Integrated Predictive Analytics & Optimization for Opportunistic Maintenance and Operations in Wind Farms

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***Abstract*—This paper proposes an integrated framework for wind farm maintenance that combines i) predictive analytics methodology that uses real-time sensor data to predict future degradation and remaining lifetime of wind turbines, with ii) a novel optimization model that transforms these predictions into profit-optimal maintenance and operational decisions for wind farms. To date, most applications of predictive analytics focus on single turbine systems. In contrast, this paper provides a seamless integration of the predictive analytics with decision making for a fleet of wind turbines. Operational decisions identify the dispatch profiles. Maintenance decisions consider the tradeoff between sensor-driven optimal maintenance schedule, and the significant cost reductions arising from grouping the wind turbine maintenances together - a concept called opportunistic maintenance. We focus on two types of wind turbines. For the operational wind turbines, we find an optimal fleet-level condition based maintenance (CBM) schedule driven by the sensor data. For the failed wind turbines, we identify the optimal time to conduct corrective maintenance to start producing electricity. The economic and stochastic dependence between operations and maintenance decisions are also considered. Experiments conducted on i) a 100-turbine wind farm case, and ii) a 200-turbine multiple wind farms case demonstrate the advantages of our proposal over traditional policies.**

***Index Terms*—Real-time sensor-driven prognosis, condition-based opportunistic maintenance, wind farm operations, mixed-integer optimization**

I. Introduction

Global investments on both on-shore and off-shore wind assets have been growing steadily in recent years. Maintenance operations, which constitute approximately 20-25% of the total levelized cost per kWh of wind power assets [1], has become a sector on its own right. This growing sector strives to adapt to the maintenance concerns of wind farms that differ significantly from conventional power systems. Firstly, wind turbines are much more prone to failures [2], however their relatively simple mechanical construction makes it easier to monitor their failure processes via integrated sensors [3]. Secondly, due to the large number of wind turbines in a wind farm, wind farm operators are usually more interested in the profitability of the entire wind farms as opposed to the prioritized reliability of individual wind turbines. This is in sheer contrast with conventional power systems that impose redundancies to eliminate the risks of any asset failure. As we will demonstrate in this paper, an integrated maintenance framework that i) effectively harnesses sensor information to predict the remaining lifetime of the turbines, and ii) considers the interdependencies between the maintenance and operations of all the turbines within a wind farm or multiple wind farms, can provide significant benefits in both profitability and reliability of wind farms.

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A successful maintenance policy hinges on the accurate understanding of failure risks. Traditionally, these risks have been estimated based on manufacturing specifications and engineering expertise on the turbine type and make. While recovering many failure patterns that are common to specific turbine populations, these traditional failure characterizations often fall short of explaining properties that are specific to the individual turbines in the field. To circumvent this problem, there has been a recent interest in inferring the actual condition of the wind turbines using integrated sensors. To do so, raw sensor signals such as temperature, vibration, noise, etc., are harnessed in real-time to recover characteristic features and fault-based patterns that capture information about the physical and performance degradation of the wind turbines in the field. In *condition monitoring (CM)*, appropriate transformations of this sensor data, called the *degradation signals*, are used to assess the current state of health of these assets. For example, Figure 1 shows three degradation signals from three rotating machines similar to the wind turbine components. The observed degradation signal is typically correlated with the level of degradation in these machines, and failure occurs when this signal exceeds a standardized failure threshold. As evidenced by the figure, identical machinery still exhibits considerable differences in when they fail, and CM is instrumental in capturing this variation. CM for wind turbines has been studied extensively in the last decade [3], [4], since i) it can be used to provide accurate predictions on the remaining life of the turbines, which, in return, ii) can support the condition-based maintenance (CBM) planning in wind farms.

Due to the highly interconnected nature of the maintenance and operations activities in wind farms, many conventional methods of CBM that focus on single turbine systems do not scale well in practical applications. A successful CBM policy for wind farms should consider operational interactions within the farm, as well as the significant cost reductions resulting from grouping the wind turbine maintenances — a concept called *opportunistic maintenance* [6]. This last point refers to the common practice of reducing the number of maintenance crew visits to wind farms by scheduling the maintenance of wind turbines together. Such a practice may reduce the cost

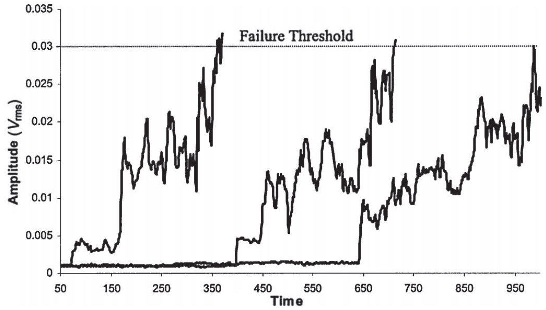

Fig. 1. Vibration Based Degradation Signals [5].

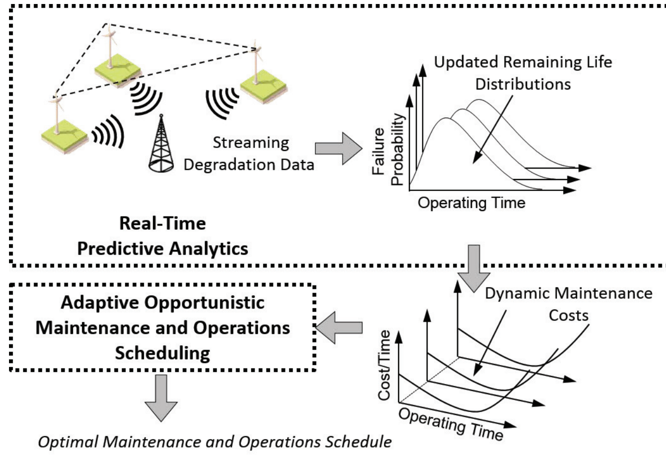

Fig. 2. Proposed Framework for Adaptive Opportunistic Maintenance.

of wind farm maintenance, since the maintenance crew visits incur significant deployment costs, especially for off-shore wind farms.

Current approaches to wind farm maintenance scheduling can be categorized under two main lines of research: i) opportunistic maintenance methods that do not use sensor information, and ii) sensor-driven methods that focus on single turbine systems. On the first line of research, maintenance and operational models for wind farms rely on a combination of i) reactive policies (*repair it after it fails*), and ii) fixed time-based periodic schedules without using the sensor information. Some of these models attempt to capture the interdependencies between different wind turbines. There is a rich literature on time-based opportunistic maintenance scheduling of wind farms [6]–[8]. These time-based schedules, however, do not account for the actual condition of the wind turbines when planning maintenance activities, and therefore cannot be used to anticipate failures. If implemented in a conservative fashion, these policies may drive up the cost of maintenance and decrease operational revenues due to frequent unnecessary maintenances and downtime. On the second line of research, wind turbine maintenance scheduling literature uses CM information but focuses primarily on single turbine systems [9]–[11]. Evidently, these models do not capture interdependencies between different wind turbines, and often perform poorly in a wind farm setting. In our experiments, we showcase how these methods perform under different cost structures.

Very few papers have used the sensor information while also capturing the turbine interdependencies. Recently, [12] has proposed a maintenance scheduling policy that considers opportunistic maintenance for wind turbines subject to condition monitoring. In this work, the authors suggest a two-threshold policy, whereby a strict failure threshold applies to the first wind turbine to be maintained, and a more conservative failure threshold is imposed on the remaining wind turbines in an effort to group them with the first wind turbine. Although this work proposes an opportunistic policy, it does not necessarily consider the complex economic and maintenance interdependencies between the wind turbines.

In this paper, we propose a unified framework that integrates i) a stochastic degradation methodology driven by the sensor information, with ii) a novel optimization of operations and maintenance (O&M) scheduling for an entire wind farm or several wind farms. Our methodology is composed of two key parts, the predictive analytics and the opportunistic O&M planning, which are shown in Figure 2 and outlined below.

In the predictive analytics part, we leverage the real-time degradation data to predict the remaining life distribution of wind turbines. In contrast to the diagnostic systems that estimate the current state of wind turbine health, our approach uses data-driven stochastic models to predict the future trajectory of health, thus providing ample response time and visibility for failure related risks. We incorporate real-time signals from each wind turbine in order to provide accurate predictions on the remaining life distributions (RLDs) that are updated based on the most recent degradation state of that wind turbine. The dynamically evolving RLDs are transformed into *dynamic cost functions* that balance the expected cost of maintenance against the cost of unexpected failure. The cost functions act as a key link between the predictive analytics and the optimization model.

In the opportunistic O&M scheduling part, the dynamic cost functions are incorporated into a mixed integer optimization model. The goal in this stage is to optimize the schedule across the entire wind farm (or multiple wind farms), based on the degradation states and predicted RLDs of each wind turbine in the field. To do so, we develop a novel integrated maintenance optimization model that provides a maintenance schedule for a fleet of wind turbines based on their individual degradation states and subject to limited labor resources and weather conditions. We also consider the effects of maintenance on electricity production by coordinating wind turbine maintenance schedules with the turbine dispatch.

The contributions of this work can be summarized as follows:

- We provide a unified framework for maintenance and operations of wind farms, which offers a paradigm shift from the two prominent approaches in literature: i) periodic and reactive approaches for wind farms that do not consider the real-time sensor information from in-situ wind turbines, and ii) sensor-driven approaches for maintenance scheduling of single turbine systems that do not necessarily consider the complex operational and maintenance interdependencies across wind turbines.
- We develop an adaptive maintenance and scheduling op-

timization model specifically for wind farms. We address a number of unique challenges in scheduling of wind farms, such as i) opportunistic maintenance, ii) optimal corrective maintenance planning based on the wind power and electricity price, and iii) optimal schedules across multiple wind farm locations. Through our adaptive optimization model, we tightly couple the maintenance and operations optimization in wind farms with the sensor-driven dynamics.

- We construct an experimental framework to evaluate the performance of the maintenance models. This framework incorporates real-life vibration based degradation data from a rotating machinery to emulate wind turbine degradation, and uses wind data to mimic the operations of the wind turbines in different wind farms.

We present the performance of our approach through an extensive set of experiments on 100 and 200-turbine systems. We set the benchmarks based on the prominent approaches in literature. Extensive studies suggest that our framework significantly lowers the risks of wind turbine failure, extends equipment lifetime, decreases the cost of maintenance, and increases the profitability of operations. These metrics are suggested by the IEEE task force on maintenance [13].

The remainder of the paper proceeds as follows. Section II introduces our proposed framework and methodology. Section III provides the integrated maintenance-operations model. Section IV presents the experimental framework and experimental results. The conclusions are provided in Section V.

II. Methodology

In this section we introduce our integrated framework for predictive analytics and optimization. We first present the sensor-driven predictive methodology and use the resulting statistical distributions of remaining lifetime to derive dynamic maintenance cost functions. In other words, we illustrate that as new sensor data is used to update the remaining life predictions, the cost functions are updated dynamically as well. We then introduce a scheduling optimization model that fully adapts to these dynamic cost functions.

A. Predictive Analytics

We first present how the degradation signal observations can be used to produce accurate predictions on the remaining life distributions of wind turbines.

We represent degradation in wind turbines as a continuous-time continuous-state parametric stochastic model. Our degradation modeling framework is based on [14]–[17]. We define two types of degradation parameters: deterministic and stochastic parameters. The deterministic parameters represent population-specific degradation characteristics that are common across all the wind turbines. The stochastic parameters, on the other hand, capture unit-to-unit variability. We define the amplitude of the degradation signal in a wind turbine as follows:

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

where $D_i(t)$ is a continuous-time stochastic process representing the amplitude of the wind turbine's degradation signal, $\phi_i(t;\boldsymbol{\kappa},\boldsymbol{\theta}_i)$ is a general functional form for the degradation signal, i.e. every unit in the population is assumed to follow this functional form. $\boldsymbol{\kappa}$ are deterministic parameters and $\boldsymbol{\theta}_i$ are stochastic parameters assumed to follow a distribution across the entire population with that of wind turbine i representing a random draw from that distribution. Finally, $\epsilon_i(t,\sigma)$ is a Brownian error term that captures signal noise.

We assume that the degradation signal is acquired during operation of the wind turbine, and the k^{th} observation is made at time t_i^o. We use the observations to update the degradation parameters within a Bayesian framework. More specifically, we condition on the observed degradation signals $\boldsymbol{d}_i^k = \{D_i(t_1),\ldots,D_i(t_k)\}$ at times $t_1,\ldots,t_k$ from wind turbine i, and obtain the posterior distribution of the parameters, $u(\boldsymbol{\theta}_i)$, as follows:

$$u(\boldsymbol{\theta}_i) = P(\boldsymbol{d}_i^k|\boldsymbol{\theta}_i)\pi(\boldsymbol{\theta}_i)/P(\boldsymbol{d}_i^k), \tag{2}$$

where $\pi(\boldsymbol{\theta}_i)$ is the prior distribution of $\boldsymbol{\theta}_i$. We note that in the general case one must resort to sampling methods to estimate this probability [18].

We define the time of failure as the first time that the degradation signal reaches the failure theshold Λ_i. Given that we have observed a sequence of degradation signals, and computed the posterior estimates of the degradation parameters, distribution of the i^{th} wind turbine's remaining lifetime at observation time t_i^o, namely $R^i_{t_i^o}$, can be estimated using the procedure outlined in Appendix A.

Next we will focus on transforming these RLDs to dynamic maintenance cost functions that are used by our optimization model.

B. Dynamic Maintenance Cost

The predictive framework introduced in the previous section is tightly integrated into our optimization model. This is achieved through a dynamic cost function that translates the RLD of wind turbines into a degradation-based function of cost over time. More specifically, the dynamic maintenance cost function quantifies the tradeoff between the cost of preventive action and the risk of unexpected failures by defining their corresponding probabilities through the sensor-updated remaining life estimates. The dynamic maintenance cost is represented as follows [15]:

$$C^i_{t_i^o,t} = \frac{c_i^p P(R^i_{t_i^o} > t) + c_i^f P(R^i_{t_i^o} \le t)}{\int_0^t P(R^i_{t_i^o} > z)dz + t_i^o}, \tag{3}$$

where $C^i_{t_i^o,t}$ represents the cost rate associated with conducting wind turbine 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.

The dynamic maintenance cost (3) uses renewal reward [19], [20] to characterize the long-run expected maintenance cost. The numerator evaluates the expected cost of maintenance, where the terms $c_i^p P(R^i_{t_i^o} > t)$ and $c_i^f P(R^i_{t_i^o} \le t)$ represent the expected cost of preventive and corrective actions, respectively. The denominator, on the other hand, represents the expected length of the cycle. The first term, $\int_0^t P(R^i_{t_i^o} > z)dz$, finds the expected remaining lifetime of the component given that the preventive maintenance is planned at time t, and t_i^o is the deterministic time of observation that is already a part of the current cycle.

We note that this function adapts to sensor observations, since the probability $P(R^i_{t_i^o} > t)$ is derived using the procedure outlined in Section II-A. This function uses the sensor information to identify the optimal maintenance time for each wind turbine. Our objective, however, is to capture the complex interdependencies for a fleet of wind turbines, and optimize maintenance for the entire wind farm. In what follows, we will integrate these cost functions from each wind turbine into a novel optimization model to accomplish this goal.

C. Optimization Model

In this section, we propose a novel mixed-integer optimization model for the sensor-driven adaptive opportunistic maintenance and operations scheduling (AOMO) of wind farms. In contrast to [16], [17], our scheduling model considers opportunistic maintenance and captures many unique considerations in wind farm maintenance, e.g., allowing a failed wind turbine to stay idle until the optimal time for its corrective maintenance.

A key aspect of our framework is the link between predictive analytics and the wind farm maintenance and operations scheduling. To connect them, a discretized form of the sensor updated dynamic maintenance cost from every wind turbine in field is incorporated into the objective function. In order to ensure the optimal scheduling of maintenance and operations for the entire farm, we consider various constraints and interdependencies, such as i) the limits on the maintenance crew capacity, ii) the operational factors dependent on electricity price and forecasted wind speed, and iii) the significant cost reductions resulting from grouping the wind turbine maintenances together. This is accomplished by coupling the operations and maintenance in two different scenarios. Firstly, a wind turbine under maintenance does not produce power. Secondly, any wind turbine that fails unexpectedly can stay in a failed state until a corrective maintenance is scheduled. Thus a tradeoff occurs in terms of when to schedule the corrective maintenance. The optimization model determines whether it is more profitable to conduct maintenance right away so that the wind turbine can start generating electricity, or if it would make more sense to delay maintenance so that the maintenance can be grouped with other wind turbines as well. Depending on the electricity price, forecasted wind speed, and the sensor-updated failure risks, our model automatically determines how aggressive it should group the maintenances of wind turbines; thus providing an optimal maintenance policy that can adapt to the operator requirements.

We also extend our model for cases where a single maintenance crew can handle a number of different locations. For these cases, we consider the factors such as travel time, and differing costs of site visits. Difference in the site visit costs are associated with the remoteness of the location and the distance to the shore for on-shore and off-shore farms, respectively.

In Section III, we formally present the development of the optimization model outlined in this section.

III. Sensor-Driven Adaptive Scheduling of Maintenance and Operations

We denote the set of maintenance epochs by $\mathcal{T}$ and the set of wind turbines by $\mathcal{G}$. The set $\mathcal{G}$ can be further partitioned into two subsets of wind turbines at the time of planning t_p. The first subset, denoted by $\mathcal{G}_o$, includes the wind turbines that are either operational or under maintenance at t_p. The second subset of $\mathcal{G}$, denoted as $\mathcal{G}_f$, includes those wind turbines that are in failed state at t_p. An operational turbine can undergo preventive maintenance. For this, we let the binary variable $\boldsymbol{z}$ determine the start time of *preventive* maintenance, thus $z_t^i = 1$ if the maintenance of an operational turbine i starts at period t. There is a dynamic maintenance cost associated with these decisions as discussed in Section II-B.

A failed turbine can only experience corrective maintenance. We use binary variables $\boldsymbol{v}$ to determine the start time of *corrective* maintenance, thus $v_t^i = 1$ if turbine i experiences a corrective maintenance at period t. There is no time-dependent maintenance cost associated with $\boldsymbol{v}$.

Moreover, $\boldsymbol{x}$ is a binary decision variable, whereby $x_t^\ell = 1$ means that the maintenance crew visits wind farm location ℓ at period t. There is a significant crew deployment cost $C_t^{v,\ell}$ associated with this variable. Each period t in $\mathcal{T}$ is divided to constituent subperiods $\mathcal{S}$ in order to model wind farm operations in more detail. More specifically, $y_{s,t}^i \in \mathbb{R}_+^n$ denotes the generation level from wind turbine i during period $t \in \mathcal{T}$ and subperiod $s \in \mathcal{S}$.

A. Objective function

The objective in the AOMO model is to maximize the net profit of maintaining and operating a wind farm:

$$\max_{\boldsymbol{z},\boldsymbol{v},\boldsymbol{x},\boldsymbol{y}} \quad \underbrace{\sum_{i\in\mathcal{G}}\sum_{t\in\mathcal{T}}\sum_{s\in\mathcal{S}} y_{s,t}^i \cdot \pi_{s,t}}_{\text{operational revenue}} - \underbrace{\sum_{\ell\in\mathcal{L}}\sum_{t\in\mathcal{T}} x_t^\ell \cdot C_t^{v,\ell}}_{\text{crew deployment cost}} \underbrace{-\xi_m \sum_{i\in\mathcal{G}_o}\sum_{t\in\mathcal{T}} z_t^i \cdot C^i_{t_i^o,t}}_{\text{expected turbine maintenance cost}}, \tag{4}$$

where $\pi_{s,t}$ is the electricity price at period t, subperiod s, and ξ_m is the maintenance criticality coefficient.

The objective function (4) evaluates the operational revenue as well as two sources of expenditures: crew deployment cost and turbine maintenance cost. Evaluation of the first two terms is trivial. The last term, the turbine preventive maintenance cost, corresponds to the dynamic maintenance cost associated with a turbine maintenance. Notice that the dynamic maintenance costs $C^i_{t_i^o,t}$'s are computed from the RLDs of operating wind turbines, which are updated based on sensor observations. In this way, the objective function (4) adapts to these dynamic sensor updates over time.

B. Constraints

1) Wind turbine maintenance coordination: Constraint (5) ensures that a wind turbine's preventive maintenance is scheduled within the time limit ζ_i, which is defined as the first time that its sensor-updated reliability falls below a control threshold η. More specifically, $\zeta_i := \min\{t \in \mathcal{T} : P(R^i_{t^o_i} > t) < \eta\}$. Constraint (6) limits the number of corrective maintenances within the planning horizon to at most one per wind turbine.

$$\sum_{t=1}^{\zeta_i} z^i_t = 1, \quad \forall i \in \mathcal{G}_o. \tag{5}$$

$$\sum_{t \in \mathcal{T}} \upsilon^i_t \leq 1, \quad \forall i \in \mathcal{G}_f. \tag{6}$$

The following constraints ensure that maintenance crew visits the wind farm ℓ if any of the wind turbines within that wind farm is scheduled for preventive (7) or corrective maintenance (8).

$$z^i_t \leq x^\ell_t, \quad \forall \ell \in \mathcal{L},\ i \in \mathcal{G}^\ell_o,\ t \in \mathcal{T}, \tag{7}$$

$$\upsilon^i_t \leq x^\ell_t, \quad \forall \ell \in \mathcal{L},\ i \in \mathcal{G}^\ell_f,\ t \in \mathcal{T}, \tag{8}$$

where $\mathcal{G}^\ell_o$ and $\mathcal{G}^\ell_f$ are the sets of operational, and failed wind turbines at location ℓ, respectively.

2) Maintenance crew coordination: Constraint (9) limits the maintenance crew visits to only one of the wind farm locations during a single maintenance epoch. Constraint (10) ensures that if the weather conditions are harsh at wind farm location ℓ, then the maintenance crew cannot conduct maintenance at that location.

$$\sum_{\ell \in \mathcal{L}} x^\ell_t \leq 1, \quad \forall t \in \mathcal{T}, \tag{9}$$

$$x^\ell_t = 0, \quad \forall \ell \in \mathcal{L}, t \in \mathcal{T}^\ell_w, \tag{10}$$

where $\mathcal{T}^\ell_w$ is the set of times when a crew cannot visit the wind farm ℓ due to extreme weather conditions.

The following constraint considers the distance between wind farm locations ℓ and ℓ', and ensures that a maintenance cannot be initiated before the required travel time $\theta_{\ell,\ell'}$ passes. For every pair of locations $\{\ell, \ell'\}$, we enforce (11).

$$x^{\ell'}_t + x^\ell_\tau \leq 1,\ \forall t \in \{\theta_{\ell,\ell'} + 1, \ldots, \mathcal{T}\}, \tau \in \{t - \theta_{\ell,\ell'}, \ldots, t\}. \tag{11}$$

3) Maintenance capacity: The following constraint (12) ensures that the number of ongoing maintenances at time t does not exceed a limit on maintenance labor capacity per period at location ℓ, namely M^ℓ_t. For onshore and offshore wind farms, this limitation may depend on the labor capacity, or the number of available workboats and helicopters, respectively.

$$\sum_{i \in \mathcal{G}^\ell_o} z^i_t + \sum_{i \in \mathcal{G}^\ell_f} \upsilon^i_t \leq M^\ell_t, \quad \forall \ell \in \mathcal{L}, t \in \mathcal{T}. \tag{12}$$

4) Operational considerations: The maintenance decision variables $\boldsymbol{z}, \boldsymbol{\upsilon}$ are coupled with the operational decisions $\boldsymbol{y}$.

Constraint (13) ensures that i) an operational turbine i produces electricity within its available capacity at epoch t, namely $p^t_{s,i}$, which depends on the forecasted wind power at period t, subperiod s; and ii) a wind turbine under maintenance can not produce electricity.

$$y^t_{s,i} \leq p^t_{s,i} \cdot (1 - z^i_t), \quad \forall i \in \mathcal{G}_o,\ t \in \mathcal{T},\ s \in \mathcal{S}. \tag{13}$$

Constraint (14) stipulates that a failed wind turbine should be scheduled for corrective maintenance before it can start producing electricity. This constraint, along with (6), allows the model to dynamically determine whether or not to schedule a failed wind turbine for corrective maintenance within the planning horizon. When scheduled, it also determines the time of corrective maintenance. Both of these decisions are driven by the potential loss in production revenue.

$$y^t_{s,i} \leq p^t_{s,i} \cdot \sum_{j=1}^{t-1} \upsilon^i_j, \quad \forall i \in \mathcal{G}_f,\ t \in \mathcal{T},\ s \in \mathcal{S}. \tag{14}$$

In summary, the AOMO model is given as

$$\begin{aligned} (AOMO) \quad & \min_{\boldsymbol{z},\boldsymbol{\upsilon},\boldsymbol{x},\boldsymbol{y}} && (4) \\ & \text{s.t.} && (5) - (14) \\ & && \boldsymbol{z}, \boldsymbol{\upsilon}, \boldsymbol{x} \text{ binary}, \boldsymbol{y} \geq \boldsymbol{0}. \end{aligned}$$

IV. Experimental Results

In this section we present three studies to highlight the performance of AOMO. In the first study, we perform a benchmark analysis. We also present the impact of different crew deployment costs on the maintenance schedule. In the second study, we analyze how different electricity prices affect the resulting maintenance schedule of AOMO. In the third study, we consider a scenario with multiple wind farm locations. The first two studies schedule the maintenance of a single wind farm with 100 wind turbines, whereas the last study considers wind farms in three different locations with 100 wind turbines in the first location, and 50 wind turbines in each of the second and third locations.

To emulate degradation in wind turbine systems, we utilize a database of vibration signals from a rotating machinery; where rolling element bearings are run from brand new state to failure, and their raw vibration spectra are acquired continuously. The raw signals are then transformed into degradation signals by using the knowledge on their physics-of-failure. The details of this transformation can be found in [21], [22]. To analyze the degradation in this setup, we use exponential base case model, where the evolution of the degradation signals are characterized by exponential stochastic trends. The predictive analytics used for this data is presented in Appendix B. The exponential base case is typically used to model degradation in machines where preliminary degradation accelerates the progression of subsequent degradation. This is typical of applications such as wind turbines, where mechanical wear, crack propagation, and fatigue leads to equipment failure.

Examples of similar degradation are omnipresent in spalling of the main bearings, teeth wear and breakage of gears in the gearbox attached to the turbine generator, among others.

To test the performance of a maintenance policy, we designed an experimental framework. Our experimental framework involves two modules: planning module, and an execution module. In the *planning module*, we solve an optimization model to schedule the maintenance and operations of the wind turbines for a 200 day planning horizon, given the dynamic maintenance costs of the operational wind turbines. We use Gurobi 5.6.0 [23]. In the *execution module*, we fix the maintenance schedule for the first 16 days (freeze period). We then model the chain of events during this period. We use the degradation data from a real-world rotating machinery application as representative of the degradation observed in the wind turbines. We ensure that the expected lifetime corresponds to wind turbine statistics provided by [24]. For each day within the freeze period, we determine which wind turbines experience an ongoing maintenance (preventive or corrective maintenance as dictated by the fixed schedule of the optimization model), an unexpected failure or an idle period. For every wind turbine $i \in \mathcal{G}_o$, an unexpected failure occurs when the degradation function of the wind turbine reaches failure threshold before the time of its scheduled preventive maintenance. The remaining wind turbines $i \in \mathcal{G}_f$ stay idle until a reactive maintenance occurs. Once the execution module reaches to the end of the freeze period, we update the dynamic maintenance costs for each operational wind turbine based on the most recent sensor observations (as in Section II-B). We also update the list $\mathcal{G}_o$ and $\mathcal{G}_f$. During this execution module, for each subperiod, we keep track of the following metrics:

- *Revenues:* Based on the availability of each wind turbine, wind profile and electricity price, we calculate the resulting operational revenue.
- *Expenditures:* We obtain the wind turbine maintenance cost by the sum of the number of preventive actions and the unexpected failures multiplied by c^p and c^f, respectively. We obtain the crew deployment cost by multiplying the crew visit instances by their associated deployment costs.
- *Maintenance Metrics:* We record the number of crew visits, unexpected failures, and preventive and reactive maintenances. We also register the total idle time of wind turbines.

We execute the experimental process 20 times in a rolling horizon fashion to cover a period of 320 days. To have a fair comparison, we repeat this experimental procedure 10 times with different initial wind turbine ages, and calculate the metrics by taking the average of the corresponding metrics from these experiments. The age of the wind turbines at the start of experiments is obtained by running them for a warm-up period. We next present the results of our experiments.

A. Comparative Study on AOMO, and the Impact of Crew Deployment Cost

In this study, we first perform a comparative study for AOMO. To do so, we compare the cost and maintenance metrics of AOMO, with three benchmark models:

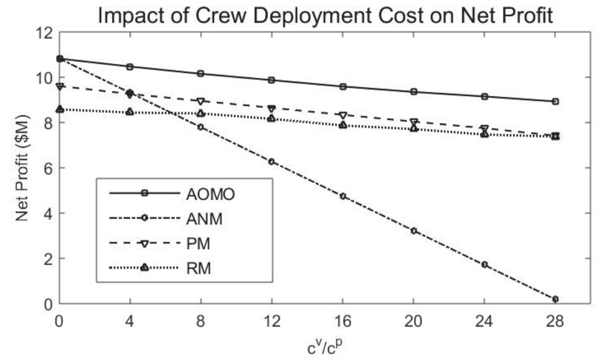

Fig. 3. Comparative Study on Net Profit of Maintenance Policies subjected to Different Crew Deployment Costs.

- *Adaptive Non-opportunistic Model (ANM):* The ANM model is identical to our proposed model AOMO, except that in ANM the crew visits do not have an associated cost, namely $C_t^{v,\ell} = 0 \quad \forall \ell \in \mathcal{L}, t \in \mathcal{T}$ in (4). ANM generalizes single turbine maintenance policies in the literature [9]–[11] to cases with multiple wind turbines.
- *Periodic Model (PM):* The PM model differs from AOMO in two aspects: i) it does not benefit from the sensor-driven dynamic maintenance costs, thus we set $C_{t_i^o,t}^{d,i} = 0 \quad \forall i \in \mathcal{G}_o, t \in \mathcal{T}$, and ii) it includes a set of constraints to ensure that the wind turbine's preventive maintenance occurs when the wind turbine's age is between 130 and 142 days. Depending on the age and type of the wind turbine, periodic maintenance frequencies of wind turbines differ between 3 months to a year [25]. The period presented herein is obtained using the degradation database and the traditional approach presented in [26].
- *Reactive Model (RM):* The RM model does not schedule any preventive actions, however it is identical to AOMO in terms of how it schedules the corrective maintenances. To do so, we replace constraint (5) with $z_t^i = 0 \quad \forall t \in \mathcal{T}, \ell \in \mathcal{L}, i \in \mathcal{G}^\ell$.

Figure 3 provides the net profits of the four policies under different crew deployment cost profiles. Net profit is defined by the difference between the operational revenue and expenditures (crew deployment and turbine maintenance). We let the price of electricity be \$25/MWh as in [27], and use the yearly wind data from [28]. We let $c^f = 4 \times c^p = \$16K$, and fix the deployment cost to a constant value, i.e. $c^v = C_t^{v,\ell} \; \forall \ell \in \mathcal{L}, t \in \mathcal{T}$, following the yearly maintenance costs provided by [29], [30]. We note that AOMO always provides a better net profit than the benchmark models, since:

- *AOMO adapts to the crew deployment costs:* When the cost $c^v = 0$, AOMO becomes identical to ANM. However, as c^v increases, AOMO significantly outperforms ANM, as cost incentives in AOMO dynamically integrate the benefits of the opportunistic maintenance. In fact, for higher values of c^v, ANM provides a worse performance compared to the more basic models like PM and RM. This clearly demonstrates that ad-hoc maintenance policies driven by single wind turbine analysis, even if they use sophisticated sensor-driven predictive models, can perform poorly as the crew deployment cost increases. To obtain the full benefit of sensor-driven maintenance, a policy should integrate the dynamics within the maintenance and operations of the wind farm as a whole.

- *AOMO is driven by sensor information:* In contrast to PM and RM, AOMO detects the condition of the wind turbines using sensor observations, and adapts the schedule accordingly. The differences in revenue represents the economic value of this sensor information.

We next analyze the value of sensor information in detail by considering the effect of crew deployment cost on different maintenance policies. Tables I, II, and III compare the cost and maintenance metrics associated with AOMO, PM and RM, respectively. All the maintenance metrics presented in the tables refer to the entire farm. For instance, "# preventive actions" is a measure of the total number of preventive actions experienced by all the wind turbines in the wind farm. Recall that some wind turbines that experience an unexpected failure would stay in a failed state until their corrective maintenance is scheduled. The total duration of time spent in this failed state is denoted as idle days. We note that, *regardless* of the crew deployment cost c^v, AOMO provides the following advantages:

- *Improve reliability while decreasing the turbine maintenance cost:* AOMO uses the sensor-driven predictive models to detect when the wind turbine condition becomes critical, and performs maintenance when needed. This significantly decreases the number of failure instances, and provides considerable savings in wind turbine maintenance cost. For instance, when $c^v = 12c_p$, AOMO decreases failure instances by 70.6% and 85.2% compared to PM and RM respectively. Reductions in wind turbine maintenance cost correspond to 44.2% and 57.3% of the costs in PM and RM respectively.
- *Increase availability and operational revenue:* Decreasing the number of failure instances reduces the number of idle days, which ensures that more wind turbines are available at any time, making the most of the available generation capacity. As a result, the operational revenue increases in AOMO (e.g. by 2.8% and 8.3% compared to PM and RM respectively, when $c^v = 12c_p$).
- *Decrease crew visits:* The AOMO schedule experiences fewer number of outages (failures and preventive maintenances). Consequently, it also significantly decreases the need for frequent crew visits (in comparison to PM) for cases when $c^v > 0$ (e.g. decrease by 18.1% and 7.3% in outages and crew visits, respectively, when $c^v = 12c_p$).

We next analyze the impact of the crew visit cost on AOM. Table I shows that as the crew deployment cost increases, the cost factors also increase, causing a rise in crew deployment cost and a decrease in net profit as a clear consequence. However there are a number of other changes that are not as obvious. With increasing c^v, AOMO groups the maintenance of wind turbines more aggressively, thus decreasing the crew visits, and the associated crew deployment cost. This inevitably deviates the maintenance policy from the optimal maintenance suggested by the sensor-driven approach, leading to a slight increase in the number of failures. This also corresponds to an increase in the turbine maintenance cost. Increasing c^v also leads to more idle days. As it becomes progressively more expensive to schedule a visit, AOMO waits for more wind turbines to degrade before fixing a failed wind turbine. We note however, that AOMO dynamically determines how to alter its schedule to find the optimal policy under different c^v scenarios. By doing so, AOMO accurately considers the tradeoff between the optimal wind turbine maintenance policy, and the significant cost reductions attained by limiting the number of crew visits; thus AOMO result in a significantly better net profit value.

B. Impact of Electricity Price on AOMO

We next analyze the impact of electricity price on the schedule of AOMO (Table IV). To do so, we consider a farm with 100 wind turbines, and fix the costs $c^v = 3 \times c^f = 12 \times c^p = \$48K$. We change the electricity price from \$12.5/MWh to \$100/MWh to study the impact of electricity price on the maintenance and operational metrics. We can clearly detect that increasing the electricity price increases the operational revenue, and therefore the net profit. In addition, we note that there is a significant dependency between the length of the idle time, and the price of electricity. If a failed wind turbine is maintained early on, the revenue from their production would not be lost. However, if the reactive maintenance can be postponed, then the number of crew visits can be decreased. As the electricity prices rise, the opportunity cost of lost revenue also increases, allowing the maintenance policy to schedule more crew visits to minimize the loss of production. As crew visits increase, the need to postpone the preventive maintenances decreases, leading to less number of failure instances. This leads to a slight increase in expenditure (increase in crew deployment cost and decrease in wind turbine maintenance cost). However, the increase in expenditure is outweighed by the production revenues.

C. Multiple Location Performance of AOMO

In the last study, we analyze a scenario where a single maintenance crew is responsible for 3 wind farm locations. The first location has 100 wind turbines, while the second and third locations have 50 wind turbines each. As in the first experimental study, the price of electricity is \$25/MWh, and the wind turbine maintenance costs are $c^f = 4 \times c^p = \$16K$. For the first and the second locations, we fix the crew deployment costs as certain multiples of the preventive maintenance cost. However, we make the crew deployment cost of the third location significantly more expensive, $c^{v,3} = 10 \times c^{v,1}$. We also enforce that it takes one maintenance period to go to location 3 from location 1 or 2, and vice versa. The results are presented in Table V.

We first analyze some of the interesting dynamics between the second and the third locations. We note that since the number of wind turbines are the same, for the case where $c^{v,3} = c^{v,2} = 0$, the maintenance metrics are similar. However as the crew deployment cost increases, location 3 crew deployment cost becomes significantly larger than that

TABLE I
BENCHMARK FOR ADAPTIVE OPPORTUNISTIC MAINTENANCE & OPERATION (AOMO)

c^v / c^p:=	**0**	**4**	**8**	**12**	**16**	**20**	**24**	**28**
Net Profit	\$10.83 M	\$10.41 M	\$10.15 M	\$9.87 M	\$9.62 M	\$9.38 M	\$9.15 M	\$8.94 M
Operational Revenue	\$11.82 M	\$11.81 M	\$11.80 M	\$11.79 M	\$11.78 M	\$11.78 M	\$11.77 M	\$11.75 M
Expenditures	\$0.99 M	\$1.40 M	\$1.65 M	\$1.92 M	\$2.15 M	\$2.40 M	\$2.62 M	\$2.81 M
· **Turbine Maintenance**	\$0.99 M	\$1.03 M	\$1.04 M	\$1.06 M	\$1.08 M	\$1.09 M	\$1.10 M	\$1.14 M
· **Crew Deployment**	\$0 M	\$0.37 M	\$0.60 M	\$0.85 M	\$1.08 M	\$1.30 M	\$1.52 M	\$1.67 M
# Preventive Actions	185.9	177.2	173.1	173.8	179.5	178.8	178.4	172.6
# Turbine Failures	15.2	19.8	21.8	23.0	22.5	23.5	24.3	27.9
# Crew Visits	95	23.1	18.9	17.8	16.8	16.3	15.8	14.9
# Idle Days	104.4	134.4	158.6	180.2	208.2	212.2	224.8	272.6

TABLE II
BENCHMARK FOR OPPORTUNISTIC PERIODIC MAINTENANCE (PM)

c^v / c^p :=	**0**	**4**	**8**	**12**	**16**	**20**	**24**	**28**
Net Profit	\$9.61 M	\$9.26 M	\$8.95 M	\$8.65 M	\$8.34 M	\$8.04 M	\$7.75 M	\$7.42 M
Operational Revenue	\$11.51 M	\$11.49 M	\$11.46 M	\$11.47 M	\$11.47 M	\$11.47 M	\$11.47 M	\$11.47 M
Expenditures	\$1.89 M	\$2.23 M	\$2.51 M	\$2.82 M	\$3.13 M	\$3.43 M	\$3.72 M	\$4.05 M
· **Turbine Maintenance**	\$1.89 M	\$1.89 M	\$1.89 M	\$1.90 M	\$1.88 M	\$1.89 M	\$1.89 M	\$1.89 M
· **Crew Deployment**	\$0 M	\$0.34 M	\$0.62 M	\$0.92 M	\$1.25 M	\$1.54 M	\$1.83 M	\$2.16 M
# Preventive Actions	160.4	162.9	162.1	162.1	161.0	162.2	160.7	161.1
# Turbine Failures	78.3	77.6	77.6	78.2	77.5	77.8	77.8	77.8
# Crew Visits	47.1	21.3	19.5	19.2	19.5	19.2	19.1	19.3
# Idle Days	823.4	1122.8	1238.8	1232.0	1236.2	1246.2	1243.6	1252.0

TABLE III
BENCHMARK FOR OPPORTUNISTIC REACTIVE MAINTENANCE (RM)

c^v / c^p:=	**0**	**4**	**8**	**12**	**16**	**20**	**24**	**28**
Net Profit	\$8.58 M	\$8.44 M	\$8.40 M	\$8.16 M	\$7.87 M	\$7.71 M	\$7.47 M	\$7.38 M
Operational Revenue	\$11.11 M	\$11.13 M	\$11.07 M	\$10.89 M	\$10.66 M	\$10.54 M	\$10.22 M	\$10.12 M
Expenditures	\$2.53 M	\$2.62 M	\$2.68 M	\$2.74 M	\$2.79 M	\$2.84 M	\$2.75 M	\$2.73 M
· **Turbine Maintenance**	\$2.53 M	\$2.52 M	\$2.51 M	\$2.48 M	\$2.44 M	\$2.44 M	\$2.39 M	\$2.38 M
· **Crew Deployment**	\$0 M	\$0.10 M	\$0.17 M	\$0.25 M	\$0.35 M	\$0.40 M	\$0.36 M	\$0.36 M
# Preventive Actions	-	-	-	-	-	-	-	-
# Turbine Failures	158.1	157.8	157.0	155.2	152.5	152.2	149.2	148.5
# Crew Visits	38.0	6.2	5.2	5.3	5.4	5.0	3.8	3.2
# Idle Days	1754.0	1806.2	2102.4	2621.2	3277.6	3616.8	4499.4	4776.4

TABLE IV
IMPACT OF ELECTRICITY PRICE ON MAINTENANCE SCHEDULE (AOMO)

Electiricty Price (\$/MWh)	**12.5**	**25**	**37.5**	**50**	**62.5**	**75**	**87.5**	**100**
Net Profit	\$4.01 M	\$9.88 M	\$15.77 M	\$21.68 M	\$27.55 M	\$33.44 M	\$39.35 M	\$45.24 M
Expenditures	\$1.89 M	\$1.91 M	\$1.91 M	\$1.92 M	\$1.94 M	\$1.95 M	\$1.95 M	\$1.96 M
· **Turbine Maintenance**	\$1.06 M	\$1.06 M	\$1.05 M	\$1.05 M	\$1.05 M	\$1.05 M	\$1.04 M	\$1.04 M
· **Crew Deployment**	\$0.83 M	\$0.85 M	\$0.87 M	\$0.87 M	\$0.88 M	\$0.90 M	\$0.90 M	\$0.92 M
# Preventive Actions	174.4	175.1	178.8	178.8	178.9	180.7	179.6	180.3
# Turbine Failures	22.5	22.5	20.7	20.7	21.1	20.4	20.1	20.0
# Crew Visits	17.3	17.8	18.1	18.1	18.4	18.8	18.8	19.0
# Idle Days	184.7	181.3	168.0	166.0	166.6	156.3	154.2	152.8

of location 2. AOMO optimizes the maintenance over all the locations, thus provides a schedule that is much more proactive in location 2. Evidently, location 3 experiences more failures, and idle days, and significantly less crew visits and preventive maintenances, in comparison to location 2.

Lastly, we compare locations 1 and 2. We note that the crew deployment cost for both locations remain the same. However, as the crew deployment cost increases, location 1 becomes more efficient than location 2. When $c^v = 12c^p$, 100 wind turbines in location 1 stay idle for a total of 266.6 days, whereas 50 wind turbines in location 2 stay idle for 210.8 days. This means that a wind turbine in location 2 is expected to stay idle significantly longer than a wind turbine in location 1. This happens because one would have to wait longer to group multiple wind turbine maintenances together in a location with a smaller number of wind turbines. Thus the schedule in location 2 deviates more from the optimal CBM policy to get the same benefits of the opportunistic maintenance. This inevitably leads to more failures. When failures occur, wind turbines wait longer for their corrective

TABLE V
MULTIPLE LOCATIONS PERFORMANCE OF AOMO

$c^{v,1}$ / c^p:=	**0**	**4**	**8**	**12**	**16**
Location 1: 100 Wind Turbines, Nominal Crew Deployment Cost					
# Preventive Actions	178.3	173.6	172.6	171.9	170.3
# Turbine Failures	19.8	22.9	22.9	25.2	28.2
# Crew Visits	47.1	23.1	18.5	16.5	14.7
# Idle Days	160.8	215.4	217.2	266.6	319.0
Location 2: 50 Wind Turbines, Nominal Crew Deployment Cost					
# Preventive Actions	87.0	84.3	84.0	82.0	77.6
# Turbine Failures	10.0	12.5	15.7	16.4	19.2
# Crew Visits	32.1	16.9	13.9	12.0	10.5
# Idle Days	111.2	155.0	192.4	210.8	276.2
Location 3: 50 Wind Turbines, Expensive (10×) Crew Deployment Cost					
# Preventive Actions	88.4	43.8	39.0	38.2	36.8
# Turbine Failures	12.2	41.1	45.1	45.8	47.0
# Crew Visits	27.7	5.4	5.0	4.7	4.4
# Idle Days	149.4	1237.8	1403.8	1588.6	1733.8

maintenance to be grouped with other wind turbines.

V. CONCLUSIONS

In this paper, we propose an integrated framework that utilizes the critical information provided by sensor-driven analytics in order to enhance wind farm maintenance and operational decisions. Unlike the traditional methods, the proposed framework effectively uses the sensor information coming from wind turbines to learn their unique degradation patterns and to dynamically estimate the remaining life distribution; this information is then incorporated into an optimal predictive maintenance and operations model. In contrast to many existing sensor driven wind turbine maintenance policies, the proposed method considers the complex interdependencies between wind turbines within a wind farm, and captures specific maintenance requirements. We conduct extensive experiments using real rotating machinery vibration signals. The results demonstrate significant improvements in terms of both reliability and profitability for large-scale wind farm maintenance.

As future work, we plan to extend the model to incorporate uncertainty in wind power, electricity price and weather conditions. In this study, we focused on characterizing and controlling the stochastic degradation of the wind turbines, but assumed a deterministic future profile on operational cost/price aspects. It would be interesting to capture the effect of uncertainty in prices and market conditions with a more detailed operations model, and illustrate how the scheduling decisions would be affected. In addition, uncertainty in weather conditions would also capture an interesting dynamic, whereby certain time periods when a maintenance crew would plan to schedule a visit, may need to be postponed or cancelled due to abrupt changes in weather conditions.

APPENDIX A
PROCEDURE TO PREDICT THE REMAINING LIFE DISTRIBUTION FOR THE GENERAL CASE

The objective is to predict the distribution of the remaining life, namely $R^i_{t_o}$, given the posterior distribution $u(\boldsymbol{\theta_i})$. The procedure can be outlined as follows:

Step 1. Select a sufficiently large number of realizations M.

Step 2. Simulate M realizations of $\boldsymbol{\theta}_i$ from the distribution $u(\boldsymbol{\theta_i})$. Denote by $\tilde{\boldsymbol{\theta}}_{i,n}$ the n^{th} realization of $\boldsymbol{\theta}_i$. For all n, condition on $\tilde{\boldsymbol{\theta}}_{i,n}$ to simulate the stochastic degradation function $D_{i|\tilde{\boldsymbol{\theta}}_{i,n}}(t)$ for all $t > t_o$, until the simulated signal reaches the failure threshold Λ_i. Register this time t as the time of failure for the n^{th} simulation, and let this realization of remaining life be $\tilde{r}^i_{t_o,n}$.

Step 3. Use the realizations $\tilde{r}^i_{t_o,n}$ from all the simulations to estimate the distribution of $R^i_{t_o}$.

APPENDIX B
EXPONENTIAL BASE CASE

The exponential base case degradation model can be formally expressed is follows:

$$D_i(t) = \phi + \theta_i e^{\beta_i t + \epsilon_i(t) - \frac{\sigma^2 t}{2}} = \phi + \theta_i e^{\beta_i t} e^{\epsilon_i(t) - \frac{\sigma^2 t}{2}}, \quad (15)$$

where $D_i(t)$ is the amplitude of the degradation signal of turbine i at time t, ϕ and σ are constant deterministic parameters, θ_i is a lognormal random variable where $\ln \theta_i$ is normally distributed with mean μ_0 and variance σ_0^2, β_i is a normal random variable with mean μ_1 and variance σ_1^2, and $\epsilon_i(t)$ is a zero-mean Brownian motion error term with variance $\sigma^2 t$. We assume that the variables θ_i, β_i and $\epsilon_i(t)$ are mutually independent variables. It is more convenient to transform this function to its corresponding logged functional form, $L_i(t) := \ln(D_i(t) - \phi)$:

$$L_i(t) = \theta_i' + \beta_i' t + \epsilon_i(t), \quad (16)$$

where $\theta_i' = \ln \theta_i$ and $\beta_i' = \beta_i - (\sigma^2/2)$ are random variables following prior normal distributions $\pi(\theta_i')$ and $\pi(\beta_i')$, with means μ_0 and $\mu_1' = \mu_1 - (\sigma^2/2)$, and variances σ_0^2 and σ_1^2, respectively.

Next we introduce our Bayesian methodology. We denote the logged degradation data until observation k occurring at time t_i^o, as $\boldsymbol{\ell}_i^k = \{\ell_i^1, ..., \ell_i^k\}$. The term $\ell_i^e = L_i(t_e) - L_i(t_{e-1})$ denotes the difference between the observed signals at time t_e and t_{e-1} for all $e \in \{2...k\}$, whereas $\ell_i^1 = L_i(t_1)$. We then condition on $\boldsymbol{\ell}_i^k$ to provide accurate predictions on the remaining life distribution of the wind turbine. We obtain the posterior distribution on the parameters θ_i', β_i', namely $u(\theta_i', \beta_i')$ as follows:

$$u(\theta_i', \beta_i') = P(\boldsymbol{\ell}_i^k | \theta_i', \beta_i') \pi(\theta_i') \pi(\beta_i') / P(\boldsymbol{\ell}_i^k), \quad (17)$$

where $P(\boldsymbol{\ell}_i^k)$ is a constant normalization factor. For this particular case, we can obtain a closed-form characterization of $u(\theta_i', \beta_i')$ 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, where:

$$\mu_{\theta'_i} = \frac{\left(\ell_i^1\sigma_0^2 + \mu_0\sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2 t_1\left(\sigma_1^2\sum_{e=1}^k \ell_i^e + \mu_1'\sigma^2\right)}{\left(\sigma_0^2+\sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\mu_{\beta'_i} = \frac{\left(\sigma_1^2\sum_{e=1}^k \ell_i^e + \mu_1'\sigma^2\right)\left(\sigma_0^2 + \sigma^2 t_1\right) - \sigma_1^2\left(\ell_i^1\sigma_0^2 + \mu_0\sigma^2 t_1\right)}{\left(\sigma_0^2+\sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1}$$

$$\sigma^2_{\theta'_i} = \frac{\sigma^2\sigma_0^2 t_1\left(\sigma_1^2 t_k + \sigma^2\right)}{\left(\sigma_0^2+\sigma^2 t_1\right)\left(\sigma_1^2 t_k + \sigma^2\right) - \sigma_0^2\sigma_1^2 t_1},$$

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

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

Details on the derivation of this Bayesian framework is provided in [5].

Given the posterior distribution $u(\theta_i', \beta_i')$, the distribution of the remaining life can be estimated using an Inverse Gaussian distribution with mean $\left(\frac{\Lambda - \ell_i(t_k)}{\mu_{\beta'}}\right)$ and shape $\left(\frac{(\Lambda - \ell_i(t_k))^2}{\sigma^2}\right)$. We refer the reader to [5], [14] for the predictive performance of similar sensor-driven degradation models.

References

[1] I. El-Thalji and J. Liyanage, "On the operation and maintenance practices of wind power asset: A status review and observations," *Journal of Quality in Maintenance Engineering*, vol. 18, no. 3, pp. 232–266, 2012.

[2] J. Andrawus, J. Watson, and M. Kishk, "Modelling system failures to optimise wind turbine maintenance," *Wind Engineering*, vol. 31, no. 6, pp. 503–522, 2007.

[3] Z. Hameed, Y. S. Hong, Y. M. Cho, S. H. Ahn, and C. K. Song, "Condition monitoring and fault detection of wind turbines and related algorithms: A review," *Renewable and Sustainable energy reviews*, vol. 13, no. 1, pp. 1–39, 2009.

[4] Z. Daneshi-Far, G. A. Capolino, and H. Henao, "Review of failures and condition monitoring in wind turbine generators," in *Electrical Machines (ICEM), 2010 XIX International Conference on*. IEEE, 2010, pp. 1–6.

[5] N. Z. Gebraeel, M. A. Lawley, R. Li, and J. K. Ryan, "Residual-life distributions from component degradation signals: A bayesian approach," *IIE Transactions*, vol. 37, no. 6, pp. 543–557, 2005.

[6] F. Ding and Z. Tian, "Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds," *Renewable Energy*, vol. 45, pp. 175–182, 2012.

[7] F. Besnard, M. Patriksson, A.-B. Strömberg, A. Wojciechowski, and L. Bertling, "An optimization framework for opportunistic maintenance of offshore wind power system," in *PowerTech, 2009 IEEE Bucharest*.

[8] F. Ding and Z. Tian, "Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions," *International Journal of Reliability, Quality and Safety Engineering*, vol. 18, no. 05, pp. 463–481, 2011.

[9] E. Byon, L. Ntaimo, and Y. Ding, "Optimal maintenance strategies for wind turbine systems under stochastic weather conditions," *Reliability, IEEE Transactions on*, vol. 59, no. 2, pp. 393–404, 2010.

[10] E. Byon and Y. Ding, "Season-dependent condition-based maintenance for a wind turbine using a partially observed markov decision process," *Power Systems, IEEE Transactions on*, vol. 25, no. 4, pp. 1823–1834, 2010.

[11] F. Besnard and L. Bertling, "An approach for condition-based maintenance optimization applied to wind turbine blades," *Sustainable Energy, IEEE Transactions on*, vol. 1, no. 2, pp. 77–83, 2010.

[12] Z. Tian, T. Jin, B. Wu, and F. Ding, "Condition based maintenance optimization for wind power generation systems under continuous monitoring," *Renewable Energy*, vol. 36, no. 5, pp. 1502–1509, 2011.

[13] J. Endrenyi, S. Aboresheid, R. N. Allan, G. J. Anders, S. Asgarpoor, R. Billinton, N. Chowdhury, E. N. Dialynas, M. Fipper, R. H. Fletcher *et al.*, "The present status of maintenance strategies and the impact of maintenance on reliability," *Power Systems, IEEE Transactions on*, vol. 16, no. 4, pp. 638–646, 2001.

[14] N. Z. Gebraeel, "Sensory-updated residual life distributions for components with exponential degradation patterns," *Automation Science and Engineering, IEEE Transactions on*, vol. 3, no. 4, pp. 382–393, 2006.

[15] A. H. Elwany and N. Z. Gebraeel, "Sensor-driven prognostic models for equipment replacement and spare parts inventory," *IIE Transactions*, vol. 40, no. 7, pp. 629–639, 2008.

[16] M. Yildirim, X. A. Sun, and N. Z. Gebraeel, "Sensor-driven condition-based generator maintenance scheduling, part 1: Maintenance problem," *IEEE Transactions on Power Systems*, 2016.

[17] M. Yildirim, X. A. Sun, and N. Z. Gebraeel, "Sensor-driven condition-based generator maintenance scheduling, part 2: Incorporating operations," *IEEE Transactions on Power Systems*, 2016.

[18] W. R. Gilks, *Markov chain monte carlo*. Wiley Online Library, 2005.

[19] A. K. Jardine and A. H. Tsang, *Maintenance, replacement, and reliability: theory and applications*. CRC press, 2013.

[20] E. A. Elsayed, *Reliability engineering*. John Wiley & Sons, 2012, vol. 88.

[21] N. Gebraeel, A. Elwany, and J. Pan, "Residual life predictions in the absence of prior degradation knowledge," *IEEE Transactions on Reliability*, vol. 58, no. 1, pp. 106–117, 2009.

[22] A. Elwany and N. Gebraeel, "Real-time estimation of mean remaining life using sensor-based degradation models," *Journal of manufacturing science and engineering*, vol. 131, no. 5, p. 051005, 2009.

[23] I. Gurobi Optimization, "Gurobi optimizer reference manual," 2015. [Online]. Available: http://www.gurobi.com

[24] P. Tavner, J. Xiang, and F. Spinato, "Reliability analysis for wind turbines," *Wind Energy*, vol. 10, no. 1, pp. 1–18, 2007.

[25] J. Nilsson and L. Bertling, "Maintenance management of wind power systems using condition monitoring systemslife cycle cost analysis for two case studies," *Energy Conversion, IEEE Transactions on*, vol. 22, no. 1, pp. 223–229, 2007.

[26] M. Armstrong and D. R. Atkins, "Joint optimization of maintenance and inventory policies for a simple system," *IIE transactions*, vol. 28, no. 5, pp. 415–424, 1996.

[27] R. Wiser, "2014 wind technologies market report," 2014.

[28] NREL. transmission grid integration - eastern wind dataset. [Online]. Available: http://www.nrel.gov/electricity/transmission/wind_integration_dataset.html

[29] J. Nilsson, "Maintenance management of wind power systems: Cost effect analysis of condition monitoring systems," 2006.

[30] R. Poore and C. Walford, "Development of an operations and maintenance cost model to identify cost of energy savings for low wind speed turbines," *National Renewable Energy Laboratory*, 2008.

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