System Level Life Cycle Cost Estimation and Maintenance Optimization P&W and Siemens Project Final Report 2010

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Abstract

The prime objectives of this project is developing a reliability-based approach for quantifying system wide gas turbine life cycle cost and performance and identifying the impact of reliability metrics on scheduled maintenance and repair. The uniqueness of the chosen approach stems from combining a light-weight fully graphical means of modeling (Stochastic Petri nets) with a compressed representation of coupling between components behavior thus avoiding a fully coupled model that tracks all the components of a gas turbine simultaneously. Realistic field processes are modeled in sufficient detail to capture relevant trends to quantifying maintenance costs.

Modeling: steps

The following critical parts to a successful system modeling are identified:

1. Modeling of a maintenance process for an individual component
2. Modeling condition-based maintenance effects
3. Coupling modeling

These three steps are described below in more detail

Uncoupled component model

First, the maintenance model for a single failure mode of a single component is developed. In general, we can identify three possible triggers for maintenance actions: time-based (regardless of the operating conditions), usage-based, and health-based. The first two triggers are cumulative in nature and therefore require continuous "monitoring" (in the case of the time-based maintenance either hours of operation or cycles are tracked). In contrast, health parameters might or might not be dependent on the history of the component, and so both periodic and continuous monitoring of those parameters are possible.

Figure 1 describes a representative maintenance process for a single component. The details of this process as well as the corresponding modeling using Stochastic Petri Nets is provided next.

Inspection

During the inspection, the components are sorted into three categories:

1. "Good" - component can be returned to service without any maintenance action.
2. "Repair needed" in this scenario, a partial reset of the component's age potentially can take place. However, in the present version repair restores the functionality of the component without affecting the effective age of the component.
3. "Replacement needed", component is replaced with a new one (so the age is reset to zero).

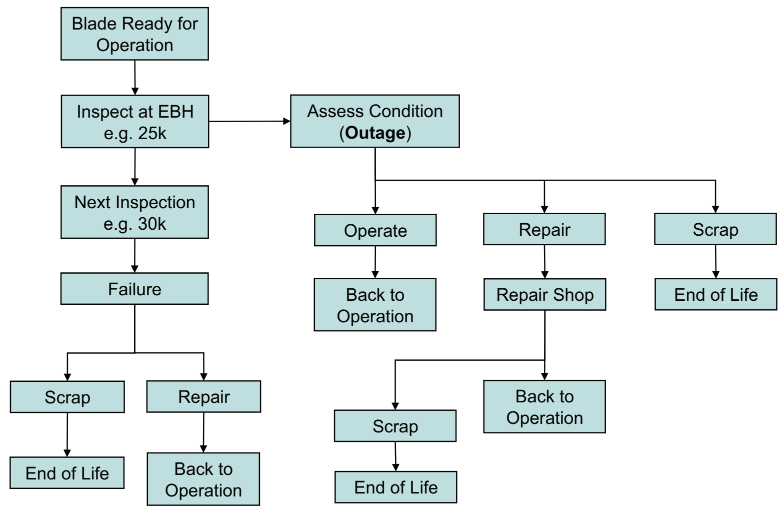

Figure 1: A representative maintenance process (Siemens)

Stochastic Petri Nets

There are two main distinguishing features of Stochastic Petri Nets (SPN) [1, 2]:

1. SPN can provide a decomposed description of the system state
2. There are objects dedicated to the description of dynamic changes occurring to the system

Effective system modeling using SPN involves its decomposition into a set of relevant entities; where each entity does not necessarily represent a physical component of the system, as it might, for example describe a phase of operation, or environmental condition (this is often referred to as component-based description). In such a setting, a combination of the states of each component describes the system as a whole implicitly, without the need to explicitly depict the corresponding system state, which potentially provides a remedy against state-space explosion. This can be contrasted with the earlier described Markov chains which rely on the explicit description of each system state.

The second unique feature of Petri nets is a separation of the model into a static (structural) part and a dynamic part with the latter visually describing the changes occurring to the system during the modeled time segment. The structural part is described by places (denoted as large hollow circles) corresponding to possible states of the systems entities and transitions corresponding to possible paths of changes between the system states (depicted as filled rectangles), or connections among the states. In other words, places can be connected to each other by means of transitions. These connections always have a specific direction: directed arcs flow from places to transitions and from transitions to places to reflect this direction. The dynamic part of the modeling is implemented by so-called tokens depicted as small filled circles initially occupying some of the places that can move (fire) between places along the directed arcs in accordance with the timing specified by the corresponding transitions. Unlike general simulation tools (e.g., Arena, etc) system reliability tools (fault trees, RBDs, Markov chains) rarely provide standard means for visualizing such dynamic changes.

Transition fires after being enabled for a specified amount of time. A transition is enabled if all its input places have tokens, although additional conditions may be specified as well (e.g., see inhibitors below). Transitions are classified in accordance with the delay between the enabling of a transition and its firing; such a delay can be absent (an immediate transition), deterministic, or sampled from a given distribution (stochastic). Upon firing, a transition removes a token from its input place and deposits a token to its output place. If, as in so-called colored Petri nets, tokens have unique identities (labels), an alternative interpretation of firing facilitates the preservation of the information about the systems past states: rather than considering removing a token from the transitions input place and depositing a (different) token to the output place as two disjoint actions, one can unite these two actions into a single action of moving the same token from an input place to the output place. Memory (continuously changing labels) can be assigned to tokens (the result is aging tokens.) [2]. Such tokens can move freely throughout the Petri net without losing their memory.

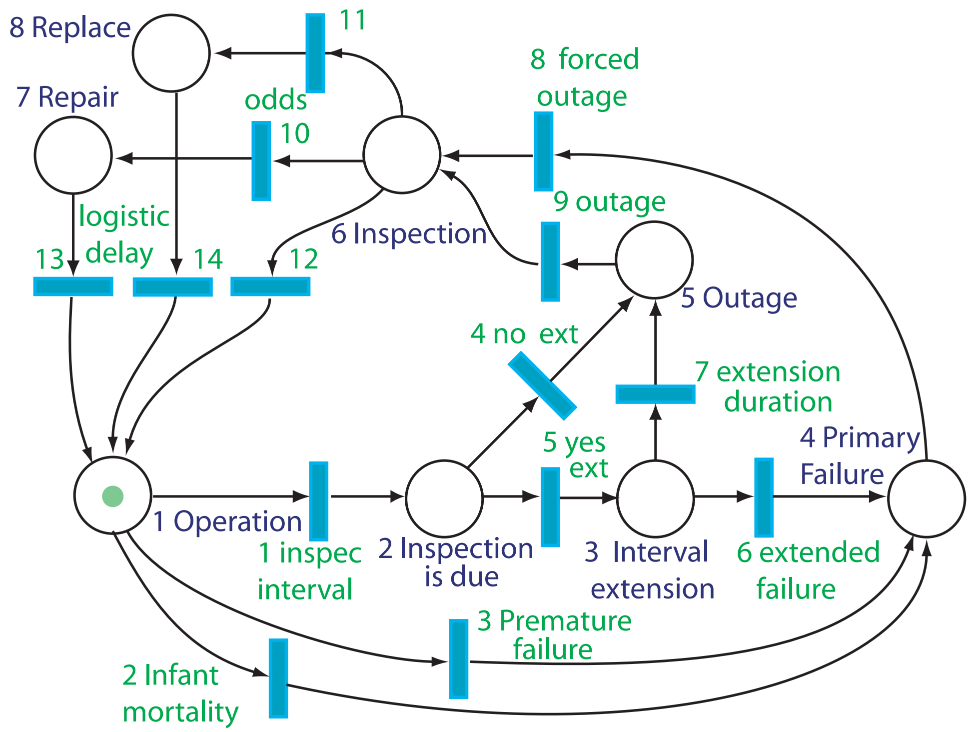

Figure 2: SPN model for a single failure mode

Firing delays for timed transitions can be interpreted by associating backward clocks: the clock starts when transition gets enabled, and once the clock reaches zero, the firing takes place. In standard SPNs, this clock is associated solely with the transition, and if more than one token is present in the input place, the token to be fired is selected at random. With aging tokens, a clock can be associated with a token-transition pair, which allows several clocks to run simultaneously for a single transition, and often results in a more compact model.

Following the process described in Figure 1 a model for a single failure mode for a given component is created Fig. 2. The following states of the component are included: operation (1), inspection is due (2), operating in extended interval regime (3), failure (4), Outage (5), inspection (decision fork) (6), replacement (8) and repair (7).

Additional features of the model include:

1. An infant mortality failure mode. This is incorporated by introducing a transition 2 "Infant mortality" from state 1(Operation) to state 4 (Failure) that follows Weibull distribution with the shape parameter $\beta < 1$, see Fig. 2

2. The model accounts for age-dependence: as the time of operation progresses the chances of the part to be scrapped follow Weibull distribution and similar distribution is provided for the repair levels.

3. Introducing extension to the regular maintenance. Transitions 4 and 5 are introduced to account for the choice between going for an extended interval of operation (5) or not (4). If no extension is provided the token moves to state 5 and scheduled outage takes place for the duration specified by transition 9. If an extension is granted, the token moves to state 3, from where it can either safely go to the schedule outage place (through transition 7 that provides the delay corresponding to the duration of the extension), or the part can fail during that extension period (transition 6), with the rate of this transition that can be made slower that the original Weibull corresponding to the aging of the component, if we account for the fact that some health assessment has been made to justify the extension of the operation interval.

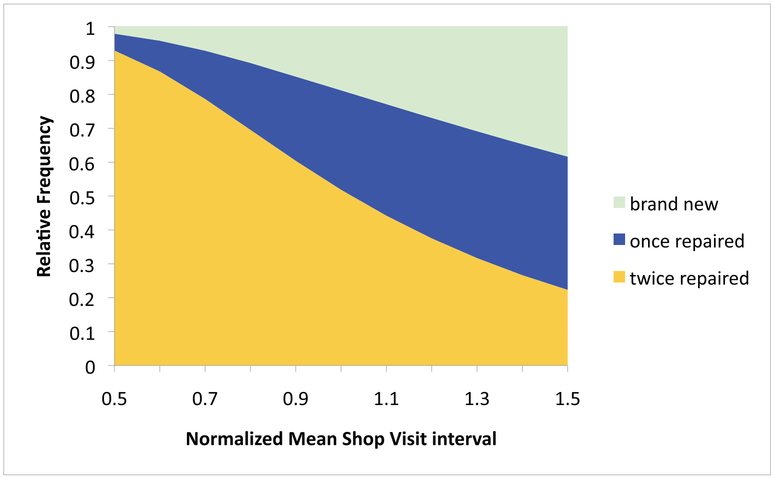

Figure 3: Fraction of the blades replaced after the first, second, and third shop visit as a function of engine mean shop visit interval

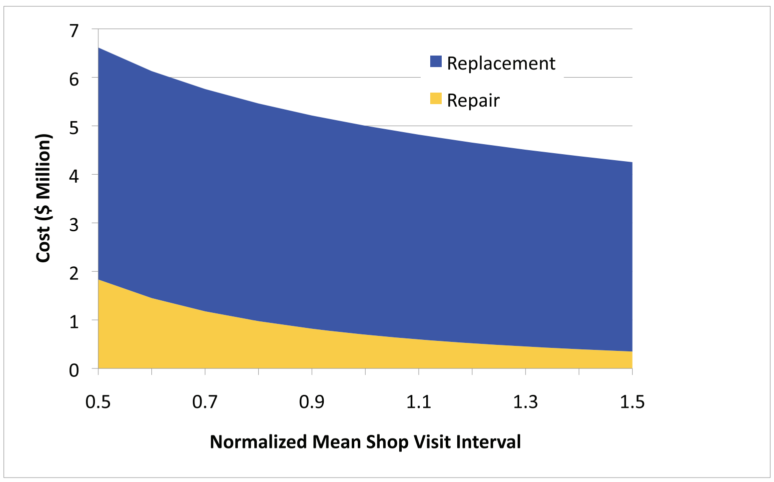

Figure 4: Expected costs as a function of engine mean shop visit interval

Pratt and Whitney simple scenario

Sensitivity of repair or replacement to refurbishing and overhaul mean time. Costs for blade maintenance 100k hours of operation of 10 engines (80 blades per engine).

Each blade repair is 500; replacement is $5,000$. Baseline scenario corresponds to mean time for engine shop visit of $37,600$ hours for new engine and $34,400$ hours for mature engine. Those times follow Weibull distributions with shape parameter $\beta = 6$ and 5, respectively. Upon the first visit to the shop 21% of blades are scrapped (while the rest is repaired), while for the during the second visit 40.8% of blades are scrapped (all blades are replaced upon the third visit to the shop.

Given the replacement rates, a Weibull distribution is fitted to describe the chances of replacement as a function of operational hours. Next, the sensitivity with respect to the engine mean shop visit interval. Figure 3 shows the steady-state results for the fractions of blades that are replaced after one, two, and three visits to the shop. The horizontal axis is the normalized mean shop visit interval (1 corresponds to the baseline, while other values correspond to the proportional adjustments of the Weibull scale parameters for the visit (shape parameters are kept the unchanged). Figure 4 shows the total maintenance costs as a function of the mean shop visit interval (the horizontal axis has the same meaning as in Figure 3).

Since the risk of failure is not considered in this scenario, the costs are decreasing as the shop visit become less frequent.

Event	Norm cost per blade
Replacement	1
Repair	0.54
Major inspecion	1
Minor inspecion	0.06
Failure	54

Figure 5: Normalized cost per event

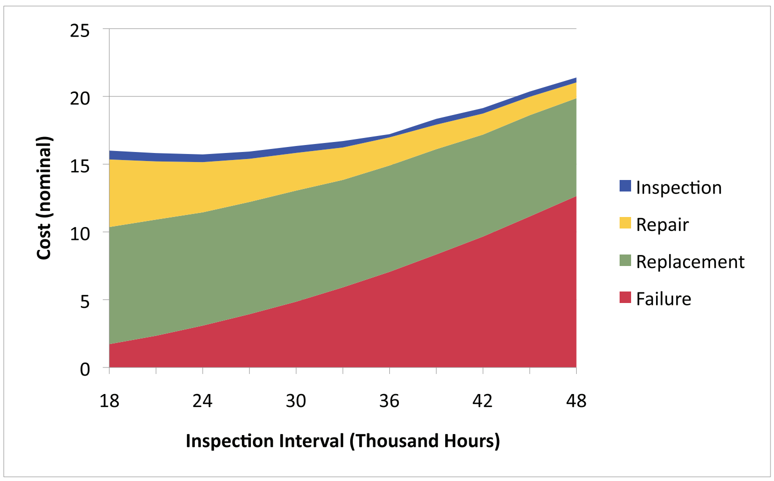

Figure 6: Total costs for 200, 000 hours of operation per blade. Removed during inspection blades have the same MTTF as the ones that passed the inspection

Siemens simple scenario

Next, a Siemens scenario that follows the process described in Figure 1 is considered. After expected frequencies of relevant events (failures, inspections, replacement) are estimated, total costs of a given maintenance policy can be evaluated. In Figure 6 total costs of 200, 000 hours of operation per blade is shown as a function of the inspection interval (here the costs of individual events are provided in Figure 5). The baseline inspection interval is 24, 000 hours. Note that in this case inspection (and removing portion of the population) does not impact the risks of failure for the remaining population. In other words, during the inspection both removed and remaining blades follow the same distrbution. In contrast, Figure 7 shows the total costs where the same baseline risk of failure is used, but the removed during inspection blades have mean time to failure (MTTF) that is one third of the blades that passed the inspection and remained in service. One can observe that there is a larger sensitivity to the inspection interval in this case. This calculations provide a motivation for the need to quantify the effectiveness of the inspection and replacement process.

Temperature as a usage/health parameter

First, the following scenario is considered: inspection intervals are established based on monitoring temperature $T(t)$. Here the interpretation of the use of the temperature can be twofold:

1. On the one hand, the temperature can characterize the usage of the component, and if is known precisely, provides a mechanism for determining the age of the component $\eta(t) = \int_0^t g(T(\tau))d\tau$. Here the age η is the cumulative distribution function (CDF) for a given failure mode that follows a known distribution (e.g., Wiebull or lognormal).

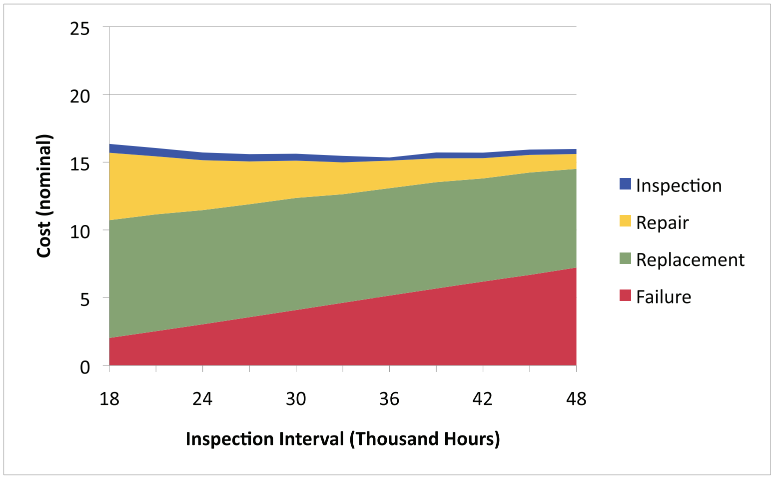

Figure 7: Total costs for $200,000$ hours of operation per blade. Removed during inspection blades have MTTF 1:3 compared to the ones that passed the inspection

2. On the other hand, the measured temperature can be considered a performance parameter indicating the health of the component, and therefore related to the component age, e.g., $\eta(t) = g(T(t))$

Since the temperature is not measured precisely, instead of $T(t)$ we actually measure $\tilde{T}(t)$, so the age is determined with a certain level of uncertainty as well.

In order to model the sensitivity of the procedure with respect to the knowledge about the temperature (including), we introduce variability of the maintenance interval. The better the knowledge about the temperature, the lower standard deviation of the interval (when measured in terms of the equivalent hours of operation).

Failure time distribution for a given strength and varying operating temperature

Let us consider that the sole source of uncertainty is the operating temperature. Then, for a fixed operating absolute temperature T, the failure time t is uniquely determined. First, we recall Arrhenius equation for the rate of chemical reactions, k, $k(T) = a \exp\left(-\frac{E_a}{RT}\right)$, where a is a pre-exponential factor, E_a activation energy, and R gas constant. So, if we have consider some two temperature T and compare the time of failure for the temperature T_0. First one can evaluate the corresponding rates k and k_0, noting the times of failure t_0 and t are related as $k_0 t_0 = kt$, so we can deduce that

$$t = g(T) = t_0 \frac{k_0}{k} = t_0 \frac{\exp\left(-\frac{E_a}{RT_0}\right)}{\exp\left(-\frac{E_a}{RT}\right)} = t_0 \exp\left(\frac{E_a}{RT} - \frac{E_a}{RT_0}\right) = \alpha \exp\left(\frac{\beta}{T}\right) \tag{1}$$

Here for convenience we introduced constants $\alpha = t_0 \exp\left(-\frac{E_a}{RT_0}\right)$ and $\beta = \frac{E_a}{R}$. Next we consider that the operation temperature is normally distributed with the mean value T_0 and the standard deviation σ, so that the probability density function has the following form:

$$f_T(T) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(T - T_0)^2}{2\sigma^2}\right] \tag{2}$$

Let us invert Eq. 1 to obtain the inverse the relationship between the T and t:

$$T = g^{-1}(t) = \frac{\beta}{\ln\left(\frac{t}{\alpha}\right)} \tag{3}$$

Taking the derivative of this function:

$$\frac{dg^{-1}(t)}{dt} = -\frac{\beta}{t\left[\ln\left(\frac{t}{\alpha}\right)\right]^2} \tag{4}$$

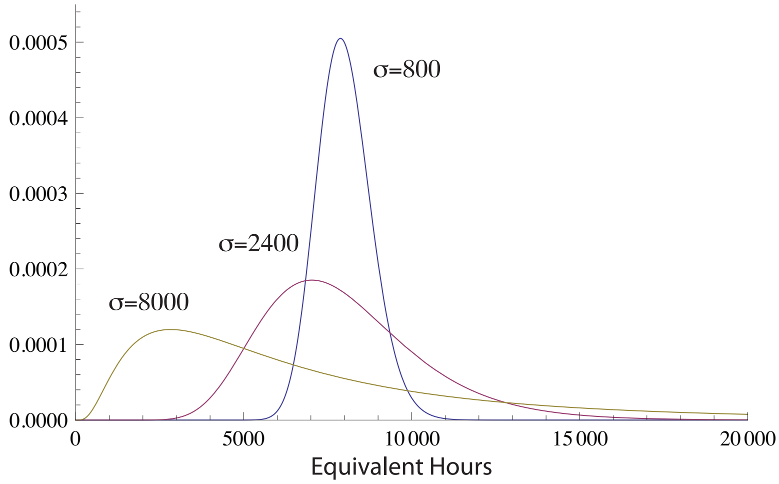

Figure 8: Lognormal distributions used as inputs for inspection interval. The same mean $\mu = 8000$ hours is used for all three distributions, but changes in standard deviation are used to model the changes in precision of estimating temperature profile of the component

We can ascertain that this derivative is always negative, and, as expected, there is one-to-one relationship between the operation temperature and the failures time. Therefore we can apply the formulae for the function of a random variable to calculate the probability density function for the time failure

$$f_t(t) = f_T(g^{-1}(t)) \left| \frac{dg^{-1}(t)}{dt} \right| = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{\left(\frac{\beta}{\ln\left(\frac{t}{\alpha}\right)} - T_0 \right)^2}{2\sigma^2} \right] \frac{\beta}{t\left[\ln\left(\frac{t}{\alpha}\right)\right]^2} \tag{5}$$

Coupling Effects: Mean field model

The model include the impact of the maintenance schedule of other failure modes for this component, as well as the maintenance schedule for other components (opportunistic maintenance).

First let us consider a simple model of aging components with the age-based replacement with several cases being introduced. We compare a fully coupled model (A) with the mean field approximation (B,C). Only opportunistic maintenance is considered first, and there are five identical components: if any of the component fail, all other components are replaced. Mean field approximation model is constructed as follows: we have a model for a single component that includes opportunistic replacement with exponential distribution (B) and Weibull distribution with the same shape parameter as the component failure distribution ($\beta = 3$) - (C). The results for three sets of parameters are presented in Fig. 10. In Case 1-1 replacements take place more often relative to the failures: the scale parameter is $100,000$ hours, while the replacements are every $20,000$ hours. One can observe that in this case the use of exponential distribution in mean field approximation suffices to predict both failures and scheduled repairs. Case 1-2 has the same frequency of replacement but the scale parameter of the failures is reduced in half. In this situation the use of exponential distribution for opportunistic maintenance in the mean field approximation still provides a good estimation of the failures, but the estimate of scheduled repairs is off (highlighted in yellow). Finally, Case 1-3 has the same failure distribution as Case 1-2, but the replacements are only every $100,000$ hours (selected so that the planned inspections are so rare that they effectively never occur, *i.e.,* all replacement are opportunistic). In this situation the use of exponential distribution is not appropriate as both expected frequencies of failures and opportunistic maintenance are not predicted correctly (as highlighted in yellow). As expected, using the same Weibull shape parameter $\beta = 3$ for the failure and for the opportunity leads to a very good mean field approximation. Importantly, while the shape of the opportunistic maintenance distribution is assumed ($\beta = 1$ for B and $\beta = 3$ for C), the scale is obtained automatically based on the balance between the effective total number of opportunities, and those implied by the failures (see Fig. 9). The limits of using the "default" (exponential) type of the distribution for opportunity is investigated. The considered case is effectively an

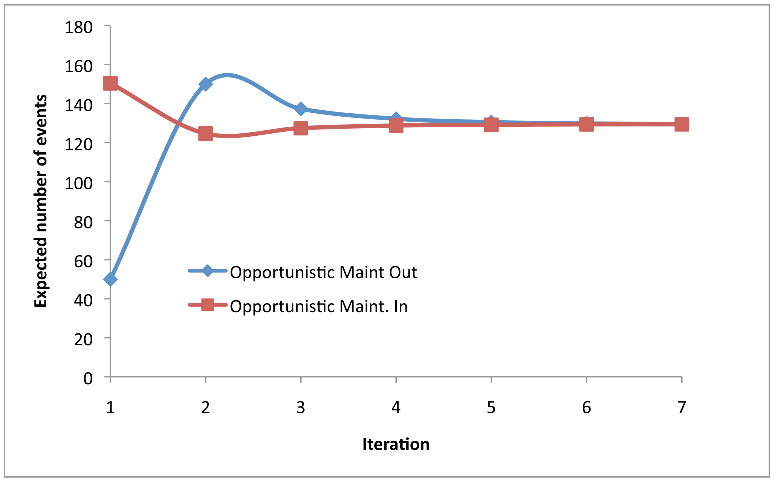

Figure 9: A typical example of Convergence of the effective total number of opportunities (output) , and those implied by the failures (input)

	Case 1-1	Weibull 100k	replacement 20k
	Failures	Sch Repairs	Opport Main
A coupled	1.96	240.21	7.85
B mean field exp	1.97	241.83	7.96
	Case 1-2	Weibull 50k	replacement 20k
	Failures	Sch Repairs	Opport Main
A coupled	14.69	193.86	58.76
B mean field exp	14.74	208.94	58.63
C mean Weibull β=3	14.75	193.76	58.84
	Case 1-3	Weibull 50k	replacement 100
	Failures	Sch Repairs	Opport Main
A coupled	37.86	0.00	151.44
B mean field exp	50.34	0.00	201.28
C mean Weibull β=3	37.87	0.00	151.44

Figure 10: Comparing the results for Case 1 - expected number of events for $1,000,000$ hours of operation

extreme case (as the opportunity follows a very "pure" pattern), as the number of components and their heterogeneity increases, it is expected that exponential distribution will perform better, as it is known that a combination of many rare-event processes converges to a Poisson process [3]. Alternative strategy for establishing the proper types of distributions for the opportunity will be explored as well.

Key results

1. A Model for individual failure mode for a given component is developed and initial results presented. The model has been further revised to better reflect the actual processes of the sponsors (both Pratt & Whitney and Siemens).

2. Simple trade-offs for total costs of operation for individual components have been demonstrated. In particular, in was shown that an optimum inspection interval that minimizes life cycle cost depends on the effectiveness of the inspection in removing blades that are more likely to fail.

3. A process for modeling effects of condition-based maintenance has been developed.

4. Procedure for rolling up models for individual failure modes for a given component has been developed. This procedure allows for including competing failure models as needed and the following coupling

effects:

(a) Failure coupling: induced, secondary, or cascading failure: failure of a component is induced by the failure of another components. For each component model cumulative probability (possible as a function of the phase of the inspection interval) of an induced failure is included.

(b) Maintenance coupling: opportunistic maintenance. For each component, additional replacement and inspection opportunities are incorporated similar to the the induced failure.

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