

Remaining Useful Life Estimation Using Hybrid Monte-Carlo Simulation and Proportional Hazard Model

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Abstract

PS PLUS™ software offers power providers the ability to implement intelligent gas turbine life cycle management processes. Operators wish to achieve higher availability by reducing unnecessary scheduled outages for either inspection or repair. PS-PLUS is a SPAR™-based application that uses the Monte-Carlo (MC) method to estimate machinery remaining useful life. The method predicts the scope and schedule of maintenance associated with important failure modes. Other works have explored the Proportional Hazard Model (PHM), using EXAKT™ software to accurately forecast the probability of failure of gas turbine components. A PHM quantitatively measures the relative importance of each influential risk factor (covariate) that affects life estimation. The propensities for failure are modeled as a function of both time dependent covariates and an item's working age. The hybrid PHM-MC prototype application demonstrates Remaining Useful Life Estimation in conjunction with time dependent covariates such as (a) key operational duty cycle profile factors i.e. load, fuel type, starts, trips, etc, (b) sensor readings, and (c) borescope inspection data indicative of component health and state. This paper presents a conceptual design, data requirements and analysis techniques needed to fuse PHM and Monte-Carlo simulation techniques. The hybrid system should generate accurate remaining useful life predictions. Those predictions form the basis of cost-effective condition-based maintenance (CBM) of gas turbines. Effective CBM, in contrast to time-based maintenance (TBM), profoundly improves life cycle performance and cost. The paper demonstrates the superiority of PHM analysis compared to traditional Weibull analysis in predicting lower-end failure probabilities, for example B1 and B5 lives. Because of the serious economic consequences of critical failures, such reliability estimates must be considered in business decisions related to gas turbine operation and warranty management.

Introduction

Traditional gas turbine maintenance policy is primarily comprised of time-based (or duty-cycle-based) maintenance (TBM). The search to avoid unnecessary scheduled maintenance and to reduce failure risk is shifting attention away from planned maintenance of gas turbines and towards advanced condition-based maintenance (CBM) (Chen et al., 1994; Reebe, 2003; Al-Bedoor et al., 2003). Current gas turbine CBM policy, however, is based mainly on conservative experience-derived engineering judgment. There is a growing interest among operators to investigate opportunities for reducing overall costs by supplementing that judgment with rigorously calculated Remaining Useful Life Estimations (RULE).

In turbine asset management, the term "inspections" refers both to information gathering (as in condition based maintenance) and scheduled renewal. "Standby" and "running inspections" are carried out to allow for minor adjustments. They can provide much recorded information that is related to maintenance cost and reliability. A disassembly inspection, of which there are three

types (Combustion Section, Turbine Section, and Turbine Rotor), is a costly event. Standby inspections apply mostly to backup and peaking units.

In gas turbine operations, failure can be catastrophic and preventive maintenance is expensive. These factors alone provide ample incentive for driving decisions from all possible information sources. Information abounds in gas turbine operations, and its very volume challenges operators in using it to greatest possible effect. The information intensive nature of gas turbine operation and maintenance and the scale of the impact of less than optimum decisions encourage the examination of novel data interpretation methodologies. Two such important decisions are 1) When to do a turbine section inspection? and 2) When to do a rotor inspection?

Information gathered during standby, running, and combustion section inspections contains potential knowledge useful for optimally planning and scheduling future Turbine Section and rotor inspections. Such information may be further supplemented with day-to-day sensor and operational profile information. Running inspections provide steady state operating parameters such as load versus exhaust temperature, vibration, fuel flow and pressure, lube oil pressure, exhaust gas temperatures, exhaust temperature spread variation, and startup time. Deviations from the norm relate to calibration errors and equipment health.

Combustion section inspections are relatively short duration disassembly inspections where the opportunity is taken to make CBM borescope and visual inspections the results of which are highly related to risk and remaining useful life, thus bearing heavily on the optimal schedule of a subsequent turbine section or rotor inspection. The combustion section inspection includes:

1. Visual inspection of first-stage turbine nozzle partitions.
2. Borescope inspect turbine buckets to mark the progress of wear and deterioration of these parts. 1st, 2nd, 3rd buckets + nozzle. (Data related to turbine section component failure.)
3. Borescope inspection of compressor, intermediate compressor rotor stages
4. Borescope observation of the condition of blading in the aft end of axial-flow compressor.
5. Visual inspection of the compressor inlet and turbine exhaust areas, checking condition of inlet guide vanes (IGVs), IGV bushings, last stage buckets and exhaust system components.

The decision of when to do disassembly inspections is based on conservatively pragmatic and simplified engineering approximations of the combined effect of diverse operational factors that are known or assumed to influence component life. The major ones are:

- Cycle effects (the number of starts)
- Firing temperature (power setting)
- Fuel type (gas, light, crude, residual)
- Level of steam or water injection used to increase power and control NOx emissions.

High cycles of "peaking machines" are associated with the failure mode "thermal mechanical fatigue". However continuous duty machines' dominant failure modes are creep, oxidation, and

corrosion leading to rupture, erosion, and deflection. Both types of duty cycles have certain failure modes in common. They are: high cycle fatigue, rubs/wear, and foreign body damage.

In this paper, we propose an approach to Remaining Useful Life Estimation of gas turbines using PHM and Monte-Carlo simulation. The combination of the aforementioned multiple factors can be included in a PHM. The proposed RULE approach will provide an advanced estimation of machinery remaining useful life and outage scope/schedule requirements associated with important failure modes. It will eventually contribute to achieving higher availability by reducing unnecessary scheduled outages for either inspection or repair.

In this hybrid PHM-MC prototype application, the PHM is first explored to depict the failure mechanism of the component associated with key failure modes. It quantifies the propensity for failure as a function of both time dependent covariates (e.g. operational factors, sensor readings, inspection information) and the working age. Then stochastic models are used to describe the behavior of covariates. The covariate behavior models are necessary since the RULE depends on future covariate values while some future covariate values are unknown and have to be forecasted. Finally, PS-PLUS Monte-Carlo simulation model will provide the RULE. These three steps will be discussed in detail in the following sections.

Failure Distribution – Weibull PHM vs Weibull

The failure mechanism of a component associated with a key failure mode can be described by a PHM. In other words, the time to failure T^c of a component due to a key failure mode, has the following expression of hazard rate

$$h(t) = h_0(t) \exp(\gamma \cdot \mathbf{z}(t))$$

where $h_0(t)$ is the baseline hazard rate, \mathbf{z} is the covariate vector and γ is the vector of covariate coefficients, which reflect the impacts of covariates on the hazard. By *covariates* we mean any type of quantity that affects the hazard rates and can be attributed to every observation point for example type of fuel, number of starts, etc. In this paper, we adopt the Weibull distribution for the baseline hazard rate, i.e.,

$$h_0(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1}$$

where β is the shape parameter and η is the scale parameter. This form of PHM is called Weibull PHM.

It should be noted that classic Weibull analysis is very sensitive to ‘mixing of populations’ i.e. when operation or environmental conditions that affect the hazard rates are ignored or erroneously accounted for in the analysis. The mixing of populations in Weibull analysis often results in a significant underestimation of the shape parameter. This phenomenon can be clearly illustrated through a simple example. Consider three sets, each consisting of 10 failure-time points, as listed in table 1. When analyzing the data sets separately, three ‘perfect’ Weibull fits are obtained (each set ‘falls’ exactly on a unique Weibull line as shown in Figure 1 with

correlation coefficients $\rho=1$) and all three Weibull lines have the same shape parameter (slop) of $\beta = 4.51$. However, if all three sets are mixed and analyzed as single set then the best fit is a Weibull line with $\beta = 2.46$ (with $\rho=0.95$) as shown in Figure 2. It should be noted that although the population size has increased three times by analyzing the sets together the end result was (a) with a lower confidence in the parameters' estimates (lower ρ) and (b) with a considerable underestimation of the shape parameter (a shape of $\beta = 2.46$ instead of $\beta = 4.51$).

Table 1: 3 sets of times to failure

Group A	Group B	Group C
26556	12645	9157
32729	15585	11286
36748	17499	12672
39989	19042	13789
42870	20414	14783
45605	21716	15726
48352	23025	16673
51298	24428	17689
54773	26082	18887
59847	28499	20637

Weibull distributions exhibit smaller variance with increasing shape parameters. This phenomenon is especially noticeable in the left-hand tail (or the head) of the Weibull distributions or for low failure probabilities as shown in Figure 3. Figure 3 displays Weibull cumulative probability (distribution) functions (CDF) with different parameters - all distributions have a mean of 48000 hours but each distribution has different shape parameter ranging from $\beta=1.01$ to $\beta=10$. Underestimation of the shape parameters (β values) results in a significant underestimation of the time period to reach a certain level of (low) risk or probability of failure. This 'type' of time period is referred to as 'B_p life'. B_p life is defined as the time period for which a new component fails with a probability of P%. In the above example, as shown in Figure 4, the B₁ and B_{0.5} lives for a Weibull distribution with $\eta=29307$ and $\beta=2.46$ obtained from the analysis when all three sets were 'mixed' together as one, are longer by 30% and 50% respectively than the B₁ and B_{0.5} lives for a Weibull distribution with $\eta=16549$ and $\beta=4.51$ obtained for the 'worst case' when the three sets were analyzed separately.

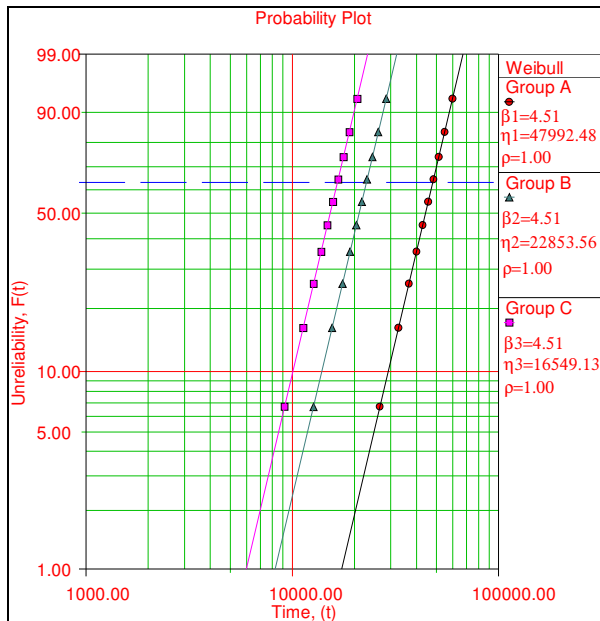


Figure 1: Weibull analysis of three individual sets

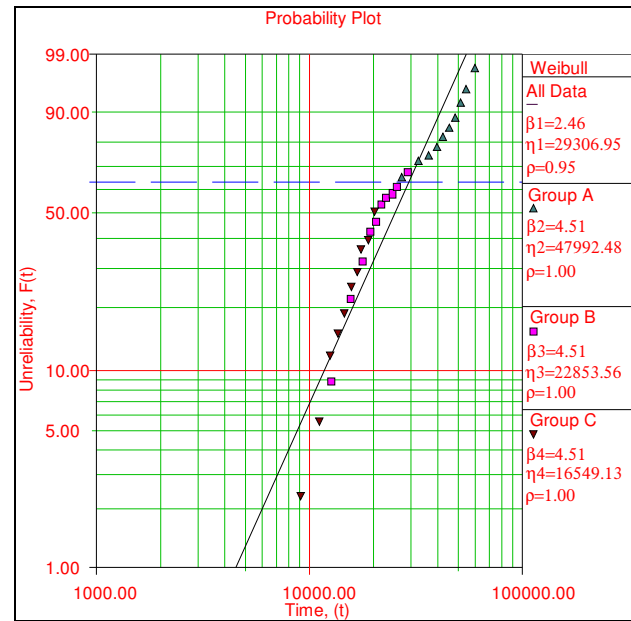


Figure 2: Weibull analysis with mixing populations

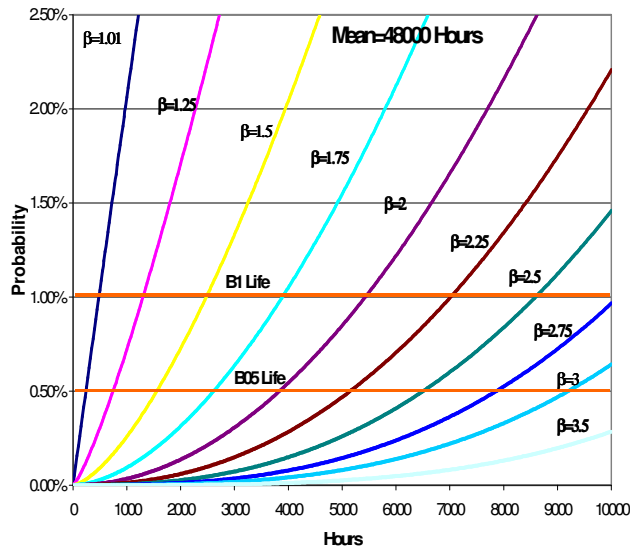


Figure 3: Weibull CDF's with same mean but different shape parameters (β -s)

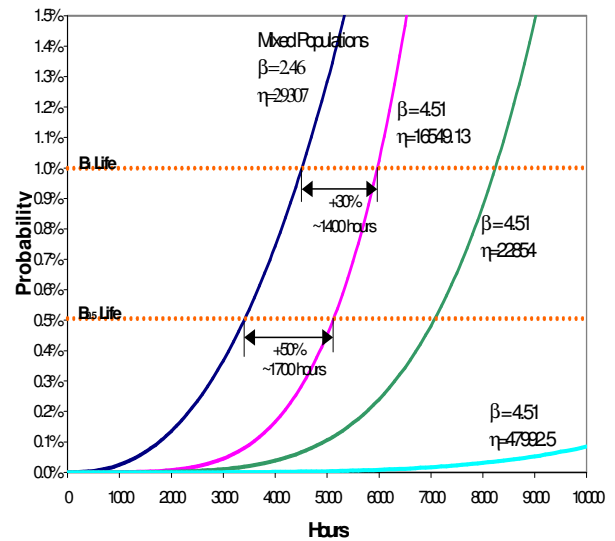


Figure 4: B_1 and $B_{0.5}$ lives with mixed and separated populations Weibull analysis

A Weibull PHM incorporates *covariates* in the analysis and should be envisaged as a method that ‘separates’ the entire population to statistically identical sub-populations. Weibull PHM analysis provides more accurate estimations of β that are often higher than the β estimates obtained from a traditional Weibull analysis. It should be noted that in reality most covariates vary with time and consequently each observation point is described by a whole ‘history’ of varying covariates values and therefore the set cannot be a-priori separated to statistically identical sub-populations. Such an effort is analogous to attempting to separate balls into groups according to their color while all the balls have many stripes of different colors. However the Weibull PHM analysis effectively overcomes this insoluble problem by incorporating the whole ‘histories’ of observed covariates values into the analysis.

Modeling Weibull PHM

The first step of the hybrid PHM-MC prototype application is to construct a Weibull PHM – i.e. to estimate the parameters in the Weibull PHM described above. Fleet-wide failure data of tracked items in conjunction with information on the duty cycle endured by those items will be used in the construction of the Weibull PHM. This includes an extensive data analysis process. It consists of three stages:

1. Data cleaning and preprocessing
2. Weibull PHM parameters estimation in conjunction with
3. Model selection.

Data Cleaning and Preprocessing

Statistical PHM failure data analysis requires the gathering of historical failure (and censored) data and operational data of similar equipment. Experience shows that it is very common that data is missing, contains errors, or is incomplete. This historical operational and failure data must be preprocessed to ensure coherency and correctness. Preprocessing helps the user to validate the data and perform corrections. It involves graphical and statistical analysis through the use of a variety of plots and through the calculation of basic statistics. EXAKT provides a series of graphical tools to assist users in data preprocessing. Figures 5 and 6 present two typical examples.

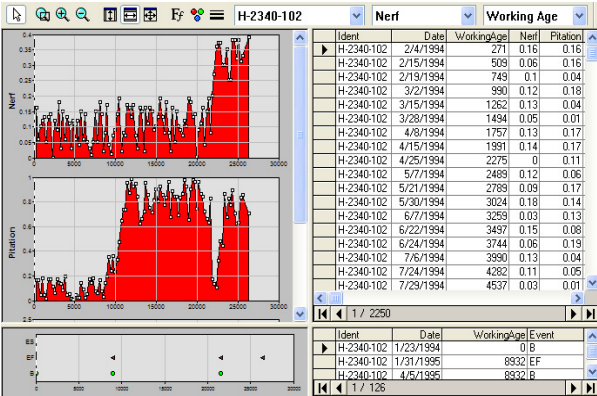


Figure 5: A graphical tool for viewing covariate readings

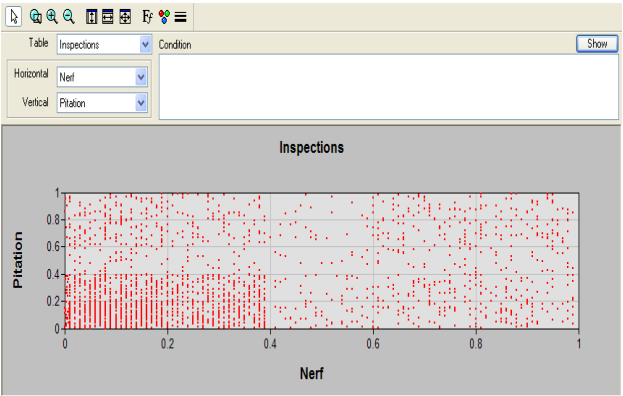


Figure 6: A graphical tool for investigating correlation between covariates

Using a database to store the historical operational and failure data will facilitate data cleaning and filtering. A database system with ODBC (Open Database Connectivity) drivers will be used so that it will be easy to interface with existing external corporate databases. The database in addition will serve as a platform for programming queries to fix data errors, to filter various data sets and to transform particular covariate values as linear combinations, rates or cumulative values.

Intuitively it is expected that sensor readings would be highly correlated to duty cycle information. Operational factors are the drivers (or causes) for the deterioration or the progression of failure modes while the sensor readings reflect (are the effects of) deterioration (progression of failure modes). Incorporating both duty cycle factors and sensor readings as possible covariates in the PHM (or using any highly correlated covariates) may lead to the problem of “collinearity” among covariates and cause inaccurate numerical calculation (or even errors) in the PHM parameter estimation. One method to address this issue is to transform the data space by using a technique such as Principal Component Analysis (PCA) or Partial Least Squares (PLS). PCA can be used to transform the covariates into principal components that are uncorrelated and thus a more accurate model that uses these transformed covariates can be obtained. In addition, this technique retains and uses all of the available information in the data when the alternative might result in a somewhat arbitrary elimination of useful covariates and thus a loss of information.

Weibull PHM Parameters Estimation

The preferred statistical method to estimate the Weibull PHM parameters is the Maximum Likelihood Estimation (MLE) method. The MLE method assumes that the observed outcomes are the most likely set of outcomes. The likelihood function measures the probability of obtaining the observed outcomes as a function of explicit distribution parameters. The estimated parameters are the distribution parameters that maximize the likelihood function. Suppose that the data obtained is the right-censored data denoted by $(T_i, \delta_i, (\mathbf{z}_i(t), 0 \leq t \leq T_i))$, where δ_i is an indicator having value 0 or 1, T_i is the observed failure time if $\delta_i = 1$ or the censored time if $\delta_i = 0$, and $(\mathbf{z}_i(t), 0 \leq t \leq T_i)$ represents the covariate readings for observed component i from beginning up to time T_i , $i = 1, 2, \dots, n$. Then the likelihood function is

$$L(\beta, \eta, \gamma) = \prod_{i=1}^n f(T_i)^{\delta_i} [1 - F(T_i)]^{(1-\delta_i)} = \prod_{i=1}^n h(T_i)^{\delta_i} [1 - F(T_i)] = \prod_{i=1}^n h(T_i)^{\delta_i} \exp(-H(T_i))$$

where $f(\cdot)$, $F(\cdot)$ and $H(\cdot)$ denote the density function, the cumulative distribution function and the cumulative hazard function of T^c respectively, and

$$h(T_i) = \frac{\beta}{\eta} \left(\frac{T_i}{\eta} \right)^{\beta-1} \exp(\gamma \cdot \mathbf{z}_i(T_i))$$

$$H(T_i) = \int_0^{T_i} \frac{\beta}{\eta} \left(\frac{u}{\eta} \right)^{\beta-1} \exp(\gamma \cdot \mathbf{z}_i(u)) du.$$

Note that, for the calculation of the likelihood function, the complete continuous covariate function $(\mathbf{z}_i(t), 0 \leq t \leq T_i)$ must be known. In practice, however, it is almost impossible to continuously record covariate readings. Instead, covariate readings are recorded at discrete times $0 \leq t_{i1}, t_{i2}, \dots, t_{im_i} \leq T_i$. A simple but efficient approach for incorporating this historical covariate data into the likelihood function is to assume that the covariate function $(\mathbf{z}_i(t), 0 \leq t \leq T_i)$ is a stepwise constant function with jumps only at discrete times $0 \leq t_{i1}, t_{i2}, \dots, t_{im_i} \leq T_i$.

For a complete and robust Weibull PHM analysis, several additional features are required. These additional issues are addressed as follows.

Cumulative Damage Conservation

The conditional probability density function (PDF) for the time to failure of the component, given that it does not fail up to time τ and given the covariate history $(\mathbf{z}(t), 0 \leq t \leq \tau)$, is

$$f(t|\tau) = \frac{f(t)}{1 - F(\tau)} = \frac{h(t) \exp(-H(t))}{\exp(-H(\tau))} = h(t) \exp\left(-\int_{\tau}^t h(u) du\right), t > \tau.$$

This conditional PDF represents the remaining useful life distribution for the component. Intuitively we expect that the propensity of failure of components with different duty cycle histories will be different. We expect that these components will exhibit different remaining useful life distributions. However, from the expression of conditional PDF above, it is obvious that the remaining useful life distribution does not depend on the past covariate history ($\mathbf{z}(t)$, $0 \leq t < \tau$). This means that different operation profiles in the past do not affect the future. Clearly this is a counterintuitive and undesirable outcome.

A simplistic way to solve the above problem is to use cumulative covariate processes rather than the original covariate processes when the corresponding covariates are believed to have cumulative effects on the hazard. However the preferred way to tackle this problem is to conserve the age or cumulative damage directly in the likelihood function at every covariate jump. The hazard function and the cumulative hazard function that conserve age or the cumulative damage have the form:

$$h(T_i) = \frac{\beta}{\eta} \left(\int_0^{T_i} \frac{du}{\eta / \exp(\boldsymbol{\gamma}' \cdot \mathbf{z}_i(u))} \right)^{\beta-1} \exp(\boldsymbol{\gamma} \cdot \mathbf{z}_i(T_i))$$

$$H(T_i) = \left(\int_0^{T_i} \frac{du}{\eta / \exp(\boldsymbol{\gamma} \cdot \mathbf{z}_i(u))} \right)^{\beta}$$

Interval Censored Data

Usually Weibull PHM parameters analysis assumes that data include only right-censored observations. In engineering practice, however, components may not be monitored continuously and consequently some of their failure modes are not detected immediately upon their occurrence. In gas turbine systems the intervals between successive inspections range from several months up to two years. The exact time of failure contains uncertainty because the failures are revealed only at inspections. If a component fails between inspections, the exact failure time is typically unknown. The only information is that the failure occurred in some time interval between two adjacent inspection times. Accounting for this, ‘interval censored’ reality needs to be added to the MLE estimation method. In the likelihood function, the part corresponding to interval-censored data takes the form:

$$\prod_{j=1}^k \{F(u_j) - F(v_j)\} = \prod_{j=1}^k \{\exp(-H(v_j)) - \exp(-H(u_j))\}$$

where u_j is the time of inspection in which the j -th component was found failed, and v_j is the time of last inspection in which the j -th component was still operational.

Incomplete Data

In some situations it may be necessary to deal with incomplete covariate data. If some covariate values are missing in a record, the record is considered incomplete but can still be used in the MLE estimation. The Expectation-Maximization (EM) algorithm is a general method of finding

the MLE of parameters in an underlying distribution based on a given data set with incomplete or missing values.

Scarce Data

Sometimes historical failure data may be scarce. A commonly used practice for scarce data in Weibull analysis is known as Weibayes. The principle of Weibayes is to set the shape parameter β to a prior believed value and then to estimate the scale parameter η using the MLE procedure. This idea can be borrowed to handle scarce data in Weibull PHM analysis. Based on prior knowledge or belief (obtained, for example, from physical models), certain parameters in the Weibull PHM can be fixed to certain values, and then the remaining parameters in the Weibull PHM are estimated by MLE.

Another popular and effective approach for handling scarce data or even no data is the Bayesian approach. First, prior distributions of the parameters in the Weibull PHM are constructed from expert knowledge or belief. Then through Baye's Theorem, the prior distributions are updated to more credible posterior distributions (or estimates) of the parameters whenever new data is available.

Multiple Failure Modes

More than one failure mechanism or mode may be the cause of a part's failure. An accurate PHM analysis will be based on failure modes rather than simply lumping all failure modes for the part into one "compound mode". If the failure modes are identified and failures can be classified according to their modes, then it would be useful for the PHM software to automatically categorize the data record for a failure into the correct mode analysis.

Weibull PHM Model Selection

The final stage of constructing a Weibull PHM is to select the most appropriate set of covariates to be included in the model. The objective is to include only significant covariates in the model or exclude all the insignificant covariates from the model. An integral part of the Weibull PHM analysis is the systematic and scientific discrimination between the significant covariates and non-influential data. Although there is no straightforward procedure to identify significant covariates, the significance of the covariates can be determined through analysis of various statistics. EXAKT provides a Graphical User Interface (GUI) to assist users to find the most appropriate PHM for the data available (see Figure 7).

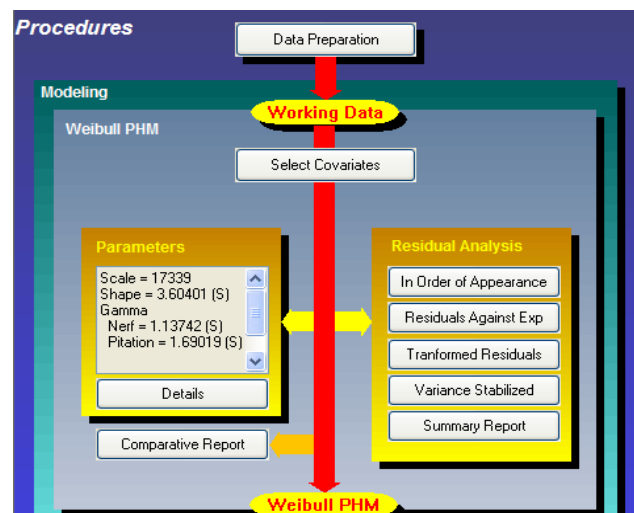


Figure 7: EXAKT GUI for Weibull PHM parameter estimation and model selection

Several standard statistical tests are available to assist the modeler in identifying significant covariates. The Wald test can be used to check various hypotheses of interest about the parameters. The test checks whether the difference between an assumed and estimated parameter value is significant or not by reporting an appropriate p-value. If the p-value is small then the assumed parameter can be rejected. The Wald test is conducted on the shape parameter (the hypothesis that $\beta=1$ is tested and if the p-value is small then the hypothesis that the working age is not an important variable is rejected). Similarly all covariate coefficients are tested (for the hypothesis that $\gamma_i = 0$) and if the p-value is small then the hypothesis that the i-th covariate is insignificant is rejected.

Another technique for model selection is to check whether a simpler sub-model can replace a more complicated one by using the chi-squared test based on the deviance change. The deviance is a numerical value obtained for every sub-model during the estimation procedure. The basic sub-model has the smallest deviance. The difference between the basic sub-model deviance and the deviance of another sub-model is called the deviance change. It is used for testing the hypothesis that two sub-models are statistically equivalent. For every deviance change, a p-value is calculated. For the basic sub-model, the deviance change is 0, and the p-value is 1, by definition. If the p-value for a sub-model is small, then this sub-model is considered not good enough to replace the basic one. If two non-basic sub-models are compared, then the one with the higher p-value can be considered as the one that better represents the data.

The method of Cox-generalized residual can be applied to test for evidence that the data points are well represented by the Weibull PHM. Residuals (i.e. the cumulative hazards) are calculated for every observed failure or suspension. The Kolmogorov-Smirnov test (K-S test) checks whether the residuals themselves follow, statistically, a negative exponential distribution as would be expected if the model fits the data. The test calculates the distance between the theoretical exponential distribution, and the distribution estimated from the residuals (adjusted for suspensions) and reports a p-value. If the p-value is small then the hypothesis that the model does not fit the data well can be rejected.

Covariate Behavior Models

Projection of significant covariate values in the future must be incorporated in Remaining Useful Life Estimation as they affect the equipment's propensity to fail in the future. Covariate projections vary with the types of covariates. We discuss two main types of covariate projection: duty cycle projections and sensor reading projections as follows.

Duty Cycle Projections

The inherent assumption is that the future operational attributes demonstrate only negligible variability (with the exceptions of unscheduled events such as trips) from that of the planned operational attributes. In practice, these plans may change considerably in time, but with every change new remaining useful life estimates will be calculated. In mathematical terms, virtually all the duty cycle attributes (with the exceptions of unscheduled events such as trips) are considered to be deterministic processes (i.e. their values in the future are known a-priori) and are direct inputs in the RULE calculations and do not require any further analysis (i.e. the

covariate behavior models are known). For unscheduled events such as trips, we will assume that they are random and their rate of occurrence is a function of other duty cycle attributes such as load level or firing temperature.

Sensor Readings Projections

Incorporating sensor data in Remaining Useful Life Estimation significantly complicates the covariate's behavior models. Sensor data demonstrate significant variability, and the construction of accurate prediction models of their future behavior is not a trivial task. Several approaches that may be utilized to create meaningful covariate behavior models are discussed as follows.

Stochastic State Transition Models

Stochastic state transition models are characterized by state transition probability or probability distributions. These types of models require that the possible range of values of the health indicator will be transformed into a series of discrete states (i.e. the continuous range is divided into a finite set of intervals, where each interval represents a different state). Once sets of discrete states for the health indicator have been established, the transition distributions between these states are analyzed using a similar technique to that used in survival data analysis. Transition probability densities between the states may depend only on the sojourn time of the present state (i.e. semi-Markov process) but may also depend on the sojourn times in previous states (non-Markov process). Finally, the distributions of the exact health indicator value within each state are analyzed. Construction of a stochastic state transition model is a two-step procedure:

1) **Determine covariates states** - In the first step, the ranges of values (i.e. the bands) that define the states of the covariates should be determined based on accepted data analysis techniques used for clustering observations. (Figure 8) The distributions of the covariate's values within each state should also be analyzed. The form of covariate distributions within each state can be expressed either by a probability histogram, or by the Beta distribution constrained to the boundaries of the state bands. Alternatively, determination of covariate bands may be based on expert knowledge on the behavior of covariates. For example, different levels of warning limits on covariates may be helpful to determine the covariate bands

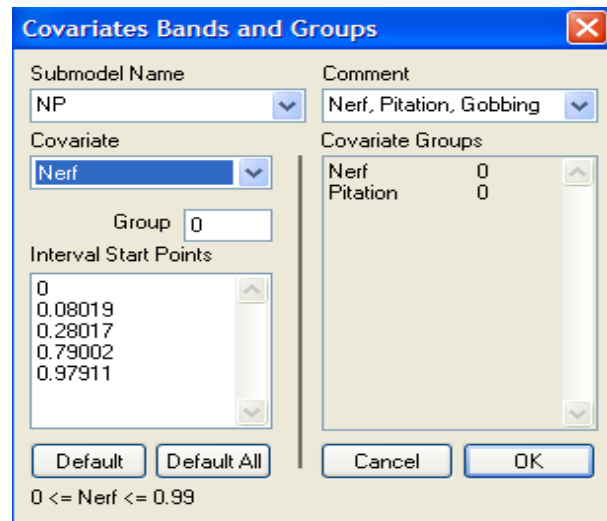


Figure 8: Covariate bands determination

2) **State transition distributions analysis** - In the second step, the transition probability densities between the states are defined. As these probabilities may depend not only on the sojourn time of the present state (i.e. semi-Markov process) and the duty cycle attributes but also on the sojourn times in previous states (non-Markov process). Both semi-Markov and non-Markov processes can be modeled as PHM in which the sojourn times in previous states may

prove to be significant (for non-Markov processes) or insignificant (for semi-Markov processes) covariates.

Time Series Models

There are two main disadvantages using stochastic state transition models. The first is the “curse of dimensionality” due to the exponentially increasing number of states as the number of covariates increases. The second disadvantage is the loss of information due to the discretization of some covariates in continuous scale into discrete bands. Utilizing time series models (in place of transition models) immediately eliminates these two disadvantages.

Time series models attempt to identify patterns or trends of covariates over time. A typical time series model is the Autoregressive Moving Average (ARMA) model that is described by

$$\mathbf{X}_r = \boldsymbol{\varphi}_0 + \boldsymbol{\varphi}_1 \mathbf{X}_{r-1} + \boldsymbol{\varphi}_2 \mathbf{X}_{r-2} + \cdots + \boldsymbol{\varphi}_p \mathbf{X}_{r-p} + \mathbf{A}_r - \boldsymbol{\theta}_1 \mathbf{A}_{r-1} - \boldsymbol{\theta}_2 \mathbf{A}_{r-2} - \cdots - \boldsymbol{\theta}_q \mathbf{A}_{r-q}$$

where \mathbf{X}_r and \mathbf{A}_r are the covariate vector and the white noise at time r respectively, p and q are order parameters, $\boldsymbol{\varphi}_i$ and $\boldsymbol{\theta}_i$ are coefficient parameters. There are three steps in developing a time series model: model identification, model estimation and model validation. For more time series models and more detail in building time series models, the reader is referred to the book by Brockwell and Davis (2002).

Non-Linear Regression Models

The underlying assumption behind non-linear regression models approach is that sensor readings demonstrate trends and these trends can be described by underlying functions of time (i.e., the component deteriorates with time and the sensor readings reveal and correspond to the levels of deterioration). The form of underlying function to which the data is fitted should therefore be based on an engineering model associated with the physics of the failure mode. However, if an appropriate engineering model cannot be predetermined then the form of function, which demonstrates of being the best fit for multiple histories of data, could be selected. The option to use non-linear regression methods, in which the data points are associated with weight that increases with time of the measurement, is also being explored.

Remaining Useful Life Estimation – PS-PLUS RULE Model

The calculation of the expected remaining useful life distribution of a system requires:

- a) The ability to model the covariates’ behavior as a function of time.
- b) The ability to change the failure modes’ distribution parameters dynamically while conserving the age of the components (or in other words, in a sampling process there is a need to take into account the cumulative damage of the components at instances at which the components’ failure modes’ distributions change because the covariates’ values have changed).
- c) The ability to initialize to the current state of the system (taking into account the cumulative damage since the time of the last inspection up to the current time on the failure modes’ distributions).

PS-PLUS is a SPAR™ based application that uses the Monte-Carlo (MC) method to predict, among several types of predictions (see Figures 10 and 11), the expected remaining useful life distributions of systems. The current RULE model already incorporates the bill of materials of the system and reliability block diagrams to provide system level information. The RULE model is associated with a Graphical User Interface (GUI) that allows “what if” analysis to include situation setup and output analysis. Users enter a planned duty cycle as an input and the GUI displays the impacts on the remaining life of the system and the criticality of components and their failure modes to system performance (see Figures 12 and 13). This is accomplished by running the simulation model that incorporates both past duty cycle attributes experienced by the system to initialize the system to its current state, and, the planned duty cycle to simulate the times of system failures.

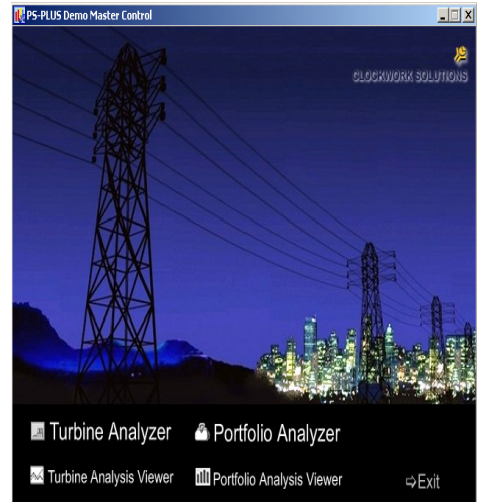


Figure 9: PS-PLUS Graphical Interface

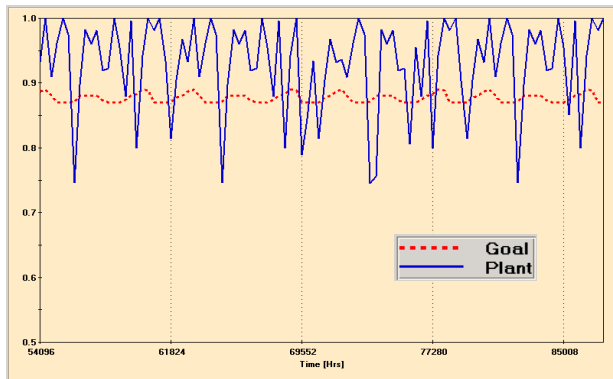


Figure 10: PS-PLUS Production Efficiency Predictions

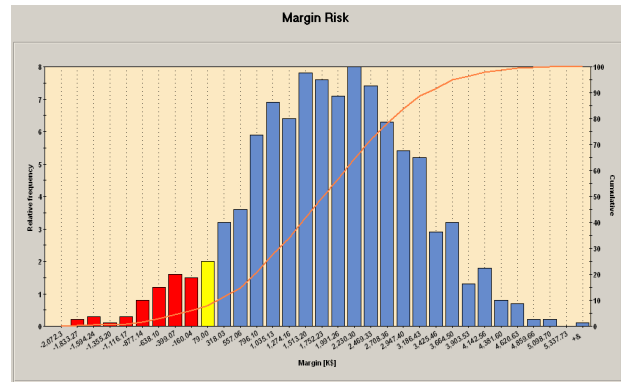


Figure 11: PS-PLUS Cost Margins Predictions

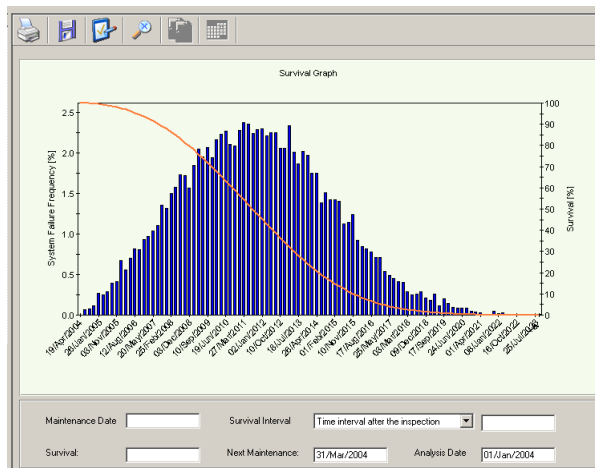


Figure 12: PS-PLUS Remaining Useful Life Estimation Graph

Component	Description	Failure Mode Name	Damage at Inspection	Survival to Interval
1	Inlet Guide Vanes 1	Inlet Guide Vanes 1 of 1	N/A	5.7135E-05
2		Cracking	5.7135E-05	9.9998E-01
3	Stage 1 Blades 1	Stage 1 Blades 1 of 20	N/A	4.4365E-05
4		Cracking	4.4365E-05	9.9998E-01
5	Stage 1 Blades 2	Stage 1 Blades 2 of 20	N/A	4.4365E-05
6		Cracking	4.4365E-05	9.9998E-01
7	Stage 1 Blades 3	Stage 1 Blades 3 of 20	N/A	4.4365E-05
8		Cracking	4.4365E-05	9.9998E-01
9	Stage 1 Blades 4	Stage 1 Blades 4 of 20	N/A	4.4365E-05
10		Cracking	4.4365E-05	9.9998E-01
11	Stage 1 Blades 5	Stage 1 Blades 5 of 20	N/A	4.4365E-05
12		Cracking	4.4365E-05	9.9998E-01

Figure 13: PS-PLUS Components and Failure Modes Criticality Table

The RULE model within PS-PLUS shall be extended to incorporate both deterministic and stochastic covariates' behaviors and their affects on the hazards. PS-PLUS, which utilizes the SPAR simulation engine, also consists of clocks (to model events in which covariates change their values) and is capable of dynamically changing distributions at events while conserving the cumulative damage (i.e. cumulative hazard).

Summary

In this manuscript, we have presented a conceptual design of hybrid PHM-MC prototype application for advanced Remaining Useful Life Estimation of gas turbines. For each critical component in a gas turbine, a PHM is established in EXAKT to relate both the working age and condition information (covariates) of the component to its risk of failure. Then a stochastic model is developed to describe the behavior of covariates included in the PHM. This covariate behavior model is required in the calculation of RULE when the future values of some covariates are unknown. Finally the SPAR Monte-Carlo simulation engine is used to simulate the remaining useful life distribution of the gas turbine based on its system structure (described by reliability block diagrams in SPAR), the PHMs built for its critical components, and the covariate behavior model built for associate covariates.

The potential benefits of utilizing the proposed hybrid PHM-MC prototype are:

- a) Providing more accurate remaining useful life estimation, with more confidence;
- b) Achieving more effective and adaptive condition-based maintenance;
- c) Reducing unnecessary costly maintenance and overhauls, and hence achieving higher availability at lower cost.

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