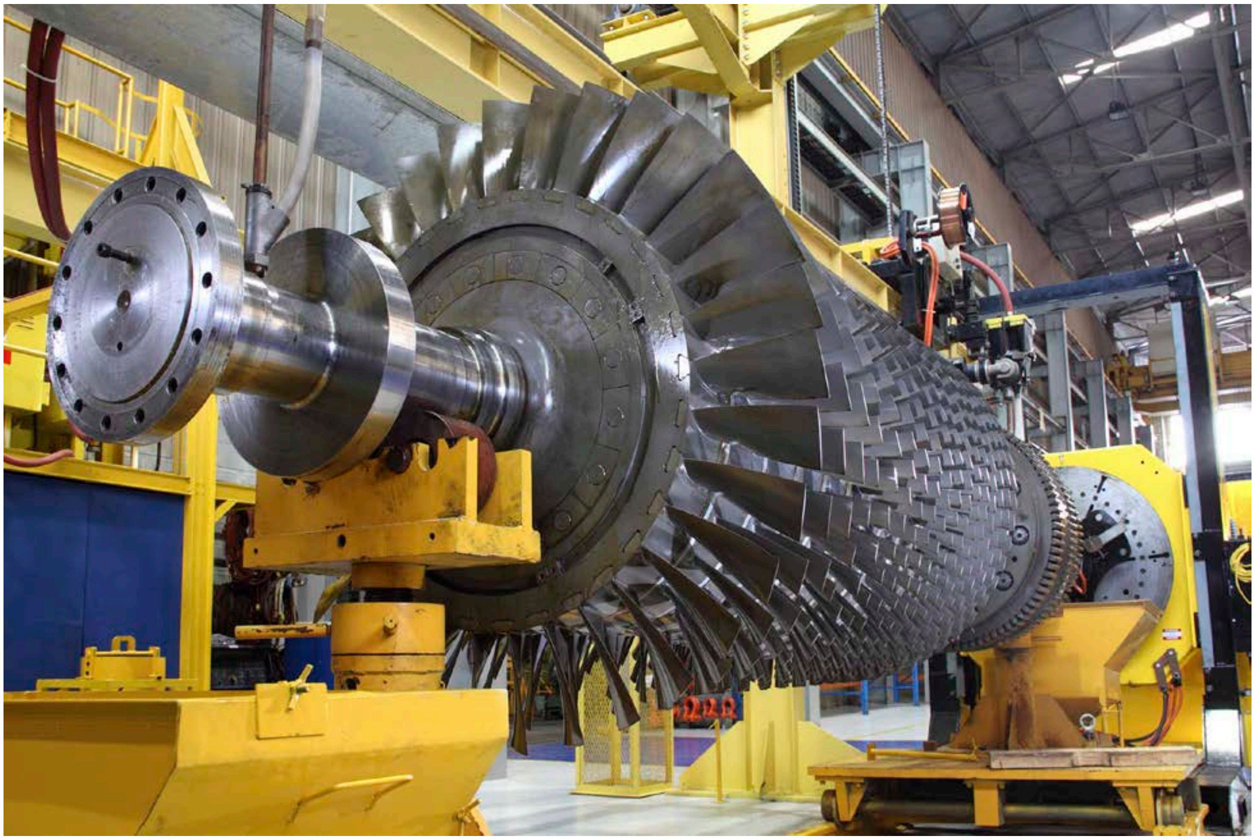

White Paper

OptiRamp® Performance Diagnostics

Maximizing Performance through Predictive Maintenance Decisions

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Table of Contents

Introduction 2
Business Challenge: Need for Predictive Maintenance 3
Data Processing 3
Performance Metric Definition 3
Diagnostics Algorithm 4
Measured Metric Diagnostics 5
  Degradation Function 5
  Maintenance Decision 6
Estimated Metric Diagnostics 6
  Degradation Function 7
  Maintenance Decision 8
Considerations 9
About Statistics & Control, Inc. 10

Introduction

One of the main challenges in economic optimization is to keep equipment efficiency at high levels while saving fuel for given operating conditions. It is known that a base load machine can degrade 0.2% to 0.3% of the nominal (when new and clean) rating after just a single month of operation. This fact makes it imperative for businesses to be able to maintain equipment not only at manufacturer-recommended intervals but also at levels that account for equipment wear and surrounding conditions. The *OptiRamp* Performance Diagnostics (PD) Module solves this problem by providing a set of tools used to track, assess, and predict process equipment degradation. The module uses sophisticated algorithms to track designated process characteristics over time and to alert users if material changes are detected.

The key benefit of integrating the PD Module into a control system is implementing predictive maintenance scheduling based on equipment state vs. planned maintenance. The *OptiRamp* PD Module provides “smart” maintenance scheduling that takes equipment state and current operating conditions into account, thereby ensuring sustained optimal performance. The module serves the essential function of developing maintenance schedules that balance maintenance costs with lost revenue and extra fuel costs.

The principal idea of the module algorithms is that efficiency decline can be measured and predicted over time, with the process resetting itself after every maintenance action. The goal is to evaluate process variable variation against set baselines and to provide the operator with proactive maintenance recommendations. The PD Module is fully integrated with the *OptiRamp* Modeling Submodule that continuously feeds model outcomes to the PD Module. This integration results in meaningful online research that can be used to minimize the impact and/or occurrence of critical failures in process equipment.

Business Challenge: Need for Predictive Maintenance

Predictive maintenance scheduling is an economically beneficial practice across various types of process equipment. For the purposes of this paper, we will primarily reference situations associated with gas turbines and process compressors.

Even under the best possible operating conditions, gas turbine and process compressor performance is subject to deterioration due to compressor fouling and corrosion, inlet filter clogging, thermal fatigue, and oxidization of hot gas path components, such as combustion liners and turbine blades. The performance degradation attributed to compressor fouling is mainly due to deposits formed on the compressor blades when the air carries in particles that are not large enough (typically a few microns in diameter) to be blocked by the inlet filter. Depending on the environment, these particles may range from dust and soot particles to water droplets or even insects. These deposits result in a reduction of the compressor mass flow rate, efficiency, and pressure ratio, which in turn decreases the gas turbine's power output while the heat rate increases. Typically, for a base load machine, the degradation can be 0.2% to 0.3% of the nominal rating after a single month of operation.

The *OptiRamp* PD Module provides operators with a real-time view of process conditions and proactively notifies operators about abnormal equipment conditions that may occur based on the system of predictions.

Data Processing

The *OptiRamp* PD Module is fully integrated within the *OptiRamp* suite of modules and has access to data processing, importing, storing, and noise reducing mechanisms described in detail in the *OptiRamp* Modeling Submodule white paper. The primary use of data processing technology in the PD Module is to smooth the key performance metrics being tracked for changes.

Performance Metric Definition

All performance metrics are split into two categories: measured and estimated. Measured metrics follow signal processing algorithms described in the Modeling Submodule white paper, while estimated metrics are smoothed during the estimation process using, for example, the static model described in the Modeling Submodule white paper and time series analysis.

Throughout the rest of the paper, the measured performance metrics are denoted by Ψ and estimated performance metrics are denoted by Y, where $Y = f\left(x_1, ..., x_n\right)$. In this equation, f is the chosen estimator, such as the general linear model, and $\left(x_1, ..., x_n\right)$ is the vector of process variables used to estimate Y given a certain set of operating conditions.

Diagnostics Algorithm

The *OptiRamp* PD Module uses stochastic modeling concepts to track chosen performance metrics. Overall, the algorithm follows similar paths for measured and estimated metrics, where additional analyses are performed for estimated metrics and where predictor variables are used to enhance the time series analysis of equipment degradation. The general concept of performance diagnostics used in the module is depicted in Figure 1, where KPI (Key Performance Indicator) denotes a hypothetical metric of interest.

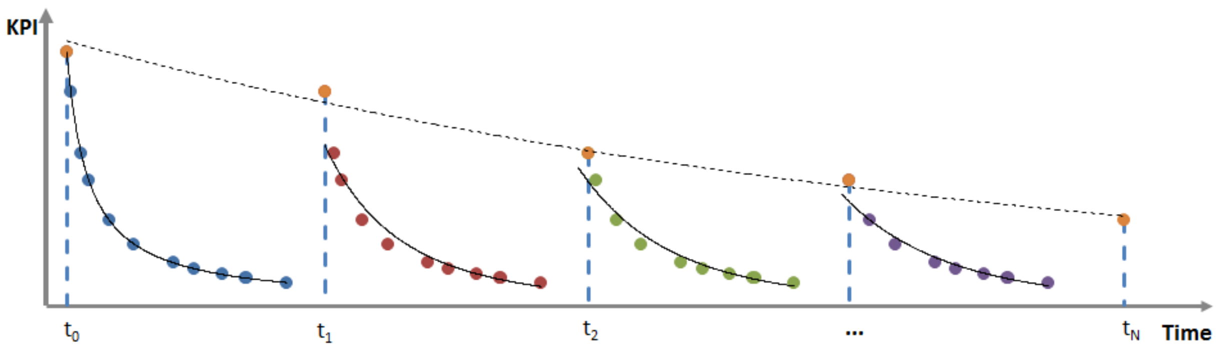

Figure 1. Performance diagnostics concept

The graph shows historical values of a hypothetical *smoothed* performance metric, where a decline is considered bad. Each time value (t_i, where $i = 0, \ldots, N$) corresponds to an instance of maintenance, such as cleaning. Immediately following an instance of maintenance, the KPI increases; however, it does not increase to its original value due to overall equipment wear. By analyzing historical KPI behavior along with current conditions, the *OptiRamp* PD Module predicts the next time maintenance that is required (which corresponds to the lowest acceptable KPI value) and issues a maintenance recommendation.

Maintenance instances (t_i) must be known in order to initialize the algorithm. The *OptiRamp* PD Module can either use the maintenance instances provided by maintenance schedule records or automatically identify the instances from trend data. Given a historical time period T consisting of M instances and given the set of measured performance metric values $\Psi(t_j) = \Psi_j$ or estimated performance metric values $Y(t_j) = Y_j$ where $j = 1, \ldots, M$, the algorithm calculates the magnitude of KPI changes over time using the appropriate following equations. The shift from point to point can be defined as $d_j = \Psi_{j+1} - \Psi_j$ or $d_j = Y_{j+1} - Y_j$ for values where $j = 1, \ldots, M-1$. Average shift is calculated as $d = \frac{\Psi_M - \Psi_0}{M}$ (or $d = \frac{Y_M - Y_0}{M}$), and the shift standard error is calculated according to equations (1) or (2).

$$\sigma_d = \sqrt{\frac{\sum_{j=1}^{M-1}\left(\Psi_j - d\right)^2}{M}} \tag{1}$$

$$\sigma_d = \sqrt{\frac{\sum_{j=1}^{M-1}\left(Y_j - d\right)^2}{M}} \tag{2}$$

The indices (j) of interest occur whenever equation (3) is satisfied.

$$d_j > 3 \cdot \sigma_d \tag{3}$$

To clarify, if $d_j > 3 \cdot \sigma_d$, then $t_j = t_i$, where t_i is the time of maintenance for $i = 1,...,N$. Depending on the type of metric being tracked, the algorithm takes a different path from here.

Measured Metric Diagnostics

The diagnostics algorithm is split into two steps: degradation function estimation and maintenance decision recommendation.

Degradation Function

The time instances t_i identified earlier split the entire time frame under analysis into $N+2$ intervals T_j, where $j = 0,...,N+1$. Then, for each value where $j = 0,...,N+1$, the smoothed measured attributes $\Psi(t)$ are regressed against time according to $\Psi_j(t) = \sum_{p=1}^{m} \alpha_p^j t^p$, where m is a parameter chosen to be the same for all j and $t \in T_j$. Thus, the *OptiRamp* PD Module is able to fit measured attributes across all time intervals between equipment maintenance instances.

The time regression fit functions yield a matrix of coefficients α_p^j for all $j = 0,...,N+1$ and $p = 0,...,m$ values. Each α_p^j may change over time due to changes in equipment degradation descent after each instance of maintenance. To predict the level of descent at the current time, the *OptiRamp* PD Module estimates the relationship of α_p over time and j according to $\alpha_p(t, j) = f_p(\beta, t, j)$, where f_p is a polynomial of parametric degree n, $t \in \left\{T_j\right\}_{j=0,...,N+1}$, β is the vector of parameter estimates, and $j = 0,...,N+1$. Thus, immediately after maintenance (initial conditions), the PD Module calculates the expected Ψ value, $\Psi_{\exp}$, according to equation (4).

$$\Psi_{\exp}\left(t_{curr}\right)=\sum_{p=1}^{m}\alpha_p t_{curr}^p=\sum_{p=1}^{m} f_p\left(t_{curr}, N+2\right)t_{curr}^p, \quad (4)$$

where t_{curr} is the current time. Next, $\Psi_{\exp}$ is compared to the current measured value Ψ_{actual}, creating the optimization constraint $\left|\Psi_{\exp}-\Psi_{actual}\right|\le\delta$. Genetic algorithms are used to reestimate parameters β in $f_p\left(\beta, t, j\right)$ until δ is sufficiently small. Genetic algorithms are discussed in detail in the *OptiRamp* Scheduling Submodule white paper.

As new values of Ψ are recorded in the current time interval T_{N+2}, the PD Module creates a new set of parameters α_p^{N+2} by regressing $\Psi\left(t\right)$ against time. Thus, estimates β are adjusted as well to ensure a better fit of $\Psi\left(t\right)$. This process results in a stable and robust function $\Psi\left(t\right)=\sum_{p=1}^{m}\alpha_p^{opt}t^p$ that describes the behavior of the measured metric Ψ as equipment degrades over time.

Maintenance Decision

The *OptiRamp* PD Module can use an operator-defined threshold value of Ψ, $\Psi_{threshold}$ (at which a maintenance decision is recommended), or can determine the value historically via the following formula: $\Psi_{threshold}=\frac{\sum_{i=1}^{N}\Psi\left(t_i\right)}{N}$, where the sum is divided by the total number of maintenance instances t_i. Finally, the PD Module analytically or numerically solves equation (5) for *t*.

$$\Psi_{threshold}=\sum_{p=1}^{m}\alpha_p^{opt}t^p \quad (5)$$

The solution method depends on the value *p*. For $p\le 4$, analytic solutions are the fastest, while numerical approximations are implemented for $p>4$. The solution of equation (5) is the time at which the metric is expected to reach the threshold and the *OptiRamp* PD Module issues a predictive maintenance decision to the operator.

Estimated Metric Diagnostics

As with the measured metric algorithm, the diagnostics algorithm for estimated metrics such as equipment efficiency coefficients is split into two steps: degradation function estimation and maintenance decision recommendation.

Degradation Function

The key difference in estimating the degradation function for estimated metrics $Y_j(t)$ vs. measured metrics is the dependence of Y on a certain set of process variables $(x_1,...,x_n)$ according to static functions produced by the *OptiRamp* Modeling Submodule. The degradation function is thus not only influenced by time but also by the multidimensional relationship between process variables. The *OptiRamp* PD Module accounts for this by enhancing time regressions with the process variables $(x_1,...,x_n)$.

For every historical time interval T_j, where $j=0,...,N+1$ (defined above), the estimated process metric $Y(t)$ is regressed according to equation (6).

$$Y_j(t)=F\left(\Gamma_j,x_1(t),...,x_n(t),t\right), \tag{6}$$

where F is a multidimensional polynomial of parametric degree q (kept the same across all j), $x_1(t),...,x_n(t)$ are the measured values of process variables $x_1,...,x_n$ at time t, and Γ_j is the vector of parameter estimates (polynomial coefficients).

Similar to measured metrics, each element γ_j^l of Γ_j is dependent not only on time and index but also on process variables $x_1,...,x_n$. The *OptiRamp* PD Module estimates this relationship to create the overall degradation function of equipment. Equation (7) shows the regression equation for each γ^l.

$$\gamma^l=g^l\left(\chi,x_1(t),...,x_n(t),t,j\right), \tag{7}$$

where g^l is a polynomial of parametric degree w, $t\in\{T_j\}_{j=0,...,N+1}$, χ is the vector of parameter estimates, and $j=0,...,N+1$. The process follows a path similar to measured metrics. The expected value of Y, $Y_{\exp}$, is calculated according to equation (8).

$$Y_{\exp}(t_{curr})=F\left(\Gamma_{curr},x_1(t_{curr}),...,x_n(t_{curr}),t_{curr}\right)=F\left(G,x_1(t_{curr}),...,x_n(t_{curr}),t_{curr}\right), \tag{8}$$

where t_{curr} is the current time and G is the vector of functions g^l evaluated for $t=t_{curr}$ and $j=N+2$. Next, genetic algorithms are applied to adjust all coefficients χ so that $\left|Y_{\exp}-Y_{predicted}\right|$ is sufficiently small. Similar to the measured metric diagnostics, as new values of Y are calculated for current conditions, estimates for Γ_{N+2} are continuously adjusted to improve F's goodness of fit. The algorithm output is the degradation function given by equation (9).

$$Y(t) = F\left(\Gamma^{opt}, x_1(t), \ldots, x_n(t), t\right), \tag{9}$$

where Γ^{opt} is the optimized set of parameters.

Maintenance Decision

The computation for the threshold value of Y, $Y_{threshold}$ (at which a maintenance decision is recommended), is dependent on current conditions, meaning that the operator cannot provide the value. The $Y_{threshold}$ has to be estimated based on past values of its original predictor variables $x = (x_1, \ldots, x_n)$. The *OptiRamp* PD Module solves this problem in two steps. First, the values of Y evaluated at time instances prior to historical maintenance (t_{i-1}) are regressed against those time instances and the original predictor variables for Y via the equation $Y = H(x,t)$, where H is a r^{th} degree polynomial where r is parametrically defined. The equation $Y = H(x,t)$ is depicted in Figure 2 as a thick black dashed line. Second, $Y_{threshold}$ is calculated according to equation (10).

$$Y_{threshold} = \frac{\sum_{i=1}^{N} H(x, t_i)}{N} \tag{10}$$

The PD Module then solves equation (11) for t.

$$Y_{threshold} = F\left(\Gamma^{opt}, x_1(t), \ldots, x_n(t), t\right) \tag{11}$$

The solution of equation (11) is the time at which the estimated metric Y will reach the threshold and the *OptiRamp* PD Module will issue a predictive maintenance decision to the operator.

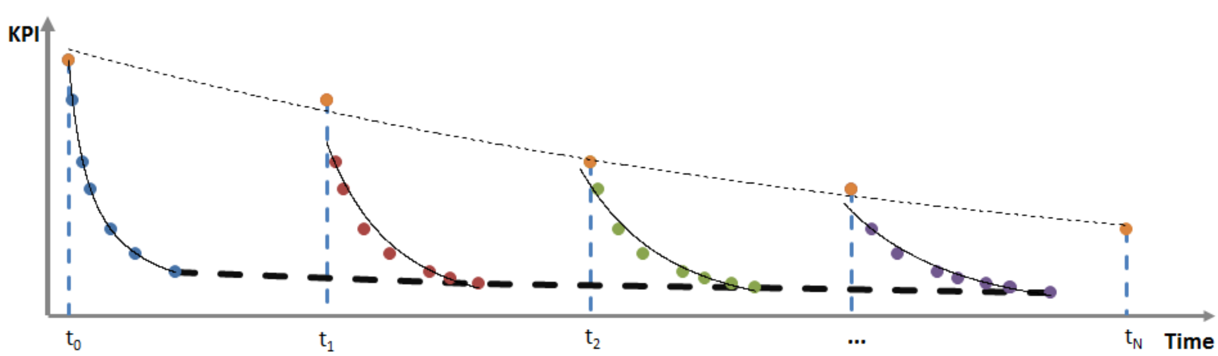

Figure 2. Estimated maintenance threshold

Considerations

The *OptiRamp* PD Module works most effectively on equipment that has been in operation with at least four maintenance actions. For brand new equipment, it is recommended to follow maintenance schedules supplied by the manufacturer. The PD Module can run in the background while it tracks changes of process key performance indicators and learns equipment degradation curves.

About Statistics & Control, Inc.

S&C—an engineering consulting and technology company headquartered in West Des Moines, IA—solves complex challenges for customers through its unique technology and its highly seasoned team of professionals. The company has a global portfolio spanning the energy, oil and gas, utility, and digital oil field industry sectors. S&C provides clients with turbomachinery control solutions that easily integrate with the existing system as well as *OptiRamp*® solutions, which focus on process and power analytics to optimize processes and, in turn, reduce costs and increase reliability. S&C also provides consulting, dynamic system studies, modeling, automation, training and OTS, and support services.

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