Predictive Maintenance Management Using Sensor-Based Degradation Models

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***Abstract*—This paper presents a sensory-updated degradation-based predictive maintenance policy (herein referred to as the SUDM policy). The proposed maintenance policy utilizes contemporary degradation models that combine component-specific real-time degradation signals, acquired during operation, with degradation and reliability characteristics of the component's population to predict and update the residual life distribution (RLD). By capturing the latest degradation state of the component being monitored, the updating process provides a more accurate of the remaining life. With the aid of a stopping rule, maintenance routines are scheduled based on the most recently updated RLD. The performance of the proposed maintenance policy is evaluated using a simulation model of a simple manufacturing cell. Frequency of unexpected failures and overall maintenance costs are computed and compared with two other benchmark maintenance policies: a reliability-based and a conventional degradation-based maintenance policy (without any sensor-based updating).**

***Index Terms*—Condition monitoring (CM), degradation models, manufacturing, predictive maintenance, prognostics, reliability, simulation.**

I. Introduction

THE ADVENT of sensor technology has brought about an increased interest in prognostic health management and its impact on maintenance management. The development of optimal maintenance strategies is necessary for improving system reliability, preventing the occurrence of unexpected system failures, and reducing maintenance costs [1]–[3]. This is particularly true in just-in-time manufacturing environments where unexpected machine breakdowns can be prohibitively expensive because they result in immediate lost production, failed shipping schedules, and poor customer satisfaction.

Preventive maintenance (PM), one of the most popular maintenance policies, involves periodic inspections necessary for maintaining equipment upkeep as well as performing corrective actions. Identifying the appropriate PM interval requires analyzing failure time data and is determined solely based on age or service time [3]. Thus, PM does not take into account the condition or degradation characteristics of a system while planning maintenance activities. This can sometimes lead to unnecessary maintenance routines and loss in production capacity. In contrast, condition-based maintenance (CBM) utilizes real-time condition monitoring (CM) information to schedule maintenance routines. CM involves observing degradation-based measures, such as temperature, vibration, acoustic emissions, from an operating system or device to determine its state of health [4]–[7].

Sensory information collected by CM techniques often exhibits characteristic patterns known as degradation signals. Degradation signals can be used to predict a system's remaining lifetime [8]. It is not unusual for degradation signals of identical components to have similar evolutionary paths that can be modeled using some functional form, for example, linear, exponential, etc. [9]. Gebraeel *et al.* [10], [11] presented base case sensor-based degradation models for estimating residual life distributions (RLDs) of partially degraded components. These distributions were continuously updated using *in situ* degradation signals in a Bayesian manner. The authors tested the predictability of their methodology using vibration-based degradation signals observed from an experimental rotating machinery setup.

This paper builds on the recently developed sensor-based degradation models and presents a sensory-updated degradation-based maintenance (SUDM) policy. Unlike conventional CBM which uses CM from a system or component being monitored, the SUDM policy combines population-based degradation characteristics with real-time monitoring information to predict the remaining lifetime. First, a general degradation model is used to estimate the RLD of a partially degraded system. The preliminary RLD is used to develop an initial maintenance schedule. The RLDs are then updated in real-time using *in situ* degradation signals. The schedule of the corresponding maintenance actions is, in turn, revised based on the most recently updated residual lifetime estimates.

It is important to note that sensory-updated degradation models have not been considered in the context of a maintenance framework. Furthermore, it is not clear how these models will perform in such a framework. Consequently, this paper studies some of the challenges associated with using these updated models to develop an adaptive maintenance policy. Some of the key challenges include the following:

1) First, the sensory-updating procedure is performed continuously over time. Thus, it is necessary to establish a stopping rule at which point the most recently updated RLD is used to estimate the residual lifetime and schedule maintenance.

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2) Second, there is a possibility that the sensory-updated degradation models will provide relatively conservative residual life estimates depending on when the updating process will be terminated. For example, in an experimental study discussed in Section III, a base case model tested on a rotating machinery application provided significantly conservative residual life estimates, particularly at the earlier stages of the degradation process. These predictions slowly improved over time until they were within $\pm 2\%$ of the actual failure times during later stages of degradation (see Fig. 2 in Section III-B). Therefore, there is a warranted concern that a maintenance policy that utilizes sensory-updated degradation models may be too conservative depending on the effect of the updating stopping rule mentioned earlier. Such a scenario may result in a high number of preventive replacements, thus, increasing maintenance costs and reducing throughput due to an increased frequency of planned shutdowns.

The remainder of this paper is organized as follows. Section II reviews some of the relevant literature. Section III describes the degradation modeling approach that will be used to developed our maintenance policy. Section IV discusses our Sensory-Updated Degradation-Based Maintenance Policy (SUDM policy). In Section V, we develop an ARENA simulation model to evaluate the performance of the proposed policy by comparing it to two benchmark policies, a reliability-based PM policy and a condition-based predictive maintenance policy that utilizes degradation models developed by Lu and Meeker [9]. Simulation Results are discussed in Section VI. Finally, Section VII discusses the conclusions and some future research directions.

II. Literature Review

Condition-based maintenance focuses scheduling maintenance activities by periodically or continuously monitoring specific measures that are related to the health and performance of the systems that are being maintained. Once these measures exceed a predefined failure threshold, the system is shutdown for repair. For example, in Nakagawa and Ito [12] present condition-based PM policies for critical components of fossil-fired power plants. They consider the plant as a system that fails once the cumulative damage of its components exceeds a predetermined managerial damage level. In [6] Sloan and Shanthikumar, assumed that the condition of equipment is monitored at equidistant time intervals. The authors also assumed that equipment can fail within an inspection interval, and the probability of failure is exponential. Marseguerra *et al.* [7] assumed continuously monitored multicomponent system and use a Genetic Algorithm (GA) for determining the optimal degradation level beyond which PM has to be performed. In [13], Wu *et al.* developed an integrated neural-network-based decision support system for predictive maintenance of rotational equipment. The integrated system focused on minimizing expected cost per unit operational time, and consisted of a heuristic managerial decision rule for different scenarios of predictive and corrective cost compositions.

A significant portion of CBM research is based on Proportional hazard models. Proportional hazard models consist of a benchmark hazard function and explanatory variables to characterize a system's hazard function based on external operating conditions [14]–[20]. They have also been used in various engineering applications, such as aircrafts, marine applications, and machinery [14]–[16]. They have also been used to determine the optimal replacement policies [21] and maintenance intervals [17], [18].

Unlike proportional hazard models, degradation models focus on modeling the evolution of condition-based sensor signals (aka degradation signals) obtained from partially degraded systems. Lu and Meeker [9] developed a two-stage methodology to model the path of a condition-based degradation signal using random coefficients growth models. Their models utilize a sample of degradation signals to estimate the RLDs for a population of components. Other studies used Brownian motion to model degradation processes examples include work done by Doksum and Hoyland [22], Whitmore [23] and Whitmore and Schenkelberg [24]. However, most of these degradation modeling approaches rarely integrate real-time degradation signals with the goal of updating the estimation of the remaining lifetime of components still operating in the field. Gebraeel *et al.* [10], [11] developed a sensor-based updating method for updating remaining life distributions of systems and their components while they operate in the field. The maintenance policy proposed in this paper is based on the degradation modeling framework proposed in [10] and [11]. The sensory-updating procedure is used to establish a linkage between maintenance scheduling and the degradation states of machines or equipment being maintained.

Maintenance policies have a significant impact on the performance of a manufacturing facility. For example, Sloan and Shanthikumar [6] developed a Markov decision process model that simultaneously determines maintenance and production schedules for a multiple-product, single-machine production systems. In this model, equipment condition was explicitly linked to yield loss. Several research efforts have worked on extending classic economic manufacturing quantity models to account for changing equipment condition and inspection policies [25]–[28]. For example in [28], the authors propose GA-based optimization procedure for scheduling of maintenance operations in a manufacturing system by considering production gains and maintenance expenses. The authors used discrete even simulation to evaluate the performance of their policy.

Simulation has been widely used to study the effectiveness of maintenance management systems [29]. Jianhui *et al.* [30] developed an integrated prognostic process based on data collected from model-based simulations under nominal and degraded conditions. Wang *et al.* [31] developed a condition-based replacement and spare provisioning policy for deteriorating systems with uncertain deterioration to failure. They developed a simulation model to characterize the operation for the system operation under the proposed condition-based methodology and use a genetic algorithm to jointly optimize replacement, inspection, and inventory decision variables.

Some research works considered the interaction between maintenance policies and manufacturing systems. Logendran and Talkington [32] used simulation modeling to compare the performance of cellular and functional work cell layouts while considering two different maintenance policies: a corrective and a PM policy. Vineyard and Meredith [33] used simulation to analyze the effect of five different maintenance policies on flexible manufacturing systems (FMS) subject to random failure. Variations of corrective, preventive, and opportunistic maintenance policies were investigated. The authors demonstrated that the choice of a maintenance policy affected the number of maintenance tasks required, and that a hybrid maintenance policy, combining reactionary, time, and event-triggered preventive characteristics, resulted in the least number of maintenance tasks and system downtime. Savsar [34] also analyzed the performance of an FMS considering corrective, preventive, and opportunistic maintenance policies. Rezg *et al.* [35] used simulation to present a joint optimal inventory control and PM strategy for a randomly failing production units operating under a just-in-time configuration. A cost function was used to evaluate optimal PM interval time and buffer stock level for the system.

III. Sensory-Updated Degradation Modeling

The sensory-updated degradation modeling framework rests on the idea that the functional form of a degradation signal is correlated with the underlying physical phenomena that occur during a degradation process. The functional form is modeled as a continuous-time continuous-state stochastic model. In general, the magnitude of the degradation signal of the ith component at time t_j is given as

$$S(t_{ij}) = \eta(t_{ij}; \Phi_{im}, \Xi_{ik}, \mathrm{B}_{il}) + \varepsilon(t_{ij}) \tag{1}$$

where $\eta(\cdot)$ represents the functional form that describes the path followed by the degradation signal. Φ_m is a vector of m deterministic parameters that represent constant degradation features common to all units of the population. $\Xi_{ik} = (\theta_{i1}, \ldots, \theta_{ik})$ is a vector of k stochastic parameters used to model the unit-to-unit variability, such as degradation rates, across the population. The stochastic parameters are assumed to follow specific distributions across the population of components with those of the individual components being an unknown "draw" from the distribution. $\mathrm{B}_{il} = (\beta_{i1}, \ldots, \beta_{il})$ is a vector of l covariates (fixed and/or stochastic) that capture external factors, such as time-varying operating and environmental conditions. $\varepsilon(t_{ij})$ are error terms that capture environmental noise and other signal transients.

Databases of historical reliability and condition-based degradation measures are used to estimate: 1) the values of the deterministic model parameters and fixed covariates and 2) the prior distributions of stochastic model parameters and stochastic covariates. The resulting model is a generalized degradation model (similar to that proposed by Lu and Meeker [9]). This preliminary model can be used to compute the RLD of a population of components. Evaluating the RLD is equivalent to computing the distribution of the time needed for the magnitude of the degradation signal to reach/cross a predetermined failure threshold η^* and can be expressed as follows:

$$\begin{aligned} &P\{T \le t | \Phi_m, \Xi_{ik}, \mathrm{B}_{il}\} \\ &\quad = P\{\eta(t_{ij}; \Phi_m, \Xi_{ik}, \mathrm{B}_{il}) + \varepsilon(t_{ij}) \ge \eta^* | \Phi_m, \Xi_{ik}, \mathrm{B}_{il}\}. \end{aligned} \tag{2}$$

Real-time degradation signals are used to revise the generalized degradation model based on the unique degradation characteristics of each device or component being monitored. This is achieved by updating the prior distributions of the stochastic parameters and covariates. The sensory-updating procedure is based on a Bayesian approach. It combines two sources of information: 1) the prior distribution of the parameters across the population of components and 2) the real-time degradation signals unique to the individual component. Consequently, the resulting degradation model represents a more precise estimate of the true trajectory of the component's degradation signal and can be used to update the distribution of the residual life of the component being monitored. In the following section, we review the exponential base case as proposed by Gebraeel *et al.* [10].

A. *Base Case Sensory-Updated Exponential Degradation Model: A Review*

The exponential base case is suitable for systems and components where preliminary and partial degradation accelerates the degradation process of a system. In this base case, we consider the special case where the error term follows a Brownian motion [10]. Under these assumptions, the amplitude of the observed degradation signal $S(t)$ is defined as follows:

$$S(t) = \theta e^{\beta t} e^{\varepsilon(t) - \frac{\sigma^2 t}{2}} \tag{3}$$

where θ is a random variable that follows a Lognormal distribution, i.e., $\ln\theta$ is Normal with mean μ_o and variance σ_o^2, and β is Normal with mean μ_1 and variance σ_1^2. The parameters θ and β are assumed to be independent. The error term $\varepsilon(t) = \sigma W(t)$ is a Brownian motion with mean zero and variance $\sigma^2 t$. For mathematical convenience, we work with the logged degradation signal. Thus, we define $L(t)$ as follows:

$$L(t) = \theta' + \beta' t + \varepsilon(t) \tag{4}$$

where $\theta' = \ln\theta$ and $\beta' = \beta - (\sigma^2/2)$.

L_i is assumed defined as the increment between two consecutive signals, i.e., $L_i = L(t_i) - L(t_{i-1})$, the difference between the observed value of the logged signal at times t_i and t_{i-1}, for $i = 2, 3, \ldots$, with $L_1 = L(t_1)$. $\pi_1(\theta')$ and $\pi_2(\beta')$ are defined as the prior distributions of θ' and β', respectively. Note that $\pi_1(\theta')$ is Normal with mean μ_0 and variance σ_0^2, and $\pi_2(\beta')$ is a Normal distribution with mean $\mu_1' = \mu_1 - (\sigma^2/2)$ and variance σ_1^2. The parameters of the prior distributions are estimated from a sample of degradation signals. The model requires that $\varepsilon(0) = 0$, and thus $L(0) = \theta'$. The distribution of θ' is estimated from the sample of signal intercepts. Due to the Brownian motion assumption, the error terms increments are independent identically distributed (i.i.d.), and the random variables X_k (6) are i.i.d. with mean β'. Thus, $\overline{X}$ is used to estimate the value of β' for an individual degradation signal

$$X_k = \frac{L(t_k) - L(t_{k-1})}{t_k - t_{k-1}}, \qquad k = 1, 2, \ldots. \tag{5}$$

Given the observed signal values, $L_1, \ldots, L_k$, observed at times $t_1, \ldots, t_k$, the updated distributions of θ' and β' can be estimated using Bayes theorem

$$P(\theta', \beta' | L_1, \ldots, L_k) \propto f(L_1, \ldots, L_k | \theta', \beta') \pi_1(\theta') \pi_2(\beta'). \tag{6}$$

As previously mentioned, this model was developed in [10]. The authors proved that the posterior distribution of (θ', β') is a Bivariate Normal distribution with mean $(\mu_{\theta'}, \mu_{\beta'})$ and variance $(\sigma^2_{\theta'}, \sigma^2_{\beta'})$, where

$$\begin{aligned}
\mu_{\theta'} &= \frac{\left(L_1\sigma_o^2 + \mu_o\sigma^2 t_1\right)\left(\sigma_1^2 t + \sigma^2\right) - \sigma_0 t_1 \left(\sigma_1^2 \sum_{i=1}^k L_i + \mu_1'\sigma^2\right)}{(\sigma_o^2 + \sigma^2 t_1)(\sigma_1^2 t + \sigma^2) - \sigma_o^2\sigma_1^2 t_1} \\
\mu_{\beta'} &= \frac{\left(\sigma_1^2 \sum_{i=1}^k L_i + \mu_1'\sigma^2\right)\left(\sigma_o^2 + \sigma^2 t_1\right) - \sigma_1 \left(L_1\sigma_o^2 + \mu_o\sigma^2 t_1\right)}{(\sigma_o^2 + \sigma^2 t_1)(\sigma_1^2 t + \sigma^2) - \sigma_o^2\sigma_1^2 t_1} \\
\sigma^2_{\theta'} &= \frac{\sigma^2\sigma_o^2 t_1 \left(\sigma_1^2 t + \sigma_o^2\right)}{(\sigma_o^2 + \sigma^2 t_1)(\sigma_1^2 t + \sigma^2) - \sigma_o^2\sigma_1^2 t_1} \\
\sigma^2_{\beta'} &= \frac{\sigma^2\sigma_1^2 \left(\sigma_o^2 + \sigma_o t_1\right)}{(\sigma_o^2 + \sigma^2 t_1)(\sigma_1^2 t + \sigma^2) - \sigma_o^2\sigma_1^2 t_1}.
\end{aligned}$$

Next, we use the updated distributions of the stochastic parameters to compute the predictive distribution of the signal $L(t_k + t)$ which is Normal with the following mean and variance [10]:

$$\tilde{\mu}(t + t_k) = L(t_k) + \mu_{\beta'} t \tag{7}$$
$$\tilde{\sigma}^2(t + t_k) = \sigma^2_{\beta'} t^2 + \sigma^2 t. \tag{8}$$

Using the predictive distribution of the degradation signal, we calculate the updated RLD of the component that is being monitored as the distribution of the time until the degradation signal reaches a predetermined failure threshold D.

Let T be a random variable that denote the residual life of the partially degraded component. Therefore, T satisfies $L(t_k + t) = D$, and its distribution is given by

$$F_T(t) = P(T \le t | L_1, \ldots, L_k) = \Phi\left(\frac{\tilde{\mu}(t + t_k) - \ln(D)}{\tilde{\sigma}(t + t_k)}\right) \tag{9}$$

where $\Phi(.)$ is the cumulative distribution function (cdf) of a standardized Normal random variable.

The following subsection highlights the prediction accuracy of the sensor-based degradation modeling approach with the aid ball bearing application.

B. Prediction Results

Twenty-five rolling element bearings were run to failure, and their degradation signals observed over time. A sample of the degradation signals is shown in Fig. 1. Remaining life distributions are computed and updated continuously as the degradation signals are observed.

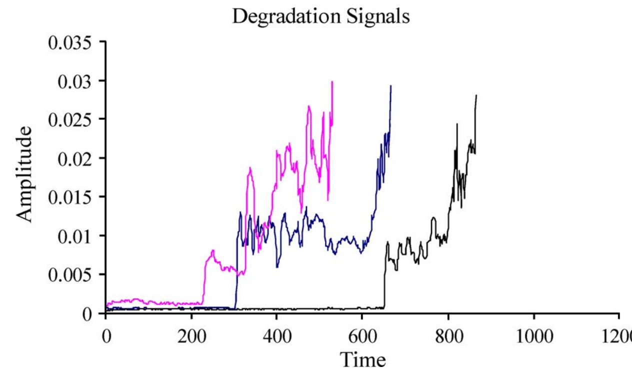

Fig. 1. Example of vibration-based degradation signals associated with the degradation of rolling element bearings.

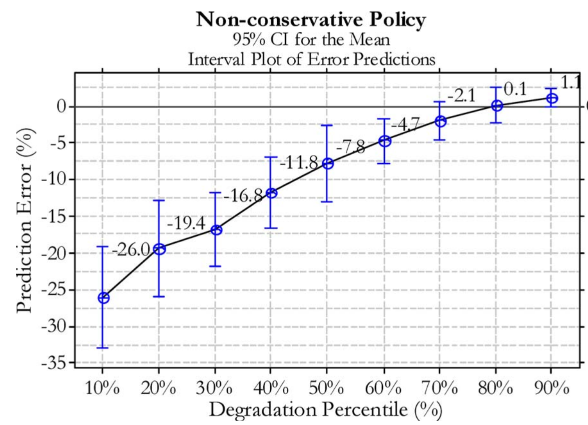

Fig. 2. Prediction errors using a base case sensory-updated degradation model.

At the end of each test, the actual failure times of the bearings are noted, and the percentage difference between the actual (observed) and the predicted failure times are computed using the following expression

$$D_k^i = \frac{\left(t_k^i + \hat{t}_k^i\right) - F^{B_k}}{F^{B_k}} \tag{10}$$

where D_k^i is the prediction error associated with bearing, B_k, computed at sampling epoch i, F^{B_k} is the actual failure time of B_k, t_k^i is the current operating time of B_k at sampling epoch i, and $\hat{t}_k^i$ is the Median of the RLD of B_k computed at the ith sampling epoch. Note that the Median was chosen because the first and second moments of the RLD could not be evaluated.

Fig. 2 shows the prediction results of a base case sensory-updated exponential degradation model. The x-axis represents degradation percentiles at which RLDs were computed or updated. In other words, the 90th degradation percentile means that the component has accomplished 90% of its service life. Note that these percentiles are evaluated after actual failure times have been observed.

IV. SUDM Policy

For a given system of partially degraded equipment, implementing the SUDM policy consists of the steps shown in Fig. 3. The first step involves defining degradation models that will be used to characterize the evolution of the degradation signals

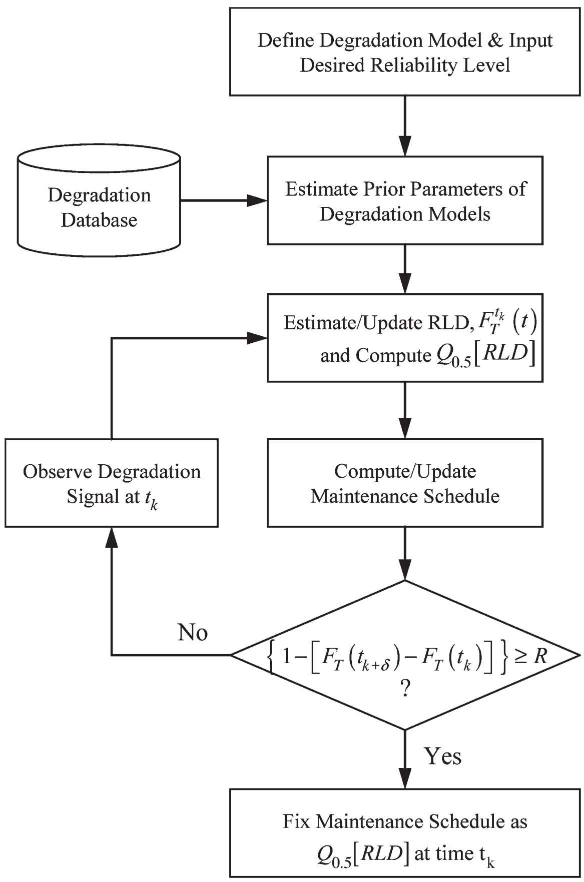

Fig. 3. Flow chart of the SUDM policy.

associated with the equipment that are being monitored. This requires identifying the functional forms of the degradation models, i.e., linear, exponential, etc. Next, a database of degradation signals is used to estimate the parameters of the degradation models. The result is set of generalized degradation models for each type of component, which can be used to estimate initial RLDs, $F_T(t)$. These preliminary distributions are used to compute expected remaining lifetimes $E[\text{RLD}]$, which will be used to develop preliminary maintenance schedule. As noted by Gebraeel *et al.* [10], it is not possible to compute the mean of the RLD. Consequently, we use the median as our estimate of the residual life, $Q_{0.5}[\text{RLD}]$, where $Q_{0.5}$ represents the 50th quantile. Hence, the initial maintenance schedule is evaluated based on the predicted remaining lifetimes, $Q_{0.5}[RLD]$. This schedule is then revised using the sensory updating methodology.

The SUDM policy uses *in situ* degradation signals acquired using CM techniques to continuously update the RLDs, in real-time. The updated predictions are then used to revise the initial maintenance schedule. Thus, the maintenance schedule is continuously modified as real-time degradation signals become available. The updating process continues until a pre-specified stopping rule is satisfied.

A. Sensory-Updating Stopping Rule

In the context of the sensory-updating procedure, the optimal stopping decision involves a tradeoff between continuing to update the RLDs and, in turn, revising the maintenance schedule versus stopping the acquisition of sensory-based signals and executing the most recently updated maintenance schedule. The benefit of continuing the sensory-updating is that the resulting RLDs capture the most recent degradation state of the system being monitored, thus providing higher prediction accuracy. This fact was demonstrated by the plot f the prediction errors in Fig. 2. In order to finalize the maintenance schedule and plan the allocation of maintenance resources, it is necessary to stop the sensory-updating process and execute the most recent schedule. Stopping becomes even more important if we consider the costs of acquiring sensory data. In some applications, these costs can be relatively expensive.

This paper takes a basic approach in developing the stopping rule and serves as a preliminary step for future research. Our stopping rule is given by the following expression:

$$\min_{0<t_k<\infty} \{1 - [F_T(t_{k+\delta}) - F_T(t_k)]\} \geq R \tag{11}$$

where R is the desired reliability level, $F_T(t_k)$ is the cdf of the remaining life updated at time t_k, t_k is the time or epoch at which the last degradation signal was observed, and δ represents a small time increment in the future (used for calculating the cdf).

Equation (11) states that given a desired reliability level R, we continuously update the RLD of an operating component until the first updating time epoch t_k, where the component's instantaneous reliability exceeds the desired reliability R. Once the stopping rule has been satisfied, the corresponding RLD is used to schedule maintenance for the component or equipment being monitored.

V. Simulation Model of the SUDM Policy

This simulation model studies the effect of the proposed maintenance policy on the performance of a simple manufacturing workcell consisting of five parallel single-stage manufacturing workstations (see Fig. 4). Preprocessed parts arrive to a staging station. The interarrival time is assumed to be exponential with a mean 0.25 min. Upon arrival, each part is processed on the first available workstation. The processing times of each workstation is assumed to follow a triangular distribution (0.6, 0.8, 1). Upon completion, the finished part is transferred to a shipping area.

An operational workstation can become unavailable for two possible reasons: a random failure occurs or a scheduled maintenance routine is performed. Workstation failures follow a Weibull failure time distribution. Specifically, a workstation's downtime is assumed to be random and follows a Normal distribution with mean 5 min and variance 0.5 min. Furthermore, we assume that each workstation degrades gradually until it fails.

A database of a bearing-application failure times and degradation signals is used to provide real-world degradation data. The degradation database is developed from a series of accelerated degradation tests in which vibration signals associated with the degradation of rolling element bearings are continuously acquired during run-to-failure tests. The degradation database contains vibration-based degradation signals of 50 bearings as

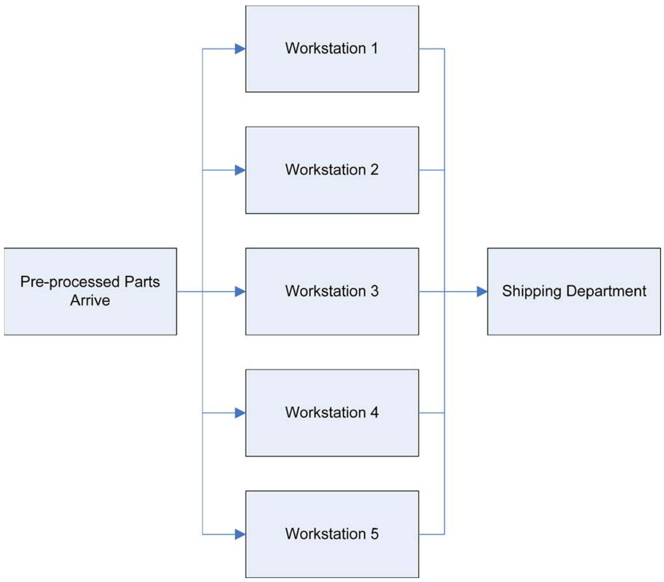

Fig. 4. Schematic of the manufacturing workcell.

well as their associated failure times. This is the same database used by Gebraeel *et al.* [10], [11]. The failure times will be used to estimate the parameters of the Weibull distribution. On the other hand, the vibration-based degradation signals will be used to simulate the degradation of the workstations. This does not imply that a bearing is the only component degrading in the workstation. This simply suggests that we are using real-world degradation signals to represent the degradation process of a workstation as a single degrading entity, as opposed to, simulating degradation signals and using them to represent workstation degradation within our simulation model.

Before we perform our simulation study, we will first divide our bearing degradation database into two sets. The first set, defined as the "prior set," will be used to estimate the parameters of the degradation model and the Weibull failure time distribution. The second set, defined as "validation set," will be used to evaluate the performance of our maintenance policy.

A. Estimation of Prior Parameters

Failure times of the first 25 bearings (bearings 1 to 25) were used to estimate the scale and shape parameters of the Weibull distribution, $\theta_{\mathrm{W}} = 3.0549$ and $\beta_{\mathrm{W}} = 784.75$ (subscript "W" is used to distinguish the parameters of the Weibull distribution from the stochastic parameters of the degradation models).

The corresponding 25 degradation signals (bearings 1 to 25) are used to estimate the prior distributions of the stochastic parameters of the exponential degradation model. The prior distribution of θ; $\pi_1(\theta) \sim N(-6.031, 0.346)$. As previously mentioned, to estimate β', we use $\overline{X}$ which is expressed by equation (6). Twenty-five estimates of β' are used to derive its prior distribution as follows: $\pi_2(\beta') \sim N(0.0081, 1.035 \times 10^{-5})$. The error terms are assumed to have independent and normally distributed increments (Brownian motion assumption). That is $\varepsilon(t_1), \varepsilon(t_2) - \varepsilon(t_1), \ldots, \varepsilon(t_k) - \varepsilon(t_{k-1})$ are assumed to be independent and normally distributed with mean zero and variance $\sigma^2(t_{k+1} - t_k)$.

At the beginning of the simulation, preliminary RLDs for each workstation are computed using the prior information. During the simulation, degradation signals from the validation set (from bearings 26 to 50) are used to represent the degradation of each workstation. As the signals are observed, they are used to update the RLD of corresponding workstation. The updating process continues until the stopping rule in (10) is satisfied. Note that in our simulation model the desired reliability level R refers to the reliability of an individual workstation. The updated RLD is used to revise the maintenance schedule.

Our simulation model consists of two submodels. The first is called the Manufacturing submodel and is used to simulate the operational characteristics of the manufacturing workcell. The second submodel characterizes the control logic of the maintenance policy and is referred to as the Maintenance Policy submodel.

B. Manufacturing Workcell Submodel

The manufacturing submodel is used to simulate part arrival, processing, and departure. Parts arrive to the system randomly at a predetermined rate and are held in a queue until one of five workstations becomes available. If all the workstations are occupied, i.e., already processing parts, the part waits in queue until a workstation becomes available. Once a workstation is available, the first part in the queue is processed according to a prespecified processing time. The processing time of each workstation is assumed to follow a Triangular distribution with the following parameters 0.6, 0.8, and 1 time units. Once processing is complete, the part exits the system.

C. Maintenance Policy Submodel

This submodel simulates workstation failures and planned replacements. This is performed using two subroutines. The first is responsible for generating workstation failure times while the second is responsible for shutting down the workstation. The two subroutines work in tandem to simulate failure and maintenance for each workstation.

1) Failure Time Subroutine: We assume that each workstation undergoes graceful degradation, and its degradation signal is simulated using a real-world vibration-based degradation signal (similar to the ones used in [11]). During simulation, the degradation signal of workstation i is used to update its RLD using (9). Once the stopping rule is satisfied, we compute a planned maintenance interval for the ith workstation, *maintenance_interval_i*, which is given by the following expression:

$$maintenance\_interval\_i = Q_{0.5}\left[\mathrm{RLD}_i^k\right] \tag{12}$$

where RLD_i^k is the RLD of workstation i evaluated at the time t_k.

A workstation experiences an unexpected failure if its degradation signal reaches a failure threshold, i.e.,

$$t_k + Q_{0.5}\left[\mathrm{RLD}_i^k\right] > failure\_time\_i. \tag{13}$$

The term $t_k + Q_{0.5}[RLD_i^k]$ represents the predicted failure time. *failure_time_i* is the actual failure time of the ith workstation. The values of the variable *failure_time* are generated from a distribution (assumed to be Weibull) given that the workstation has survived up to t_k.

2) Resource Shutdown Subroutine: The resource shutdown subroutine is responsible for identifying the type of shutdown that occurs, i.e., unexpected failure or planned maintenance/replacement. There are two cases described below.

1) If $(t_k + Q_{0.5}[\mathrm{RLD}_i^k]) > failure\_time\_i$, the shutdown is for a planned maintenance routine. Once maintenance is complete, the workstation is assumed to be "as good as new." A variable N_{m} is used to track the total number of planned replacements.
2) If $(t_k + Q_{0.5}[\mathrm{RLD}_i^k]) < failure\_time\_i$, the shutdown is due to an unexpected failure. A variable N_{f} is used to track the total number of failure replacements. Unexpected failures occur only if the workstation's degradation signal reaches or exceeds a failure threshold before a planned maintenance is scheduled.

D. Benchmark Policies

We compare the performance of our proposed maintenance policy with two benchmark maintenance policies: a conventional reliability-based PM policy and a degradation-based maintenance (DM) policy that uses a similar exponential degradation model but without the updating procedure (similar to Lu and Meeker [9]).

1) PM Policy: The reliability-based PM policy uses a failure time distribution to calculate the planned PM interval. For the purpose of this analysis, we assume that the failure time of the workstations follows the same failure distribution obtained using failure times of the 25 bearings discussed earlier. We are interested in evaluating the maintenance interval t_R. To do this, we solve for t_R in the following expression:

$$F(t_R) = (1 - R) = 1 - e^{-(t_R/\theta_{\mathrm{W}})^{\beta_{\mathrm{W}}}} \tag{14}$$

where $F(t_R)$ is the cdf of a Weibull distribution, θ_{W} is the scale parameter and β_{W} is the shape parameter of the Weibull distribution, and R is the desired reliability level of the system.

We would like to emphasize that the PM policy is a time-based policy. Thus, it does not consider the condition or degradation state of the equipment being maintained.

2) DM Policy: The second benchmark maintenance policy is based on the degradation modeling framework developed by Lu and Meeker in [9]. This policy differs from the SUDM in that there is no updating of the RLDs. Similar to the SUDM policy, we focus on the exponential degradation model

$$S(t) = \theta e^{\beta t} \tag{15}$$

where θ and β are random variables whose distribution follows the prior distribution evaluated earlier for the degradation models used in the SUDM policy.

Once again for mathematical convenience, we work with the log of the degradation signal

$$L(t) = \ln(S(t)) = \ln(\theta) + \beta t \tag{16}$$

where $\ln\theta \sim N(\mu_0, \sigma_0^2)$ and $\beta \sim N(\mu_1, \sigma_1^2)$.

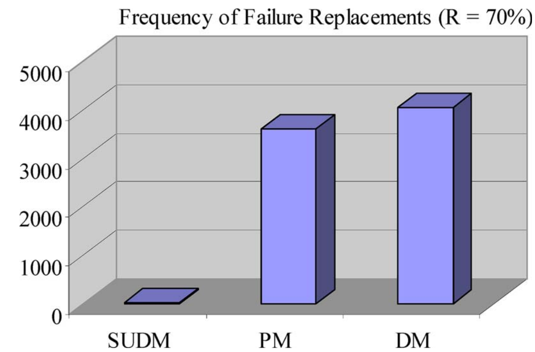

Fig. 5. Frequency of failures for $R = 70\%$.

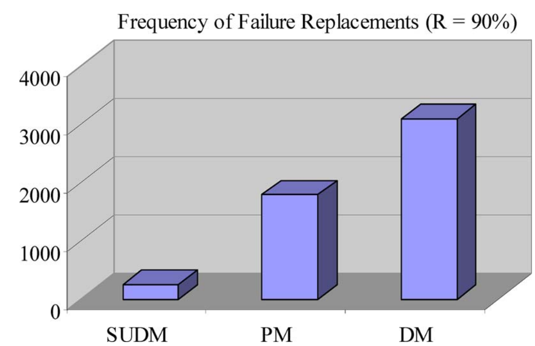

Fig. 6. Frequency of failures for $R = 90\%$.

The RLD is equivalent to the distribution of the time it takes a partial degradation signal to reach a predetermined failure threshold, D. For this degradation model, the cdf residual of the residual life is expressed as follows:

$$F_T(t_R) = \mathrm{P}(T \le t_R) = \Phi\left(\frac{t_R - [\ln(D) - \mu_0]/\mu_1}{\sqrt{[\sigma_0^2 + \sigma_1^2 t_R^2]/\mu_1^2}}\right). \tag{17}$$

Given a desired reliability level $R = 1 - F_T(t_R)$, we solve the above expression and find the corresponding planned maintenance interval, t_R. This policy is different from the PM policy in that planned maintenance routines are based on condition-based information. However, it does not account for the recent state of health of the workstation that is being monitored.

In the next section, we evaluate the performance of the proposed policy by observing the number of failures, planned replacements, and total maintenance costs. The results are compared with those of the two benchmark maintenance policies.

VI. Implementation and Results

Arena simulation is used to simulate the continuous operation of the manufacturing workcell. The simulation consists of several runs. Each run is 365 days, and each day is assumed to be two 8-h shifts. Separate runs were performed for each maintenance policy.

Figs. 5 and 6 show frequency plots of the number of failures associated with each maintenance policy at two levels of target reliability, $R = 70\%$ and $R = 90\%$. It is clear that the SUDM maintenance policy results in a significantly lower number of unexpected workstation failures at both levels of reliability.

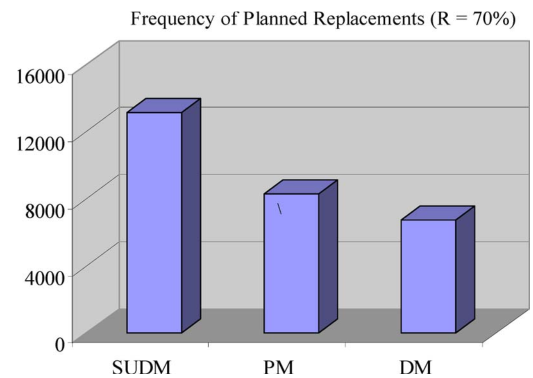

Fig. 7. Frequency of maintenance routines for $R = 70\%$.

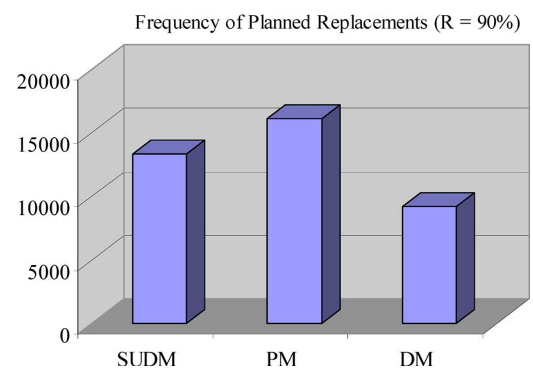

Fig. 8. Frequency of maintenance routines for $R = 90\%$.

TABLE I
MEANS AND STANDARD DEVIATIONS OF NUMBER OF FAILURE REPLACEMENTS FOR $R = 70\%$ AND $R = 90\%$

	N_f (R = 70%)		N_f (R = 90%)	
Policy	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
SUDM	84.00	3.36	129.00	13.12
PM	3,601.66	24.13	1,788.65	33.04
DM	4,039.00	36.32	3,089.67	40.78

TABLE II
MEANS AND STANDARD DEVIATIONS OF NUMBER OF PLANNED REPLACEMENTS FOR $R = 70\%$ AND $R = 90\%$

	N_m (R = 70%)		N_m (R = 90%)	
Policy	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
SUDM	13,142.67	4.69	13,305.01	18.35
PM	8,277.65	29.17	16,115.65	45.83
DM	6,739.67	44.41	9,239.99	52.08

We believe that this difference is due to the sensory-updating process that occurs in the SUDM policy.

Figs. 7 and 8 show the frequency of planned maintenance routines for each maintenance policy. The plots represent the number of preventive workstation replacements at the 70% and 90% reliability levels.

Tables I and II show the means and standard deviations of the number of failure replacements and planned replacements, respectively, at 70% and 90% reliability levels. We observe that the SUDM policy has the lowest mean and standard deviation for the number of failure replacements (Table I). Our policy has a higher number of planned replacements (Table II).

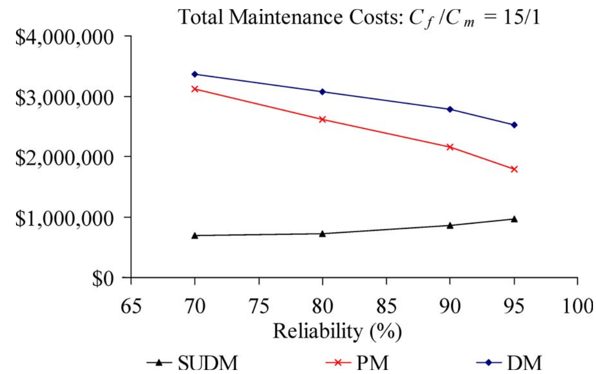

Fig. 9. Total costs of maintenance policies assuming $C_{\mathrm{f}}/C_{\mathrm{m}} = 15/1$.

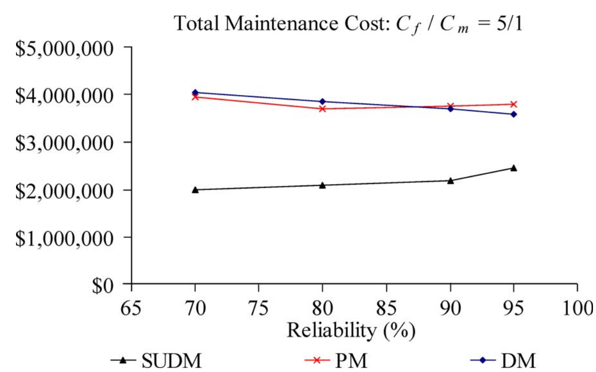

Fig. 10. Total costs of maintenance policies assuming $C_{\mathrm{f}}/C_{\mathrm{m}} = 5/1$.

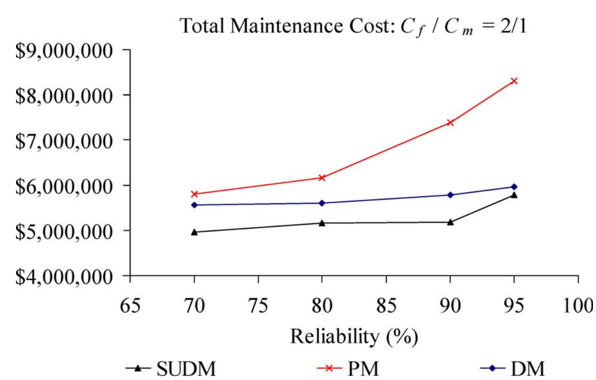

Fig. 11. Total costs of maintenance policies assuming $C_{\mathrm{f}}/C_{\mathrm{m}} = 2/1$.

We also analyze the total maintenance costs TC of each policy, i.e., costs of planned replacement plus costs of failure replacements

$$TC = N_{\mathrm{f}} C_{\mathrm{f}} + N_{\mathrm{m}} C_{\mathrm{m}} \tag{18}$$

where N_{f} is the number of failure replacements, C_{f} is the cost of performing a failure replacement, N_{m} is the number of workstation planned replacements, and C_{m} is the cost of performing a planned replacement.

The analysis was performed for three different $C_{\mathrm{f}}/C_{\mathrm{m}}$ ratios; "15/1," "5/1," and "2/1." Figs. 9–11 show the total maintenance costs for each maintenance policy as a function of different reliability levels. For each ratio, C_{f} is assumed to be \$750. The SUDM policy has the lowest total maintenance cost across all three cost ratios.

It is clear from Fig. 9 that the total costs associated with the PM and the DM policies tend to decrease as the reliability level increases. This observation is expected. Higher target reliability levels correspond to lower number of failures and, thus, lower failure costs. At the same time, higher reliability levels result in more frequent planned replacements. Due to the large ratio between the cost of failure and the cost of planned replacement (15 : 1), the effect of the planned replacement costs is offset by the high failure replacement costs. However, as the ratio decreases this phenomenon becomes less evident. In other words, the effect of the costs of planned replacements becomes a significant component and indeed increases the total maintenance cost, see Fig. 11 (also see Tables I and II).

It is interesting to note that the total maintenance cost of the SUDM policy always increases with increasing target reliability levels. This is true across all the cost ratios that were tested. We believe that this trend results from the lower amount of degradation signals that are used to update the RLDs, thus compromising the accuracy of the life predictions.

Higher target reliability levels imply that the stopping rule (10) is invoked at an earlier stage. In other words, the portion of the degradation signal that is used to update the RLD at a 95% target reliability level is smaller than that used to update the life distribution at a 70% target reliability level. We believe that the reduced level of health information acquired from a degradation signal at 95% target reliability level results in less accurate residual life predictions compared to their counter parts at 70% reliability. Consequently, this results in a higher number of unexpected failures, hence more failure replacements and higher total maintenance costs. Thus, sensory-updating is crucial to ensuring accurate estimation of the residual lifetime.

VII. Conclusion

This paper presents a Sensory-Updated Degradation-Based Maintenance (SUDM) policy that uses residual life distributions (RLDs) to evaluate predictive maintenance schedules. The RLDs are computed using a stochastic degradation models that can be updated in real-time using *in situ* degradation signals.

The updated distributions are used to revise the schedule of maintenance routines based on the most recently observed degradation information. A stopping rule uses instantaneous reliability levels to define a stopping time after which the recently updated RLDs are used to finalize the maintenance schedule.

A simulation model of a small manufacturing facility with five parallel workstations is used to evaluate the performance of the proposed maintenance policy. We consider two main cost components: cost of planned replacement and failure replacement. Three cost ratios were studied. The performance of the proposed policy policy is also compared with two benchmark policies: a reliability-based PM policy and DM policy.

Our results show that the SUDM policy have the lowest maintenance costs. Future research is still needed to investigate the effect of the proposed maintenance policy on larger systems. The research can also be extended to study maintenance-related logistics, specifically replacement and spare parts inventory costs. Another very important topic to be investigated within this maintenance framework is the degradation of the sensors that are used in CM and the fidelity of the sensor signals.

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