A PROGNOSTIC MODELING APPROACH FOR PREDICTING RECURRING MAINTENANCE FOR SHIPBOARD PROPULSION SYSTEMS

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Abstract: Accurate prognostic models and associated algorithms that are capable of predicting future component failure rates or performance degradation rates for shipboard propulsion systems are critical for optimizing the timing of recurring maintenance actions. As part of the Naval maintenance philosophy on condition based maintenance (CBM), prognostic algorithms are being developed for gas turbine applications that utilize state-of-the-art probabilistic modeling and analysis technologies. NSWCCD-SSES Code 9334 has continued interest in investigating methods for implementing CBM algorithms to modify gas turbine preventative maintenance in such areas as internal crank wash, fuel nozzles and lube oil filter replacement. This paper will discuss a prognostic modeling approach developed for the LM2500 and Allison 501-K17 gas turbines based on the combination of probabilistic analysis and fouling test results obtained from NSWCCD in Philadelphia. In this application, the prognostic module is used to assess and predict compressor performance degradation rates due to salt deposit ingestion. From this information, the optimum time for on-line waterwashing or crank washing from a cost/benefit standpoint is determined.

Keywords: Compressor Cooling, Cost/Benefit, Prognostics

Nomenclature:

C, F – Normal Distributions
N – Speed
P – Pressure
Q – Volumetric Flow
S – Weighted Coefficients
T – Temperature
y - Predicted Value

CIT – Turbine Inlet Temperature
CDT – Turbine Discharge Temperature
CDP – Compressor Static Discharge Pressure
CDP_T – Compressor Discharge Total Pressure
TIT – Turbine Inlet Temperature

Φ - Normalized Cumulative Distribution
α - Weighting Factor
γ - ratio of Specific Heats
σ - Standard Deviations
τ - prediction interval

Introduction: With a growing presence of gas turbine technologies, a stronger focus is being placed on trade-off analysis between performance optimization and O&M costs. As a result, cost/benefit evaluation of performance recovery methods has been at the forefront of these efforts. In both the military and private sectors, reducing the extra costs encountered by degraded performance parameters such as fuel consumption or power loss, have prompted research into prognostic and diagnostic technologies. Kurtz et al (2000) gives an excellent discussion of many performance degradation mechanisms; the majority of which are recoverable either through washing procedures, variable geometry adjustment or component replacement. However, optimization of both compressor crank and on-line washing intervals from the standpoints of fuel consumption and proactive maintenance is of primary interest to the US Navy and the focus of this paper.

The economic benefits associated with an optimized and condition-based on-line and off-line waterwash predictor are significant. Research by Haub et al (1990) showed that as much as 1188 Mw-hrs could be saved through the use of on-line washing. Additional savings of 450 MW-hrs was attributed to reduced maintenance costs and extended operating time between crank-washings. The study performed by Peltier et al (1995) showed that the use of on-line washing decreased average performance degradation from 1% per 100 operating hours without on-line washing to 0.2% per 100 operating hours with on-line washing.

An automated process is desired that is capable of detecting the severity of compressor fouling and relating that to the optimal time to perform maintenance based on O&M costs. When a compressor undergoes fouling, several key performance factors are affected. The most sensitive of these factors is the compressor capacity or referred mass flow Peltier et al (1995). This is because loss of capacity comes from throat blockage and increases in roughness on the suction side of the blading. Unfortunately, in most practical naval applications, compressor capacity is not reliably determinable. The compressor outlet temperature and discharge total pressure can typically be used to find compressor efficiency (Boyce 1995) however CDT, CDP_T are not standard sensors in most Naval platforms.

$$\eta_{adb} = \frac{\left[\left(\frac{CDP_T}{CIP_T}\right)^{\gamma-1/\gamma} - 1\right]}{\left[\left(\frac{CDT}{CIT}\right) - 1\right]} \tag{1}$$

Compressor fouling has also been shown to increase vibration, (Ozgur et al (2000) and Tsalavoutas et al) but there are many drawbacks to using this method to predict fouling severity. First is the complexity of separating out other modes that contribute to vibration increases and secondly is the poor reliability with which performance degradation severity may be assessed. In lieu of these practical issues, a primary goal of this effort was to be capable of predicting the optimal time to waterwash or crankwash using only the most essential parameters that are

currently available on most Naval installations. Specifically, the developed technique utilizes available performance parameters such as fuel flow and CDP, relates them to performance degradation levels utilizing the prognostic model, and then predicts the optimal timing for cleaning procedures.

Accelerated Fouling Testing on the LM2500 and Allison 501: The prognostic model was developed based on data from fouling tests taken at NSWCC in Philadelphia, PA. In order to simulate the amount of salt the typical Navy gas turbine is exposed to on a normal deployment, a 9% salt solution was injected into the engine intake. Over the course of the entire test (3 days) approximately 0.0057m^3 of salt was used to induce compressor degradation at four different load levels (1/3, 2/3, standard and full load levels or "bells"). This method of testing was performed on both Allison 501 and LM2500 Units. Figure 1 shows a borescope image of the salt deposits on the LM2500 1st stage blading.

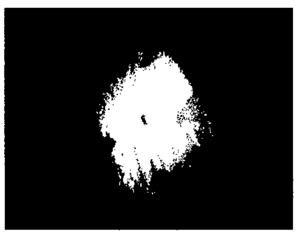

Figure 1 – Borescopic Image of salt deposits on 1st stage blading

In addition to fouling the two engines, testing was also performed on the effects of on-line washing for the Allison 501. The machine was crank washed and fouling was reinitiated. Specifically, at approximately 2% CDP drops, an on-line waterwash was performed using detergent. This cycle was completed 4 times at four different load levels.

During the testing, several of the critical parameters were monitored and their response to degradation was tended. Table 1 contains the measured parameters with their units and ranges (Shaft RPM and Ngg are for the LM2500 testing only).

Table 1 – Recorded Parameters from the DCS

Parameter	Units	Ranges
N_{gg}	RPM	0→9575
Q_{fuel}	GPM	0→97
TIT	°F	0→2000
CDT	°F	0→1468
CDP	psig	0→300
CIT	°F	0→500
Load	k-lbf	0→300
Shaft RPM	RPM	0→274
$P_{barometric}$	inHg	

This list is much smaller than the *Required Instrumentation List* for performance testing purposed by Kurz et al (1999), it represents a much more realistic view of what instrumentation is actually installed on Naval platforms with the exception of CDT. However, through the use of experienced-based correlations, compressor degradation can still be accurately monitored. This

reduced list emphasizes how the methods described in the next section can bypass the need to know all the state variables at all the key gas turbine stations and still be able to track important performance parameters and their trends. The focus is to generate reliable indicators of compressor fouling not necessarily standard thermodynamics features.

Degradation Features: Before any performance features was generated the test data was referred (corrected) to standard day conditions to account for the changing environmental conditions that occurred over the three days of testing. In addition, due to difficulties in holding water brake load constant in the LM2500 test, corrections were also made for speed variations at the various load levels as well. Therefore, correction curves were developed for Q_{fuel} vs. N_{shaft}, CDT vs. N_{shaft} and CDP vs. N_{shaft} to compensate for the fluctuations encountered during testing.

As previously stated, the best features for identifying compressor degradation would be compressor capacity and total pressure ratio changes. The latter feature not only accounts for changes in static pressure drop but also losses in axial velocity due to wake losses and blade exit angle distortions. With total pressure measurements absent there is not enough information to calculate compressor adiabatic efficiency in its strict form (as was shown in eq.1).

Alternately, Eq.2 may be used whose components are shown in Figure 2.

$$\eta_{adb} = \frac{(h_{3t} - h_{1t})_{ideal}}{(h_{3t} - h_{1t})_{actual}} \tag{2}$$

where: $h = Cp(\Delta T)$

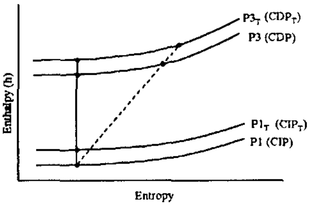

Figure 2 – H-S diagram

With the knowledge of inlet mass flow (and hence velocity) at various load levels and associated bleeds (for an unfouled compressor) obtained from experience, an pseudo-efficiency feature may be calculated which cannot account for axial velocity changes. However, this feature was acceptable considering the degradation feature of interest is the percent change in performance. It should be noted that the Navy intends to place total/static pressure probes on certain K-17s and LM-2500's to improve the accuracy of these fouling features and performance assessment capabilities.

Figure 3 shows the pseudo-efficiency as compared to an unfouled state for the 501–K17 test. Four waterwash events occur in this data set. It is important to note the trend in non-recoverable losses that will require a compressor crank wash, or more detailed overall, to recover.

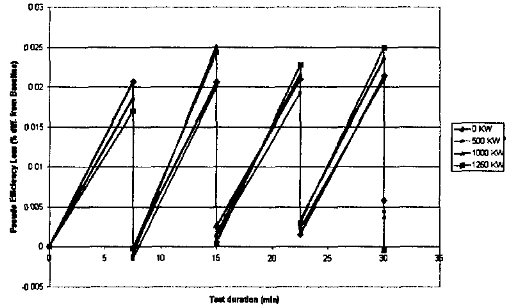

Figure 3 – Fouling / Waterwash Test Results

In addition to this feature, it was found that at higher loads Static Pressure Ratio, CDT and Fuel Flow were all major indicators of degradation due to fouling. The increase in CDT was relatively minor and even risks overlapping thermocouple sensitivity. These results from the LM2500 test are shown in Figure 4.

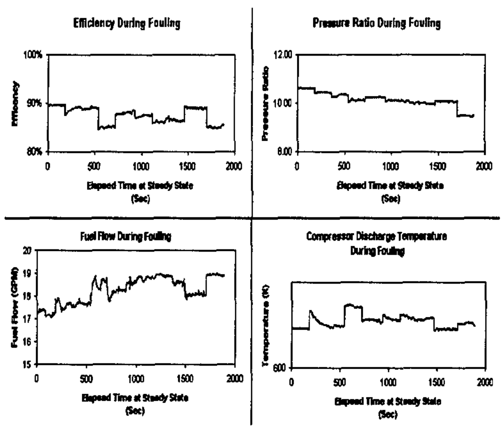

Figure 4 – Parameter Deviation at Full Load (LM2500 test)

Prognostic Model for Predicting Degradation: The compressor performance prognostic module consists of a data preprocessor and specific diagnostic/prognostic algorithms for assessing the current and future conditions of the gas turbine. The data preprocessor algorithms examine the unit's operating data and automatically calculate key corrected performance parameters such as pressure ratios and efficiencies at specific load levels in the fashion already described. As fouling starts to occur in service, probabilistic classifiers match up corresponding parameter shifts to fouling severity levels attained from these tests with corresponding degrees of confidence.

A probabilistic-based technique has been developed that utilizes the known information on how measured parameters degrade over time to assess the current severity of parameter distribution

shifts and project their future state (see Figure 5). The parameter space is populated by two main components. These are the current condition and the expected degradation path. Both are multi-variate Probability Density Function (PDFs) or 3-D statistical distributions. Figure 5 shows a top view of these distributions. The highest degree of overlap between the expected degradation path and the current condition is the most likely level of compressor fouling.

In general, the probability that the current condition (C), may be attributed to a given fault (F) is determined by their joint probability density function. If C and F can be assumed to be normally distributed, the probability of association (Pa) can be found using:

$$p_a = 2\Phi(-\frac{\overline{F-C}}{\sqrt{\sigma_f^2+\sigma_c^2}}) = 2\Phi(-\beta) \tag{2}$$

where:

$\overline{F},\overline{C}$ = the mean of the distributions F and C respectively

σ_f, σ_c = the standard deviation of the F and C distributions

The function Φ( ) is the standard normal cumulative distribution. The notation β is defined as the fault index.

Once the current severity level is known with a high degree of confidence, a fault-weighted projection is performed using a modified double-exponential smoothing technique. This approach is a better that a simple multi-variate regression because it weights the most recent performance degradation trends and evolve the current conditions toward the expected degradation path.

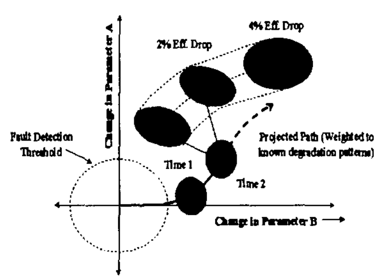

Figure 5 – Prognostic Modeling Approach

To manipulate the data into the form of this model, the time dependency of the test results had to be removed because of the unrealistic fouling rates. This was performed by viewing percent changes in static pressure ratio, fuel flow and CDT in relation to ¼ % pseudo-efficiency drops. This increment was chosen because it was the highest resolution that still permitted statistical analysis. With the assimilation of the data into these discrete bands, the statistical parameters (e.g., mean and standard deviation) can be ascertained for use in the prognostic model.

Figure 6 shows the evolution of the compressor degradation for the LM-2500 test at 1% pseudo-efficiency drops (for visual clarity). The top two plots show the distributions of pressure ratio and fuel flow respectively while the bottom two illustrate the joint probability distributions.

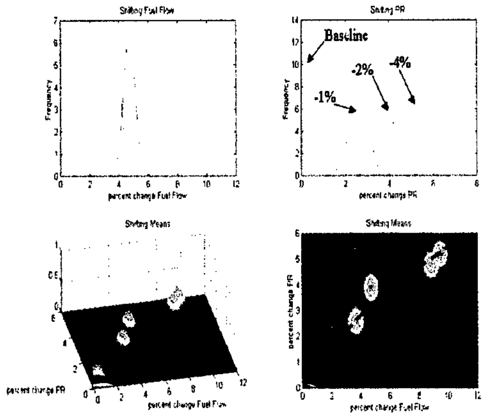

Figure 6 – Prognostic Model Visualization

Once the statistical performance degradation path is realized along with the capability to assess current degradation severity, the final step was to implement the predictive capability.

All compressors will not foul in exactly the same way and certainly not at the same rate as the accelerated tests. Fouling rates may even change between waterwashes or crankwashes for a given compressor. However, the percent changes of parameters relative to each other is still information that should be accounted for when projections of future fouling severity are to be made. The actual unit-specific fouling rate is combined with historical fouling rates with a double exponential smoothing method. This time series technique weights the two most recent data points over past observations. Eq. 3a,b, and c, give the general formulation, Bowerman (1993). Figure 7 shows how this technique can give significantly different results than standard regression.

$$S_T=\alpha y_T+(1-\alpha)S_{T-1} \tag{3a}$$

$$S^{[2]}_T=\alpha S_T+(1-\alpha)S^{[2]}_{T-1} \tag{3b}$$

$$\hat{y}_{T+\tau}(T)=\left(2+\frac{\alpha\tau}{(1-\alpha)}\right)S_T-\left(1+\frac{\alpha\tau}{1-\alpha}\right)S_T^{[2]} \tag{3c}$$

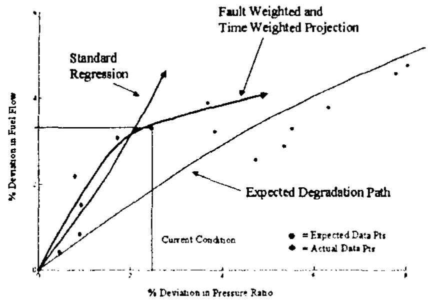

Figure 7 – Prediction of Degradation Rates

Benefits of Test Results: The test data made two essential contributions to the development of this prognostic model. First, they provided a means by which to validate an analytical model of how performance parameters change as a function of compressor fouling. Secondly, they gave insight into the sensitivity and statistical distributions of performance parameters as a function of load. Hence, having been developed and validated on real data, a large amount of knowledge is "built in" to the prognostic model. Along similar lines, the prognostic model may be developed for any particular gas turbine if data is made available on pre and post on-line waterwashing and crank washing.

Optimizing Compressor Wash Intervals: Referring back to the accelerated fouling test results of Figure 3, it is clear that on-line compressor washing was able to recover a majority of the compressor efficiency degradation. Initially, a large portion of these non-recoverable losses are recovered by crank washing but eventually a hot section overall will become necessary to regain performance (Figure 8).

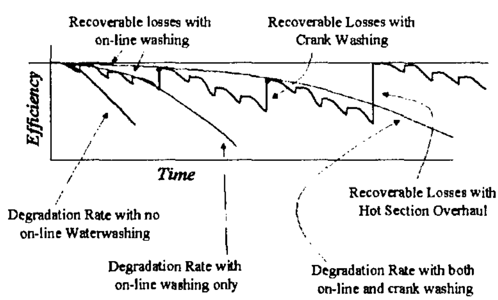

Figure 8 - Types of Degradation Rates

Hence, the question shifts from <u>if</u> washing should be done to <u>when</u> it should be done from an optimal cost/benefit standpoint. To perform this optimization, results from the engineering-based, compressor fouling prognostic model are combined with an economic-based analysis that accounts for the costs associated with efficiency degradation and performing compressor washing.

The compressor washing optimization algorithm developed predicts the optimal time to perform the wash based on the projected efficiency difference between performing the wash (action) to correct the degradation and continuing to run the gas turbine in its current condition (no action). The compressor wash should occur at the point in the future when the benefits of performing it outweigh its costs.

In this process, the engineering projections are merged with the O&M economic information on compressor degradation consequential costs. Factors such as reduced load, downtime, and other replacement "value" costs are all taken into account to quantify the decision to either not perform a type of wash (at the expense of increased degradation) or to perform the wash (but incurring a cost). (Figure 9).

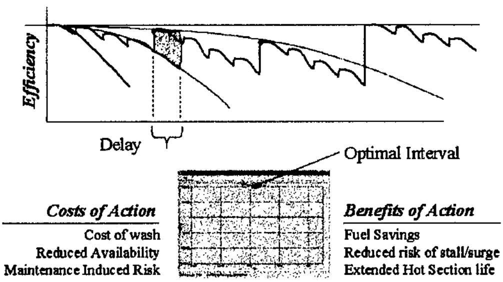

Figure 9 - Optimal Time for waterwashing

The Net Present Value (NPV) is calculated into the future for a specified time period. The NPV is a simple calculation once consequential costs have been determined from the above factors. When the costs and risks associated with keeping the gas turbine operating are thought of as "benefits" the NPV may be thought of as the following mathematical form:

NPV = (Total Expected Cost Associated with Efficiency Degradation) - (Total Expected Cost of Recovering Losses) - (Costs of the Waterwash or Crankwash) (4)

A simplified cost function version of this NPV calculation can be represented as follows:

$$C(\text{total}) = (\Delta\text{Fuel Flow} * \text{Fuel Cost/Amount of Fuel}) - (\text{Cost}_{\text{labor}} + \text{Cost}_{\text{materials}} + \text{PowerLost})_{\text{Wash}} \quad (5)$$

In this formulation, a simple minimization problem exists. The prognostic model's gas turbine degradation statistics, forecasting and the probabilistic analysis are used as inputs to the development of this cost minimizing procedure. Eq. (5) will produce a minimum when the costs of performing an online wash equals the amount of extra fuel being consumed due to degradation. Figure 10 shows an actual trend in Δ% fuel flow for the K-17 test and the prediction of future degradation based on the double exponential regression and experience from previous fouling/waterwash/crankwash results. The line in Figure 10 represents the point of the NPV curve beyond which costs outweigh benefits.

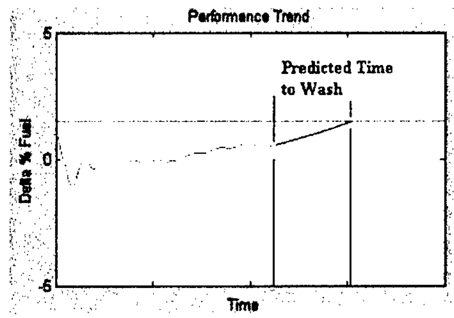

Figure 10 – Wash prediction

Figure 11 illustrates how the cost function changes as a function of fouling severity at "Full" and "Standard" load levels or "bells". This shows that, on a relative basis, a waterwash at "Standard" load need only be performed nearly ½ as frequently than if the unit is always operated at "Full" load. Lower load levels would warrant even less frequent washing. The relative time used in Figure 11 is due to the fact that the actual fouling rate was accelerated. It is assumed that the relative waterwash frequencies will be applicable to the actual operating times of a unit undergoing normal fouling rates. Figure 11 also assumes that the costs associated with performing the online wash are *fixed*. This allows the costs associated with compressor fouling (i.e., excess fuel expenditures) to be the only *variable costs* within the algorithm.

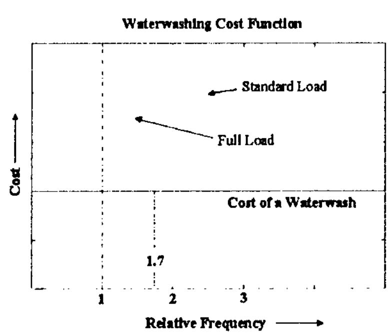

Figure 11 – Water Wash Frequency

Conclusion : A method has been presented that assesses the compressor performance degradation of Naval gas turbines with standard instrumentation and predicts the optimal time for washing processes based on a cost/benefit analysis. The approach utilizes built-in knowledge from accelerated fouling tests for model validation and to predict future performance of an arbitrary unit in-service. With continuous monitoring and cost/benefit analysis the Navy can make informed decisions about incorporating on-line waterwashing and altering crankwash intervals.

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