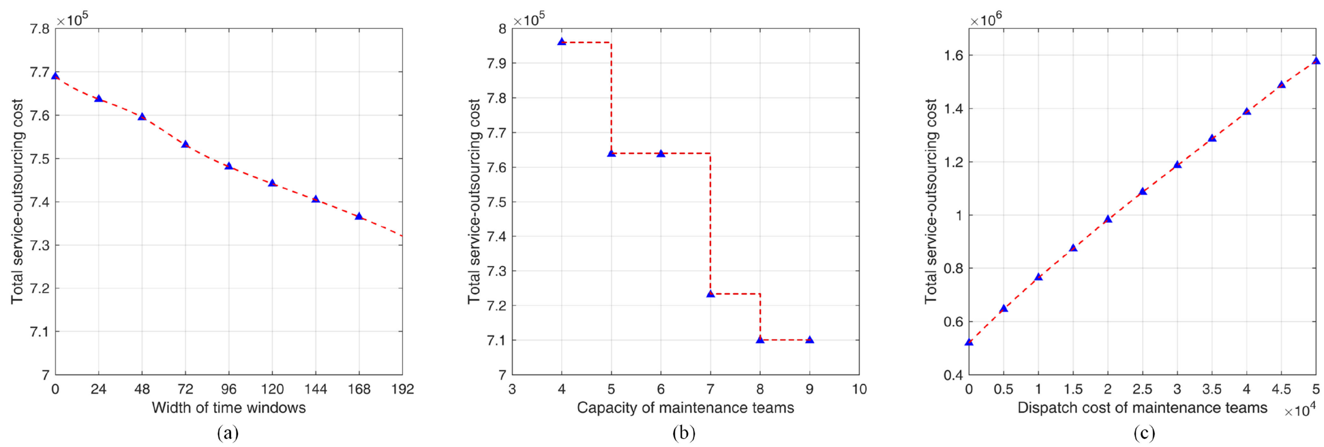


Fig. 6. Impact of routing parameters on total service-outsourcing cost.

framework leverages on the updated maintenance information to provide a long-term O&M management for OEMs.

Besides, to discuss how SPOM effectively adapts various routing parameters to acquire optimal outsourcing maintenance schemes, we further provide the following analysis.

1) *Analyzing the Impact of the Width of Time Windows* w_i: To focus on the impact of various time window sizes, SPOM is applied for different cases where the width of time windows is varied from 24 to 168 (hour), while the other given data remain unchanged. The evolution of total service-outsourcing cost when the width of time windows increases from 24 to 168 is plotted in Fig. 6(a).
2) *Analyzing the Impact of the Capacity of Maintenance Teams* Q_m: Generally, PdM actions of scattered machines should be gathered among several lessees to fully utilize the capacity of each team in a deployment. To highlight the impact of maintenance capacity, we set the width of time windows as 24 h while keeping the other given data the same as previous. The capacity of maintenance teams is set from 4 to 9 (machine/time), and the trend of cost change is shown in Fig. 6(b).
3) *Analyzing the Impact of the Dispatch Cost of Maintenance Teams* c_m: SPOM dynamically determines how aggressive it should group PdM actions to balance out the technician dispatch cost. To reflect this effect, we only change the cost per dispatch from \$5000 to \$50 000, as illustrated in Fig. 6(c). Note that in this study, the width of time windows is set as 24 h, and the maintenance capacity is set as 6 machines/time, while the other given data remain unchanged.

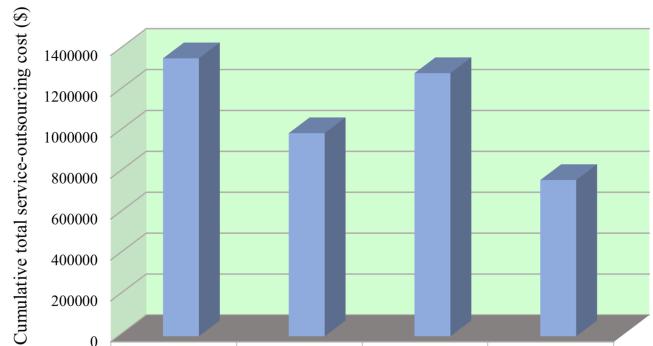
Based on the above analysis of different routing parameters, we can observe some important conclusions as follows: First, the time window with different widths will affect the late penalty cost, which directly reflects the change in the total service-outsourcing cost. If w_i increases gradually, the time constraints of maintenance requirements are loose, and the total cost accelerates to decline. This variation means that the transportation cost becomes increasingly essential as w_i increases, and the optimum service route will tend to the route with minimal transportation distance. Second, we note that when Q_m becomes larger, fewer maintenance teams are required to service global lessees, thus results in the reduction of costs associated with dispatch and transportation. As expected, we observe that SPOM starts improving the choice and the sequence of group PdM actions for maintenance teams as the capacity of teams increases. These improvements significantly indicate that SPOM can utilize the existing maintenance teams more effectively. Third, as a direct consequence, it can be seen that the total service-outsourcing cost shows an increasing pattern. More importantly, we observe that as the dispatch cost c_m increases, SPOM makes more of an effort to limit the number of teams to satisfy maintenance requirements of multi-location lessees. This trend means that the number of maintenance teams becomes increasingly important and dominant as their associated dispatch cost rises.

D. Comparative Study on Various O&M Methods

Finally, to evaluate the effectiveness of the proposed O&M framework, we benchmark the hierarchical SPOM methodology with three conventional policies. We ensure a fair comparison by using the same parameters and basic models for all policies. Moreover, the detailed descriptions of different maintenance policies are represented as follows.

1) *Periodic Reliability-Based Maintenance Policy*: Population-specific reliability characteristics from historical data are used for each machine at the equipment layer. We replace the sensor-driven online hazard rates with the Weibull estimate counterparts to obtain periodic PM plans. These periodic maintenance plans are outputted to local-layer opportunistic maintenance and global-layer routing optimization same as our proposed framework to acquire the service routes.
2) *Local Predictive Group Maintenance (LPGM) Policy*: Pulling PdM intervals based on real-time TTF distributions, we use a simple criterion at the local layer to combine various maintenance operations. Based on the maintenance time window (MTW) arisen by the first PdM opportunity, this criterion groups all PdM actions within the time window as the service requirement [30]. The width of MTW is set to the optimal 350 h.
3) *Fixed Service Routes Maintenance (FSRM) Policy*: Equipment-layer sequential PdM intervals and local-layer group PdM sets are scheduled as in the SPOM methodology. However, the OEM's maintenance teams execute follow a fixed service route at the global layer, which is just arranged at the lease starts and does not optimize the service routes by integrating service time window and multiple geographical locations. Fig. 7 exhibits the cumulative total service- outsourcing cost during the same lease period (448 days) of the above four O&M methods.

Based on the comparative study, the advantages of SPOM can be summarized as follows: Firstly, SPOM methodology decreases the number of PdM actions and unexpected failures since it uses the real-time sensor information to forecast the degradation trend. Thus, the corresponding maintenance actions are conducted before cumulative failure. Second, differ from the simple group criterion of LPGM policy, SPOM methodology accurately identifies which machine is triggering and advances other PdM actions according to the calculation of LPSs. Thus, it can ensure the production balancing and minimize the unnecessary maintenance actions on those scatted systems. Third, SPOM methodology decreases the \$6 350 500 compared with FSRM policy by optimizing the number of the maintenance team,



	PRBM	LPGM	FSRM	SPOM
CTSC	1358707	992784	1286300	763680

Fig. 7. Service-outsourcing cost comparison under different frameworks.

service routes, and arrive time points. By integrating individual equipment degradations, complex system structures, and global network layout, the SPOM methodology helps to effectively maintain leased machines all around the world, resulting in more economy, availability and robustness of multilocation leased systems.

VII. Conclusion

This article develops a SPOM methodology for a multilocation network to dynamically provide outsourcing PdM schemes. In contrast to conventional O&M policies, we comprehensively integrate individual degradations of various equipment, series-parallel structures of leased systems, and geographical layouts of multiple locations in this multilayer methodology. Prognostic Updating and dynamical optimizations helps to achieve quick responses to random requirements from multilocation lessees.

Other than population-specific reliability characteristics from historical data, real-time signals acquired from each leased machine were used to accurately update predictive distributions and sequentially output PdM intervals. By extending traditional opportunistic maintenance policies, PLPO and SLPO policies were then proposed for each multiprocedure leased system to balance production capacity and optimize maintenance decisions. Furthermore, the global-layer NRO policy was proposed by integrating service time windows and multiple geographical locations to optimize the lessor's workforce teams and service start times. The mechanism with real-time prognostic updating and dynamical O&M optimization of this hierarchical SPOM methodology significantly ensures cost reduction, service timeliness, and network robustness.

Future extensions of this article will focus on investigating the impacts of multiple maintenance centrals on extending our global-layer outsourcing maintenance policy for the global OEM. In addition, the obstacle in the industrial application of this multilayer SPOM framework in the actual O&M environment with high risk leased machines, more complex leased systems, various system working conditions and larger scale service network should also be handled.

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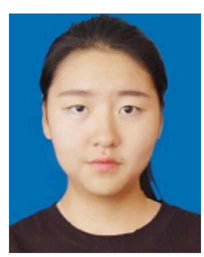

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