Sensor-Driven Condition-Based Generator Maintenance Scheduling Part 1: Maintenance Problem

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Abstract—**Traditionally, generator maintenance scheduling has been implemented using highly conservative maintenance policies based on manufacturing specifications and engineering expertise on the type of generators. However, recent advances in sensor technology, signal processing, and embedded online diagnosis provide more unit-specific information on the degradation characteristics of the generators. In this two-paper study, we propose a new generation maintenance framework that integrates the sensor-driven predictive maintenance technologies with optimal maintenance scheduling models. In Part 1, we propose a new mixed-integer optimization model for generation maintenance scheduling, which effectively incorporate the dynamic information of generators' health and maintenance cost provided by the Bayesian prognostic models. In Part 2, we propose a framework that extends the maintenance model presented herein, and consider the effects of maintenance on network operation by coordinating generator maintenance schedules with the unit commitment and dispatch decisions. We introduce new reformulations and efficient algorithms for solving large-scale instances of the proposed maintenance scheduling model. Extensive computational studies using real-world degradation data demonstrates the effectiveness of the new framework.**

Index Terms—**Condition based maintenance, sensor-driven prognosis, asset reliability and sustainability, generator maintenance scheduling, mixed integer optimization**

I. Introduction

Increasing electricity consumption, aging generators, and the lack of investments on the power system infrastructure impose strict requirements on generator maintenance scheduling. Traditionally, maintenance activities have been scheduled at regular intervals using the engineering expertise, manufacturing specifications, and failure statistics. These programs often recommend frequent unnecessary maintenance routines otherwise they run high risks of unexpected failures. Utility companies strive to find more effective ways to extend the equipment lifetime, to minimize the failure instances, to reduce the frequency of the maintenance interruptions, and to alleviate the negative impacts thereof [1]. Evidently, some major original equipment manufacturers (OEMs) have started engaging utility companies in long-term service agreements where they remotely monitor their assets for potential faults. Typically, sensor data from various generators are transmitted to a centralized hub where conventional classifiers and control limit based techniques are used to trigger alarms. The decisions are typically restricted to imminent repairs with limited advance

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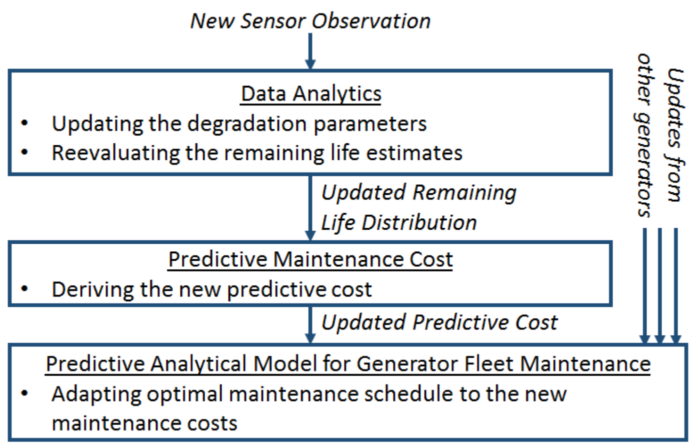

Fig. 1: Set of changes triggered by a new sensor information

warning capability [2], [3]. Considering the time-sensitive nature of the decision making processes, e.g., unexpected shut down of a power plant, any viable maintenance policy must provide ample response time. On this end, predictive analytical approaches can provide significant opportunities. Advances in sensor technology and on-line diagnosis allows commercial systems to detect the tractable degradation signals representative of the level of deterioration in the generator components [4]–[7]. These systems can acquire and process sensor data in real time to provide accurate analysis on the current degradation level (diagnosis), and to estimate the progression of these signals in the future (prognosis). Improved understanding of the degradation processes in the generators can potentially help improve the maintenance objectives.

In this paper, we propose a new framework for generation maintenance scheduling that combines state-of-the-art sensor-data analytics and mixed-integer programming techniques to construct sensor-driven condition-based maintenance scheduling models. Figure 1 presents the structure of the framework, which consists of two modules: the predictive analytics module and the optimal scheduling module. The predictive analytics module employs Bayesian prognostic techniques to dynamically estimate the remaining life distribution (RLD) of generators from sensor data and update the dynamic maintenance cost for each generator. The optimal scheduling module incorporates the sensor analytics results into a mixed-integer programming (MIP) model that coordinates the maintenance and operation decisions in a generation fleet.

The immediate advantages of our approach is threefold. First, we leverage the sensor based information for accurate and real-time prediction of RLD for individual generation assets. Second, using these predictions, we develop optimal fleet-wide condition based maintenance policies. Typically, optimal maintenance time for an individual generator might not be optimal for the generator fleet, hence we need a fleet-wide framework. Third, the integration of the fleet maintenance schedule with the operational problem allows a maintenance schedule that is adaptive to both the real-time sensor information coming from the generation assets, and to the operational considerations such as transmission flow and demand satisfaction.

The contributions of this work can be summarized as follows:

1) We provide a general degradation modeling framework for generators in service. Unlike most approaches in the literature, we present a sensor-driven method that combines the population degradation data with unit specific information to further refine the failure probability and the RLD. Using this estimate, we generate dynamic maintenance cost functions for every generator. This function considers the trade-off between the risks associated with unexpected failures and the cost of preventive maintenances in each generator.
2) We propose two sensor-driven adaptive maintenance scheduling models:
   a) We first consider a fleet maintenance model that provides a generator fleet maintenance schedule subject to limited labor resources and no operational constraints.
   b) In the second approach, we expand the previous model to consider the effects of maintenance on network operation by coordinating generator maintenance schedules with the unit commitment (UC) and dispatch decisions.

   Proposed models differ significantly from the existing models due to two main reasons: i) they incorporate the dynamic sensor information into the optimization model, and ii) they allow the optimization model to determine the number of maintenances to be scheduled within the planning planning horizon.
3) We provide a novel two-stage reformulation for the second maintenance model and an effective solution algorithm to solve large-scale instances. In particular, the proposed maintenance model can be viewed as a MIP with integer recourse variables (the UC decisions). The reformulation relaxes the integer recourse but effectively compensates for the cost difference between the original and the relaxed models so that the exact cost of the maintenance is recovered. This reformulation inspires a two-level algorithm which essentially decomposes the maintenance and operation decisions and iteratively searches for the best maintenance solutions.
4) We construct a platform on which extensive experiments using real-world physical degradation signals are conducted. In particular, the predictive analytics module acquires vibrational signals from rotating bearings in a lab experiment to emulate generation degradation signals. Extensive tests on the IEEE 118-bus system show that the proposed maintenance model significantly outperforms the traditional periodic maintenance and reliability based maintenance models in key metrics such as the number of unexpected failures, the frequency of scheduled maintenances, the effectiveness in the use of equipment life, and operation costs. These metrics coincide with the objectives presented in [1].

Contribution 1, amd 2-a are addressed in this paper, while contributions 2-b, and 3 are discussed in the Part II of this study. Contribution 4 is presented separately for each paper.

The remainder of the paper proceeds as follows. In section II, we present the fundamental works in the generator maintenance scheduling literature, and survey the developments in condition monitoring techniques for generators. In section III, we introduce the sensor-driven approach for estimating the RLD of a generator. In section IV, we then use this estimation to develop the dynamic maintenance cost of a generator, which is communicated to the fleet maintenance models. Section V introduces detailed formulation for the basic adaptive maintenance model. In Section VI, we present the degradation framework used as the basis for the experiments. We first present a method to estimate the population parameters of the degradation signals using real world data. We then present an experimental framework that uses this degradation database to study a number of test cases. We show the effectiveness of our model, and the impact of the maintenance updating frequency on the maintenance performance. In section VII, we conclude this paper with some closing remarks.

II. Literature Review

In the generator maintenance literature, most of the techniques are based on the concept of periodic maintenance. In particular, maintenances for each generator are conducted within allowed maintenance windows, typically in a yearly maintenance schedule [8]. Some approaches consider additional maintenance dependencies between generators, such as priorities, exclusions, and separations between consecutive maintenances [9]. Much work has been focused on operational and market-related challenges such as the interaction between generation companies and independent system operators [9]–[11], the consideration of operational uncertainties in load forecast, price, water inflow levels [12]–[14], and the integration with the transmission maintenance [15]–[17]. Shahidehpour and Marwali provides a coherent review of the problems in generator maintenance in [18], also highlighting the fundamental works contributed by the authors. Recently, [19] integrated the failure distribution of the generators into the maintenance scheduling problem. To do so, the paper used an approximation of a Weibull distribution to represent the failure rate and maintenance dependency. This technique is called the reliability-based maintenance approach since it captures general failure behaviors of the generator type, but does not consider any unit specific information.

This unit specific information from the generators can be captured through the use of integrated sensor-based monitoring systems. Three main monitoring techniques are common in practice: Mechanical, Electrical, and Chemical [4], [20]–[27]. Among these monitoring techniques, mechanical analyses provide the most sophisticated tools available to the operators [4]. Recently, there has been an emphasis on increasing the predictive power of condition monitoring systems in wind turbines by considering seasonal effects [28], [29]. The interest on condition monitoring has not been confined to the academic communities. A number of case studies have been published on the implementation of condition monitoring guided maintenance in medium sized combined-cycle power plants [30], gas turbine engines [31], nuclear power plant components [32], and wind turbines [7], [33], [34]. These single-generator implementations are expected to increase in the future as the studies show that investments on condition monitoring systems are cost effective [5]–[7].

To our best knowledge, there is no comprehensive model that incorporates state-of-the-art sensor analytics techniques into the generation maintenance scheduling problem. The paper sets out to propose such a framework.

III. Predictive Analytics

Generators are equipped with hundreds and sometimes thousands of sensors to monitor their condition and performance. These sensor signals can be transformed into unique measures known as degradation signals. Degradation signals capture the current degradation state of the generator and provide information about how that state is likely to evolve in the future. Degradation signals provide the basis for estimating the remaining lifetime of the asset. Typically, a set of similar generators would exhibit a common functional form for their degradation signals, i.e., degradation signals follow an increasing exponential trend over time. However, the generators experience different degradation rates. Failure time is the time at which the degradation signal crosses a prespecified failure threshold. Our underlying assumption is that the amplitude of the degradation signal is directly correlated with the severity of the degradation process. Although the generators may operate under the same operating conditions, they still experience different degradation rates, and hence different failure times. This variability is due to numerous sources that include homogeneity in manufacturing, materials used, etc.

In what follows, we will characterize the degradation in generators, and use sensor observations to obtain accurate predictions of their RLD.

A. Degradation Modeling and the Bayesian Framework

In this section, we develop a parametric model to characterize generator degradation. Our approach revolves around modeling the degradation signal as continuous-time continuous-state stochastic process. The basis of this approach is the degradation modeling framework proposed by [7, 8, 9] where a parametric stochastic model is used to model degradation signals from a population of generators. The model consists of deterministic and stochastic parameters. Deterministic parameter is used to capture fixed degradation attributes that are constant across the generator population. Stochastic parameter is assumed to follow a known distribution and capture the unit-to-unit variability among the individual generators. Specifically, stochastic parameter is used to capture the variability in the degradation rates. We represent the observed degradation signal from generator i, or its suitable transformation, as follows:

$$D_i(t) = \phi_i(t;\kappa,\theta_i) + \epsilon_i(t;\sigma), \tag{1}$$

where $D_i(t)$ is a continuous-time stochastic process representing the generator degradation measure observed through sensors, $\phi_i(t;\kappa,\theta_i)$ is a general parametric degradation function, whose specific form depends on generators, and $\epsilon_i(t,\sigma)$ is the error term defined through the variance parameter σ. In (1), κ characterizes the deterministic population-specific degradation parameter common to all generators of the same type, and θ_i represents the stochastic degradation characteristics unique to generator i.

We define the *time of failure* τ_i of generator i as the first time that the degradation signal $D_i(t)$ crosses the failure threshold Λ_i, namely:

$$\tau_i = \min\{t \geq 0\,|D_i(t) \geq \Lambda_i\}. \tag{2}$$

Given the degradation model parameters κ, σ and θ_i, the probability that generator i survives until time t can be found as follows:

$$\begin{aligned} P(\tau_i > t|\theta_i) &= P(\sup_{0\leq s\leq t} D_i(s) < \Lambda_i|\theta_i) \\ &= P(\sup_{0\leq s\leq t} \{\phi_i(s;\kappa,\theta_i) + \epsilon_i(s;\sigma)\} < \Lambda_i|\theta_i). \end{aligned}$$

In most cases, the stochastic parameter θ_i may be unknown. We assume that it follows a certain prior distribution $\pi_i(\theta_i)$. This prior distribution reflects the engineering knowledge, manufacturing specifications, and studies on failure statistics. In cases where the degradation data from other generators are available, $\pi_i(\theta_i)$ can also be estimated.

The unconditional probability that generator i survives until time t can then be presented as follows:

$$\begin{aligned} P(\tau_i > t) &= \int P(\sup_{0\leq s\leq t} D_i(s) < \Lambda_i|\theta_i)\pi_i(\theta_i)d\theta_i \\ &= \int P\left(\sup_{0\leq s\leq t} \{\phi_i(s;\kappa,\theta_i) + \epsilon_i\left(s;\sigma\right)\} < \Lambda_i|\theta_i\right)\pi(\theta_i)d\theta_i. \end{aligned}$$

Observed degradation signals allow us to improve our estimation on the parameter θ_i. More specifically, conditioning on the degradation signal observations, we can update the prior parameter distribution $\pi_i(\theta_i)$ to the posterior distribution $\upsilon_i(\theta_i)$ via Bayesian learning.

To accomplish that, for generator i, we observe the degradation signals $\boldsymbol{d}_i^o = (d_i^1,\ldots,d_i^{t_i^o})$ at times (in terms of the generator's age) $\boldsymbol{t}_i = \{t_i^1,\ldots,t_i^o\}$ such that $t_i^1 < t_i^2 < \cdots < t_i^o$. We consider the observations from working generators. The conditional joint density function of $\boldsymbol{d}_i^o = (d_i^1,\ldots,d_i^{t_i^o})$ given the parameters $\boldsymbol{\psi}_i$ can be represented as follows:

$$P(\boldsymbol{d}_i^o|\theta_i) = \prod_j P(D_i(t_j) = d_i^j|\theta_i, A_j),$$

where A_j denotes the condition that $D_i(t_k) = d_i^k$ for all $t_i^k \in \boldsymbol{t}_i^o$ such that $t_i^k < t_i^j$. Given the observations $\boldsymbol{d}_i^o$, the posterior distribution of the parameter set $\boldsymbol{\psi}_i$ is given as follows:

$$\upsilon(\theta_i) = P(\theta_i|\boldsymbol{d}_i^o) = P(\boldsymbol{d}_i^o|\theta_i)\pi_i(\theta_i)/P(\boldsymbol{d}_i^o).$$

The denominator $P(\boldsymbol{d}_i^o)$ does not need to be computed since it is a normalization factor. If an appropriate conjugate pair can be found for the particular parameter distributions, the posterior distribution $\upsilon(\theta_i)$ might have a closed form expression.

B. Estimating the Remaining Life - Prognosis

For a partially degraded generator i, once the distribution of the degradation parameter θ_i is updated, the next challenge is to estimate the distribution of its remaining life $R^i_{t_i^o}$ at observation time t_i^o:

$$P(R^i_{t_i^o} > t) = P(\tau_i > t + t_i^o|\boldsymbol{d}_i^o).$$

In other words, we estimate the distribution of the remaining life $R^i_{t_i^o}$ of generator i at observation time t_i^o, given the posterior distribution $\upsilon(\theta_i)$ as follows:

$$P(R^i_{t_i^o} > t) = \int P\left(\sup_{t_o \le s \le t_o + t} D_i(s) < \Lambda_i|\theta_i\right)\upsilon(\theta_i)d\theta_i. \tag{3}$$

In some cases, a closed form solution can be acquired for this expression, e.g, linear models with normal i.i.d. error, and brownian models with constant drift [35]. For other models, sampling methods may be needed [36].

IV. Dynamic Maintenance Cost

A key aspect of our methodology is linking our predictive model with the optimization framework. This is accomplished by a dynamic maintenance cost function that models the tradeoff between the cost of preventive maintenance (early repair before failure) versus the cost of unexpected failure. In this paper, we use the long-run average maintenance cost per cycle as out dynamic cost function [37]:

$$C^{d,i}_{t_i^o,t} = \frac{c_i^p P(R^i_{t_i^o} > t) + c_i^f P(R^i_{t_i^o} \le t)}{\int_0^t P(R^i_{t_i^o} > z)dz + t_i^o}, \tag{4}$$

which is the cost rate associated with conducting generator maintenance t time periods after the time of observation t_i^o; c_i^p and c_i^f are the costs of planned maintenance and failure replacement, respectively; c_i^f is typically higher than c_i^p, since unexpected failures requires maintenance to be conducted on demand without prior planning. This leads to increased costs in materials and labor. Additionally, any unexpected failure might lead to a series of damages to the generator subcomponents, further increasing the cost of maintenance. The probability $P(R^i_{t_i^o} > t)$ in this function is derived from the RLDs evaluated by expression (3). In essence, the dynamic cost functions are directly related to the RLDs and hence the degradation states of each generator.

Certain generators might be scheduled more than once. Thus it would be beneficial to characterize the associated maintenance cost of a new generator that has just completed its maintenance. For a new generator, the maintenance cost function $C_t^{n,i}$ takes the following form:

$$C_t^{n,i} = \frac{c_i^p P(\tau_i > t) + c_i^f P(\tau_i \le t)}{\int_0^t P(\tau_i > z)dz}. \tag{5}$$

The dynamic cost functions help identify the optimal time to repair a generator based on their most recently updated RLD. Our goal is to optimize these decisions across *all the generators*. In what follows, we discuss two types of optimization models. The first focuses on maintenance optimization for a fleet of generators while the second focuses on an integrated maintenance-operations optimization model.

V. Adaptive Predictive Maintenance Model I

In this section, we present the first adaptive predictive maintenance model (APMI). In this model, the decision maker leverages the condition monitoring information coming from generation assets to decide on both the *time* and the *number* of maintenances to be scheduled within the planning horizon. We assume the operational decisions such as unit commitment and dispatch are not significant, therefore they are ignored in the APMI model. This assumption is applicable to problems where the outage of an individual generator does not necessarily cause significant impact on the system operations. For example, in a fleet maintenance scheduling problem of a wind farm composed of a large number of wind turbines, the outage of one wind turbine has limited impact on the overall wind farm operation.

A. Decision Variables

Before introducing the objective and constraints, we first use a simple example to illustrate the meaning of the decision variables $\boldsymbol{z}$ and $\boldsymbol{\nu}$. To ease exposition, we define $\boldsymbol{\nu}_{:,i,k} = \{\nu_{1,i,k}, \ldots, \nu_{H,i,k}\}$ and $\boldsymbol{z}_{:,i,k} = \{z_{1,i,k}, \ldots, z_{H,i,k}\}$. In this example, there are 14 maintenance epochs, each corresponding to a week. Consider the following schedule:

$$\begin{aligned}
\boldsymbol{\nu}_{:,i,1} &= [0,0,1,0,0,0,0,0,0,0,0,0,0,0] \\
\boldsymbol{\nu}_{:,i,2} &= [0,0,0,0,0,0,0,1,0,0,0,0,0,0] \\
\boldsymbol{\nu}_{:,i,3} &= [0,0,0,0,0,0,0,0,0,0,0,0,0,1] \\
\boldsymbol{z}_{:,i,1} &= [0,0,1,0,0,0,0,0,0,0,0,0,0,0], \; z^o_{i,1} = 0 \\
\boldsymbol{z}_{:,i,2} &= [0,0,0,0,1,0,0,0,0,0,0,0,0,0], \; z^o_{i,2} = 0 \\
\boldsymbol{z}_{:,i,3} &= [0,0,0,0,0,1,0,0,0,0,0,0,0,0], \; z^o_{i,3} = 0.
\end{aligned}$$

In this schedule, the first maintenance of generator i starts at week 3. The following maintenances start at weeks 8 and 14, respectively. $\boldsymbol{\nu}_{:,i,k}$ indicate these starting times. $\boldsymbol{z}_{:,i,1}$ is defined identical to $\boldsymbol{\nu}_{:,i,1}$. The remaining $\boldsymbol{z}_{:,i,k}$'s indicate the time difference between two maintenances. For instance, the time difference between the first and the second maintenance is 5 weeks, and this difference is captured by $\boldsymbol{z}_{:,i,2}$.

Unique to our modeling is the predetermined input M_i defined as the maximum number of maintenances to be scheduled on generator i within the planning horizon H. Given M_i, the model dynamically decides how many maintenances to schedule. For this particular example we allow the model to schedule up to 4 maintenances for generator i. In this example, 3 maintenances are scheduled within the planning horizon of 14 weeks. Therefore, $\boldsymbol{z}_{:,i,4}$ is a zero vector, and the corresponding vector of $\boldsymbol{\nu}_{:,i,4}$ is identical to that of the third maintenance which is the last scheduled maintenance.

$$\boldsymbol{\nu}_{:,i,4} = [0,0,0,0,0,0,0,0,0,0,0,0,0,1]$$
$$\boldsymbol{z}_{:,i,4} = [0,0,0,0,0,0,0,0,0,0,0,0,0,0], z^o_{i,4} = 1.$$

Since the first three maintenances are scheduled for the generator, $z^o_{i,k} = 0, \quad \forall k \in \{1,2,3\}$. The fourth maintenance is not scheduled, therefore, $z^o_{i,4} = 1$.

B. Objective Function

The objective in the APMI model is to minimize the total dynamic maintenance cost of the generator fleet:

$$\sum_{i\in\mathcal{G}} \sum_{t=R_i+1}^{H} z_{t,i,1} \cdot C^{d,i}_{t^o_i, t-R_i} + \sum_{i\in\mathcal{G}} \sum_{t=Y+1}^{H} \sum_{k=2}^{M_i} z_{t,i,k} \cdot C^{n,i}_{t-Y}. \quad (6)$$

Recall that the binary variable $z_{t,i,k} = 1$ if the k-th and the $(k-1)$-th maintenances of generator i are separated by t maintenance epochs. $\mathcal{G}$ denotes the set of generators. The constants H, R_i, M_i, and Y refer to the planning horizon in terms of maintenance epochs, the remaining time required for maintenance of generator i at the start of the planning period, the maximum number of maintenances to be scheduled for generator i within the planning horizon, and the maintenance duration, respectively.

The objective function evaluates the dynamic costs associated with the first and the consecutive maintenances separately. The first maintenance might benefit from sensor information, whereas the consecutive maintenances are conducted based on new generator costs.

For the first maintenance, we consider two cases: 1) If $R_i = 0$, then partially degraded generator i is operational at the time of planning t_p. In these cases, the cost function for the generator i is determined using the sensor updated RLDs. The age of generator i at t_p is t^o_i. For generator i, sensor observations until time t^o_i change the estimate on the degradation parameters $\boldsymbol{\psi}_i$, and therefore the estimate on $P(R^i_{t^o_i} > t)$. Since the dynamic maintenance cost $C^{d,i}_{t^o_i, t-R_i}$ depends on this estimate, the objective function of APMI also adapts to this update. Otherwise, 2) if $R_i > 0$, then generator i has an ongoing maintenance at the time of scheduling and a new generator will be available at time $R_i + 1$. For generator i, we cannot observe any sensor information, therefore, the dynamic cost for these cases will correspond to a time shifted cost function of a new generator, namely, $C^{d,i}_{\cdot, t-R_i} = C^{n,i}_{t-R_i}$.

Certain generators might be scheduled for more than one maintenance. We assume that when a generator is maintained, it starts a new degradation cycle. In other words, the generator becomes as good as new. For these generators, the variable $\boldsymbol{z}$ indicates the time difference between the start of two consecutive maintenances. To find the generator age at the time of maintenance, we simply shift the time in $\boldsymbol{z}$, by the duration of maintenance Y. When estimating the remaining life distribution of these new degradation cycles, we use only the prior estimations since no other information is revealed to the decision maker at the time of planning.

We next introduce the model constraints.

C. Constraints

1) *Maintenance time limits:*

- Constraint (7) ensures that the first maintenance occurs within ζ^d_i maintenance epochs, where ζ^d_i depends on the RLD of unit i. Depending on the application, ζ^d_i can be set to a limiting period, when the updated cumulative failure probability exceeds a specific control threshold. Similarly, constraint (8) limits the duration between the start times of two consecutive maintenances using the threshold ζ^n.

$$\sum_{t=1}^{\zeta^d_i} \nu_{t,i,1} \geq 1, \quad \forall i \in \mathcal{G}. \quad (7)$$

$$\sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k} - \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k-1} \leq \zeta^n, \quad \forall i \in \mathcal{G}, \ k \in \mathcal{K}_i \setminus \{1\}. \quad (8)$$

where $\mathcal{T}$, and $\mathcal{K}_i$ refer to the sets of maintenance epochs within the planning horizon, and possible maintenances for generator i, respectively.

2) *Maintenance coordination:*

- APMI allows a number of maintenances to be scheduled within the planning horizon. Constraint (9) ensures that for every such maintenance, a start time is selected.

$$\sum_{t\in\mathcal{T}} \nu_{t,i,k} = 1, \qquad \forall i \in \mathcal{G}, \ k \in \mathcal{K}_i. \quad (9)$$

- Constraint (10) controls two factors. Firstly, for generator i, it dictates whether the k^{th} maintenance is scheduled within H (namely, $z^o_{i,k} = 0$) or is projected to take place beyond H ($z^o_{i,k} = 1$). Secondly, for any maintenance that is scheduled within H, it ensures that a certain time is selected to register the difference between two consecutive maintenances.

$$z^o_{i,k} + \sum_{t\in\mathcal{T}} z_{t,i,k} = 1, \quad \forall i \in \mathcal{G}, \ k \in \mathcal{K}_i. \quad (10)$$

- Constraint (11) ensures the k-th maintenance is scheduled only if the $(k-1)$-th maintenance is scheduled.

$$z^o_{i,k} \geq z^o_{i,k-1}, \quad \forall i \in \mathcal{G}, \ k \in \mathcal{K}_i \setminus \{1\}. \quad (11)$$

- Constraint (12) ensures the k-th maintenance cannot be scheduled before the $(k-1)$-th maintenance.

$$\sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k} \geq \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k-1}, \quad \forall i \in \mathcal{G}, \ k \in \mathcal{K}_i \setminus \{1\}. \quad (12)$$

- Constraint (13) stipulates that if the $(k-1)$-th maintenance is scheduled within ζ^n periods from the end of the planning horizon, then the k-th maintenance cannot be scheduled after the $(k-1)$-th maintenance. Therefore, constraints (12)-(13) together ensure that if the $(k-1)$-th maintenance is scheduled within ζ^n periods from the end of the planning horizon, then the k-th maintenance is not scheduled.

$$\sum_{t=1}^{H-\zeta^n} H \cdot \nu_{t,i,k-1} + \sum_{t=H-\zeta^n+1}^{H} t \cdot \nu_{t,i,k-1} \geq \sum_{t=1}^{H-\zeta^n} H \cdot \nu_{t,i,k} + \sum_{t=H-\zeta^n+1}^{H} t \cdot \nu_{t,i,k}, \quad \forall i \in \mathcal{G},\ \ k \in \mathcal{K}_i \setminus \{1\}. \tag{13}$$

- Constraints (14) and (15) couple the $\boldsymbol{z}$ and $\boldsymbol{\nu}$ variables. For the first maintenance, $\boldsymbol{z}$ and $\boldsymbol{\nu}$ variables are identical as in constraint (14). For the remaining maintenances, $\boldsymbol{z}$ captures the time difference of two consecutive maintenances as in constraint (15).

$$z_{t,i,1} = \nu_{t,i,1}, \quad \forall t \in \mathcal{T},\ \ i \in \mathcal{G}. \tag{14}$$

$$\sum_{t\in\mathcal{T}} t \cdot\ z_{t,i,k} = \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k} - \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k-1}, \quad \forall i \in \mathcal{G},\ \ k \in \mathcal{K}_i \setminus \{1\}. \tag{15}$$

- The following set of constraints ensure that a unit maintenance cannot be started if there is an ongoing maintenance. Constraints (16) and (17) represent this relationship for the first maintenance and the consecutive maintenances, respectively.

$$\sum_{t=1}^{R_i} \nu_{t,i,1} = 0, \quad \forall i \in \mathcal{G}. \tag{16}$$

$$H \cdot z^o_{i,k} + \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k} - \sum_{t\in\mathcal{T}} t \cdot \nu_{t,i,k-1} \geq Y + 1 \quad \forall i \in \mathcal{G},\ \ k \in \mathcal{K}_i \setminus \{1\}. \tag{17}$$

*3) **Maintenance capacity**:*

- The following constraints (18) ensure that the number of ongoing maintenances at time t does not exceed a limit L, e.g., a limit on the available labor capacity. Such constraints have been proposed in literature for problems considering one maintenance per generator [18]. Since our model allows a flexible number of maintenances, we need to consider three cases separately: 1) if $t \in \{1, \ldots, H-\zeta^n\}$, we need to check for every maintenance k (constraint (18a)); 2) if $t \in \{H-\zeta^n+1, \ldots, H-\zeta^n+Y-1\}$, we check all maintenances scheduled up to time $H-\zeta^n$ and then check only the last maintenance afterwards (constraint (18b)); 3) if $t \in \{H-\zeta^n+Y, \ldots, H\}$, we only check the last maintenance to eliminate double counting (constraint (18c)).

$$\sum_{i\in\mathcal{G}} \sum_{k\in\mathcal{K}_i} \sum_{e=0}^{Y-1} \nu_{t-e,i,k} \leq L \quad \forall t \in \{1, \ldots, H-\zeta^n\} \tag{18a}$$

$$\sum_{i\in\mathcal{G}} \sum_{k\in\mathcal{K}_i} \sum_{e\in\mathcal{J}^1(t)} \nu_{t-e,i,k} + \sum_{i\in\mathcal{G}} \sum_{e\in\mathcal{J}^2(t)} \nu_{t-e,i,M_i} \leq L \quad \forall t \in \{H-\zeta^n+1, \ldots, H-\zeta^n+Y-1\} \tag{18b}$$

$$\sum_{i\in\mathcal{G}} \sum_{e=0}^{Y-1} \nu_{t-e,i,M_i} \leq L \quad \forall t \in \{H-\zeta^n+Y, \ldots, H\} \tag{18c}$$

where the sets $\mathcal{J}^1(t) = \{t-H+\zeta^n, \ldots, Y-1\}$ and $\mathcal{J}^2(t) = \{0, \ldots, t-H+\zeta^n-1\}$.

D. APMI Model

In summary, the APMI model is given as

$$(APMI) \quad \min_{\boldsymbol{\nu},\boldsymbol{z}} \quad (6) \qquad \text{s.t.} \quad (7)-(18) \qquad \{\boldsymbol{z}, \boldsymbol{v}\} \in \mathcal{F}^m.$$

where $\mathcal{F}^m$ is defined as: $\mathcal{F}^m = \{\boldsymbol{z}, \boldsymbol{\nu} |\ z_{t,i,k}, \nu_{t,i,k}, z^o_{i,k} \in \{0,1\} \quad \forall t \in \mathcal{T}, \forall i \in \mathcal{G}, \forall k \in \mathcal{K}_i\}$.

VI. Experiments

In this section we present the design of our experiments and the results for APMI. We first use a special case of the degradation model introduced in Section III to model real world degradation data. We then show how we use this data to conduct our experiment. Finally, we present the experimental results to show the performance of the proposed models.

In this paper, we use vibration data acquired from a rotating machinery application; namely rolling element bearing degradation captured through condition monitoring. Rolling element bearing is chosen for several reasons: i) In condition monitoring of generating units, mechanical methods constitute the most mature branch of technologies used in industry practice [4]. ii) Rolling element bearings are typical examples of components that experience degradation during operation [38].

We use the degradation from bearings as representative of the degradation observed in the generating units. An experimental setup is used to observe the degradation of bearings from brand new state until their failure. Details of this setup can be found in [35].

A. Degradation Modeling

We next present a special case of the degradation framework introduced in Section III to be used for analyzing the condition monitoring data from our rotating machinery application.

We define $D_i(t)$ as the amplitude of the degradation signal of generator $i \in \mathcal{G}$, at time t. The magnitude of $D_i(t)$ is assumed to be correlated with the underlying physical degradation severity in the generator, and will be used to model the generator degradation. For the degradation data we consider, exponential degradation function provides the best fit. We represent this function, $D_i(t)$ as follows:

$$D_i(t) = \phi + \theta_i e^{\beta_i t + \epsilon_i(t) - \frac{\sigma^2 t}{2}} = \phi + \theta_i e^{\beta_i t - \frac{\sigma^2 t}{2}} e^{\epsilon_i(t)}, \tag{19}$$

where ϕ and σ are constant deterministic parameters, θ_i and β_i are random variables, and $\epsilon_i(t)$ is a Brownian motion [35]. We focus on the log exponential degradation function denoted by $L_i(t) := \ln(D_i(t) - \phi)$,

$$L_i(t) = \theta'_i + \beta'_i t + \epsilon_i(t) \tag{20}$$

where $\theta_i' = \ln(\theta_i)$ and $\beta_i' = \beta_i - (\sigma^2/2)$ are assumed to follow prior normal distributions $\pi(\theta_i')$ and $\pi(\beta_i')$, with means μ_0 and μ_1, and variances σ_0^2 and σ_1^2, respectively.

We use a two-stage method to estimate the population prior distributions, $\mu_0, \mu_1, \sigma_0, \sigma_1$. In stage 1, we develop estimates for θ_i', and β_i' for each specimen. The resulting estimates are used in stage 2 to evaluate the prior distributions. We denote the log degradation function amplitude at observation time t_k as $\ell_i(t_k)$, and assume that we monitor $\ell_i(t_k)$ at times $t_1, t_2, ..., h_i$, where $t_1 < t_2 < ... < h_i$. In our experiment, the sensor data is observed with constant intervals.

Stage 1 Estimate. In this stage, we estimate the component specific degradation parameters θ_i, and β_i, based on data acquired from one tested specimen. We require that the error term $\epsilon_i(0) = 0$, thus $L_i(0) = \hat{\theta}_i$. Since the error increments in Brownian motion are i.i.d, we use the incremental values to estimate β_i as follows:

$$\hat{\beta}_i = \frac{1}{h_i} \sum_{k=1}^{h_i} \frac{\ell_i(t_k) - \ell_i(t_{k-1})}{t_k - t_{k-1}}$$

where h_i is the time of last observation before generator i fails. Once $\hat{\beta}_i$ is obtained, we can estimate σ_i^2 as follows:

$$\hat{\sigma}_i^2 = \frac{1}{(h_i - 1)} \times \sum_{k=1}^{h_i} \frac{\left(\ell_i(t_k) - \ell_i(t_{k-1}) - (t_k - t_{k-1})\hat{\beta}_i\right)^2}{(t_k - t_{k-1})}$$

since the term $\left(\ell_i(t_k) - \ell_i(t_k - 1) - (t_k - t_{k-1})\,\hat{\beta}\right)$ is normally distributed with mean 0, and variance $\sigma^2(t_k - t_{k-1})$.

Stage 2 Estimate. In this stage, we use the estimates in Stage 1 from a number of components to obtain the estimates for the population degradation parameters. We use the sample mean of $\hat{\theta}_i$ and $\hat{\beta}_i$ for components $i \in \{1, 2, ..., G\}$, to find the estimates $\hat{\mu}_0$ and $\hat{\mu}_1$. We use the corresponding sample variances to acquire the estimates $\hat{\sigma}_0^2$ and $\hat{\sigma}_1^2$. Lastly, we obtain the estimate $\hat{\sigma}^2$ from $\{\hat{\sigma}_1^2, \hat{\sigma}_2^2, ..., \hat{\sigma}_G^2\}$.

B. Prognosis

Degradation signals are acquired during operation of the generator. Using this data, the degradation parameters can be updated in a Bayesian manner. Given that the observed logged degradation signal $\{\ell_i(t_1), \ldots, \ell_i(t_k)\}$ at times $t_1, \ldots, t_k$ from a particular generator i, the posterior distribution of the degradation parameters (θ_i', β_i') can be estimated as a bivariate normal distribution with means $(\mu_{\theta_i'}, \mu_{\beta_i'})$, variances $(\sigma_{\theta_i'}, \sigma_{\beta_i'})$ and correlation coefficient ρ_i [35]:

$$\mu_{\theta_i'} = \frac{\left(\ell_{i,1}\sigma_0^2 + \mu_0\sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2 t_1 \left(\sigma_1^2 \sum_{e=1}^{k} \ell_{i,e} + \mu_1\sigma^2\right)}{\left(\sigma_0^2 + \sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\mu_{\beta_i'} = \frac{\left(\sigma_1^2 \sum_{e=1}^{k} \ell_{i,e} + \mu_1\sigma^2\right)\left(\sigma_0^2 + \sigma^2 t_1\right) - \sigma_1^2\left(\ell_{i,1}\sigma_0^2 + \mu_0\sigma^2 t_1\right)}{\left(\sigma_0^2 + \sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\sigma_{\theta_i'}^2 = \frac{\sigma^2\sigma_0^2 t_1\left(\sigma_1^2 t_k + \sigma^2\right)}{\left(\sigma_0^2 + \sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\sigma_{\beta_i'}^2 = \frac{\sigma^2\sigma_1^2\left(\sigma_0^2 + \sigma^2 t_1\right)}{\left(\sigma_0^2 + \sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\rho_i = -\frac{\sigma_0\sigma_1\sqrt{t_1}}{\sqrt{\left(\sigma_0^2 + \sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right)}},$$

where $\ell_{i,e} = \ell_i(t_e) - \ell_i(t_{e-1})$.

The failure time τ_i of generator i is defined as the first time that the logged degradation signal $L_i(t)$ crosses failure threshold Λ. More specifically, $\tau_i = \inf\left(t : t > 0, L_i(t) = \Lambda\right)$.

A conservative estimate for the probability of failure can be presented as the boundary crossing probability of the Brownian motion process [39]. In this context, the failure time τ_i follows an Inverse Gaussian distribution with mean parameter $\chi = \frac{\Lambda - \ell_i(t_k)}{\mu_{\beta'}}$ and shape parameter $\gamma = \frac{(\Lambda - \ell_i(t_k))^2}{\sigma^2}$, that is:

$$P\{\tau = t | \ell_1, \ldots, \ell_k\} = f_{t_k}(t) = \sqrt{\frac{\gamma}{2\pi t^3}} \exp\left\{-\frac{\gamma(t-\chi)^2}{2\chi^2 t}\right\}.$$

C. Experimental Implementation

In order to test our model, we design an experimental framework. In this framework i) we first solve the maintenance problem to determine the maintenance schedule, and then ii) we execute the chain of events during a freeze period. Based on what happens during this period, we update the operating environment and resolve the maintenance problem. This procedure exhibits a rolling horizon fashion.

We present the two main modules of the experimental procedure as follows:

1) Optimization module: Given dynamic maintenance costs and remaining maintenance downtimes for each generator, this module solves APMI.
2) Execution module: Given the maintenance plan, this module mimics the system behavior for the duration of the freeze period. More specifically, it uses the degradation database from the rotating machinery application to represent the degradation processes in each generator. For every maintenance epoch during the freeze period, the module checks if any of the generators are experiencing a maintenance downtime, a scheduled preventive maintenance, or an unexpected failure. To detect failure, the module checks if the degradation signal associated with the generator exceeds the failure threshold. This process is repeated for every maintenance epoch within the freeze period. For any failed generator, the module keeps the asset under maintenance for a specified duration. Then, a new degradation signal from the database is chosen to represent the degradation of the new generator after maintenance. Once the execution module reaches to the end of the freeze period, it updates the

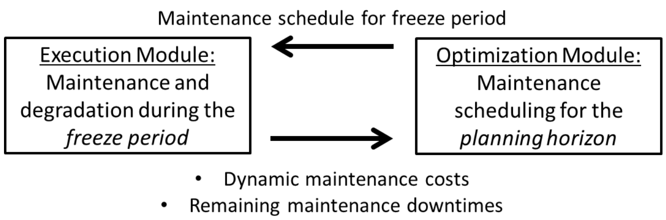

Fig. 2: Experimental Framework

dynamic maintenance costs for each generator based on the most recent sensor observations. More specifically, the execution module utilizes the observations from the degradation signals of the generators, and derives new RLD and dynamic maintenance cost estimates following the procedure in section VI-B. The module also takes account of the generators that have undergoing maintenances.

During the execution module process, the key metrics such as the number of unexpected failures & successful preventive maintenances, and the unused life of every generator that experiences preventive maintenance, is computed to present the effectiveness of the current maintenance policy.

Figure 2 presents this experimental framework.

D. Experimental Results

In this section we present a series of studies to show the performance of APMI. In our analyses, we use a 54 generator system. We obtain the age of generators at the start of the experiments by running the generators for a warming period. In all our studies, we set the preventive maintenance cost $c^p = \$200,000$ and the failure cost $c^f = \$800,000$. In order to ensure a fair comparison, we repeat every scenario ten times with different generator ages, and take the average of these experiments. All the models are solved using Gurobi 5.6.0 [40].

For the purposes of this paper, the generator maintenance decisions are weekly as suggested by [8], and the system level generator maintenance scheduling is updated according to the specified freeze period τ_R. Planning horizon for every optimization model is 110 weeks. Depending on the type of generator and the comprehensiveness of the maintenance study, different periods can be considered for the maintenance decision blocks and the updating frequency.

All experiments involve executing the maintenance framework introduced in the previous subsection. More specifically, to test the performance of a maintenance policy, we first solve the maintenance problem, then run the execution module, which i) mimics the system behavior during the freeze period, and ii) collects the important performance metrics for the analysis. We repeat this process in a rolling horizon fashion.

1) Comparative Study on APMI: In this study, we perform a benchmark test for APMI. To do so, we compare the performance of APMI with two policies: periodic maintenance and reliability based maintenance (RBM). In the periodic maintenance policy, we modify the existing APMI model as follows: i) we let the dynamic maintenance cost be zero, that is $C^{d,i}_{t^o_i,t} = C^{n,i}_t = 0 \quad \forall i \in \mathcal{G}, \forall t \in \mathcal{T}$, and ii) we include an additional constraint to ensure that maintenance is conducted when the generator's age is between 66 and 69 weeks. This period is obtained by using the traditional approach proposed by [41]. The problem solves as a feasibility problem with labor capacity constraints. For the RBM case, we use the exact optimization model of APMI, however the cost function for this scenario is derived using a Weibull distribution. We first derive a Weibull estimate using the failure times from the rotating machinery application $F_W(t)$, and then condition this distribution on the time of survival to estimate the remaining life distribution and the associated maintenance costs. $F_W(t)$ in this model, provides the best available prediction of the remaining life distribution without condition monitoring [35]. We let the freeze period $\tau_R = 8$ weeks, and solve the maintenance problems in a rolling horizon fashion to cover a period of 48 weeks.

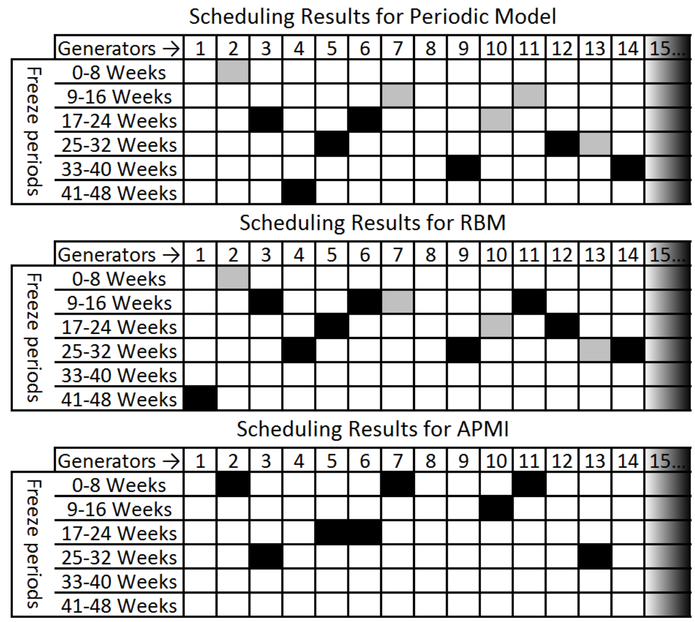

Fig. 3: A Scheduling Plan from Comparative Studies of APMI

In Figure 3, we illustrate different maintenance policies in one of the scheduling scenarios obtained during the comparative studies. Note that the maintenance decisions are weekly. For the sake of illustration, we present the maintenance schedules using time blocks of 8 weeks. We also present the schedule for 14 generators only. A black box indicates a preventive maintenance, and gray box indicates a failure.

We first note that APMI detects when the generator's condition becomes critical, and conducts a preventive maintenance. For instance, APMI schedules a maintenance between week 25 and 32 for generator 13. This maintenance was not conducted by the periodic model or the RBM model. Therefore, both of them incurred an unexpected failure. In some cases, APMI required maintenance to be conducted at earlier time blocks. For instance, APMI conducts maintenance for generator 7 in the first 8 weeks, otherwise the generator would have failed between the weeks 9 and 16. This means that APMI conducts the maintenance of the generator earlier in order to decrease the risks of failure. This leads to the concept of unused life. Unused life is defined as the time difference between the time of maintenance, and the failure time of the generator under no maintenance regime. This metric quantifies how much of the generator's available life is sacrificed by the maintenance policy. Evidently, as this value decreases, the risk of failure increases. If the maintenance scheduler would have infinite labor crew resources and perfect information about the component's failure time, the maintenance would be conducted right before failure. This forms a theoretical bound on the maintenance performance. Since this is not the case in any practical scenario, any additional information helps the policy use more of generators' useful life. For instance, generator 9 was put under schedule by the periodic and the RBM, although it could survive the 48-week period. Sensor information provided this insight for APMI policy, and thus a maintenance was not scheduled.

TABLE I: Benchmark for APMI

APMI with $\tau_R = 8$	**Periodic**	**RBM**	**APMI**
# Preventive	23.5	33.4	26.6
# Failures	13.7	9.6	1.5
# Total Outages	37.2	43.0	28.1
Unused Life (weeks)	908.6	1409.3	309.5
Maintenance Cost	$15.66 M	$ 14.36 M	$ 6.52 M

We next analyze the results of the comparative study as shown in Table I. The comparative study involves running ten instances of the 48-week experimental implementation for each method. In other words, the results in Table I come from 30 experiments, and every presented metric is obtained by taking the average of ten experiments.

The first set of metrics relate to the average number of preventive maintenances, failures and total outages observed during these studies. Unused life refers to the average number of sacrificed weeks among all generators. Given the same information, a scheduling model that increases the number of preventive maintenances is expected to create a more conservative maintenance policy, and therefore incur less number of unexpected failures, and sacrifice more lifetime. In our experiment, RBM policy is more conservative, scheduling more preventive maintenances (33.4 v.s. 23.5) than periodic, and consequently incurring a decreased number of unexpected failures (9.6 v.s. 13.7), and sacrificing more weeks of generator lifetime (1409.3 v.s. 908.6 weeks). In terms of the maintenance cost, however, RBM provides significant benefits.

APMI, on the other hand, utilizes the sensor information to improve upon both of these benchmark policies. APMI conducts slightly more preventive maintenances than the periodic model, while incurring significantly less unexpected failures (1.5 for APMI v.s. 13.7 for Periodic) and saving substantial unused lifetime (34.1% of that of the periodic model).

The maintenance cost presented in table is calculated by multiplying the average number of successful preventive maintenances and unexpected failures by c^p, and c^f respectively, and then by calculating the total cost incurred. The cost of APMI is 41.6% of the cost in the periodic model. Compared to the RBM model, APMI conducts less preventive maintenances and incurs significantly less failures and unused lifetime. This shows that the maintenance schedule of APMI is superior to that of the periodic and RBM models in terms of both reliability and cost.

TABLE II: Impact of the Freeze Time on APMI

	$\tau_R = 8$	$\tau_R = 6$	$\tau_R = 4$	$\tau_R = 2$
# Preventive	26.6	27.2	26.9	26.8
# Failures	1.5	1.1	0.7	0
# Total Outages	28.1	28.3	27.6	26.8
Unused Life (wks)	309.5	306.9	255.2	187.7
Maintenance Cost	$6.52 M	$6.32 M	$5.94 M	$5.36 M

2) Impact of the Freeze Time on Maintenance Schedules: Having a flexible maintenance crew that can adapt to more frequent changes in the maintenance schedule might be a feasible economic option for the fleet maintenance for generators of smaller capacities. Since APMI model mainly considers this type of generator fleets, it might be beneficial to study the effect of the freeze time τ_R on the maintenance performance. In this study we compare the performance of the maintenance models when the freeze period: i) $\tau_R = 8$ weeks, ii) $\tau_R = 6$ weeks, iii) $\tau_R = 4$ weeks, and iv) $\tau_R = 2$ weeks. Table II presents the results.

As the freeze time decreases, in other words, as the updates in the maintenance schedule become more frequent, APMI can learn more about the generator's degradation characteristics before making the final maintenance plan. This corresponds to a better understanding if a maintenance can be postponed (thus getting more out of the available resources), or scheduled to an earlier time (thus decreasing the risks of failure). We note that the average costs of maintenance decreases as the maintenance schedule is updated more frequently. Thus, it would be reasonable to invest up to $\$200,000$ to improve the maintenance crew flexibility to be capable of $\tau_R = 6$ weeks, as opposed to $\tau_R = 8$ weeks. Additional investment of up to $\$380,000$ can be made to further improve the flexibility so that the crew can respond to monthly changes in maintenance. $\tau_R = 2$ follows a similar pattern.

VII. Conclusion

In the Part 1 of this two-part study, we proposed a mathematical framework that incorporates the sensor-driven predictive analytics that estimates the remaining life distribution of generators, into the maintenance scheduling optimization problem. To do so, we proposed an innovative mixed-integer optimization model for the fleet maintenance problem. Experimental results indicate that using our method provides significant advantages in both cost and reliability. More specifically, APMI significantly reduces the number of unexpected failures by $\geq 84.37\%$, the unused life by $\geq 65.93\%$, and the maintenance cost by ≥ 54.59 (See Table I). We also note that APMI favors flexible maintenance workforce. As the maintenance crew's ability to adapt to changes in the maintenance schedule increases, the APMI model allows observation of more sensor information before making decisions, therefore improving the quality of the maintenance schedule (See Table II).

In part II, we expand the model presented herein to consider the effects of maintenance on network operation by coordinating generator maintenance schedules with the unit commitment (UC) and dispatch decisions. We also propose an effective solution algorithm to solve the new model, and conduct computational experiments.

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