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# DIAGNOSTICS OF HIGHLY DEGRADED INDUSTRIAL GAS TURBINES USING BAYESIAN NETWORKS

**Brian K. Kestner, Young K. Lee, Gautham Voleti, Dimitri N. Mavris**
Aerospace Systems Design Laboratory
School of Aerospace Engineering
Georgia Institute of Technology
Atlanta, GA 30332

**Viren Kumar**
**TsungPo Lin**
Services Engineering
GE Energy
Atlanta, GA 30339

## ABSTRACT

This paper presents an offline fault diagnostics method for highly degraded industrial gas turbines. The method recasts gas path analysis to an inference problem using Bayesian networks where the health condition of each component is quantified in comparison to an expected value. The health parameters are inferred from available gas path measurements, which are sometimes erroneous due to sensor faults or miscalibration. The sensor errors should be inferred as well as the health parameters. Thus, typically in gas path analysis the unknowns are more than the knowns. To address this issue, the present method uses multiple Bayesian network models each of which contains a subset of the unknowns. Their results are averaged according to how much each of the models is supported by the data. Although this method has been reported successful for the faults affecting a few unknowns, its results are still less accurate and confident when it is applied to highly degraded gas turbines. Such gas turbines are likely to have health parameters deviated from the new and clean condition as well as have component faults and sensor errors. Because of this, the present method must infer too many unknowns at the same time to result in a solution with high confidence. In addition, this method cannot differentiate normal or expected degradation from an actual fault. These issues are resolved by fusing extra information to the method. First of all, a sensor calibration report, if available, eliminates the sensor errors from the unknowns. Consequently, the number of possible subsets decreases, and so does the number of Bayesian models. Second, a degradation model provides meaningful prior guesses for the health parameters. It is equivalent to change the point of reference from a brand new gas turbine to a normally degraded one. It will be demonstrated that the method accompanying with the degradation model and the sensor calibration report shows significant improvement in accuracy and confidence.

## NOMENCLATURE

A Coefficient matrix
a Lower bound of a distribution
B Vector of sensor biases
b Upper bound of a distribution
M Categorical variable representing all models
m A particular model in M
n Total number of health parameters and sensor biases
T Ambient temperature
X Vector of health parameters
Y Vector of measurements
$\varepsilon$ Vector of random error
$\gamma$ Binary variable associated with $\theta$
$\mu$ Vector of mean values
$\theta$ Union of X and B vectors
$\tau$ Precision matrix

## INTRODUCTION

As the power generation market becomes competitive, power plant owners strive to make larger profit with lesser cost of ownership. Maintenance cost accounts for a large part of the cost of ownership. The current maintenance strategy for most machines is preventive in the sense that maintenance actions are performed along schedules suggested by manufacturers. These schedules are made by the manufacturers based on historical data, empirical knowledge, and tests performed along design processes [1]. However, these schedules have little to do with the actual condition of the machine subject to the scheduled maintenance actions. To reduce the maintenance cost it is desirable for the power plant owners to perform maintenance actions when they are actually needed. This desire has led to a new maintenance strategy called predictive maintenance with which maintenance experts assess the condition of a machine at the current time, predict the failure time in the future, and decide the best maintenance action. The first two steps are called fault diagnostics and prognostics, respectively. For the predictive maintenance to be successful, it is important for diagnoses to be accurate because not only a wrong diagnosis results in unnecessary maintenance and consequently high maintenance cost but also diagnoses are used in prognostics and other tasks downstream.

Fault diagnostics and prognostics are not new concepts in the gas turbine industry for power plants. A gas turbine is such a crucial component of conventional combined cycle power plants that it has been of great interest for power plant operators to estimate the condition of a gas turbine from test or operation data. The condition of the gas turbine is quantitatively represented by, commonly called, *health parameters*, which scale gas turbine performance relative to a baseline, e.g., the performance of a brand new gas turbine. The health parameters are immeasurable and can only be estimated from measurable data. Estimation of the health parameters from test data is often referred to as gas path analysis (GPA), which was pioneered by Urban [2]. A few classical approaches for GPA are the method of least squares [3] and Kalman filters [4]. More recently, several artificial intelligence techniques such as neural networks [5], fuzzy logic [6], and Bayesian networks [7], [8], [9] have been applied to GPA.

No matter which technique is used, there is a common difficulty in applying these techniques to an assessment of the condition of a gas turbine. When a health parameter estimator is built using one of these techniques, the estimator should be general enough to be applicable to various fault situations. However, a general estimator is not tailored to each fault situation so that its result may not be as accurate as the tailored ones. A general estimator often gives rise to the so called *smearing effect* [10] in its results. The smearing effect refers to the spread of inaccuracy over several irrelevant health parameters.

One of the approaches to reduce the smearing effect in diagnoses is to find the best one among multiple models each of which is tailored to a fault situation. The fault logic [3], a combinatorial approach [11], and a bank of Kalman filters [12] are examples of this multiple model approach. Instead of finding single best model, Lee et al. [8], [9] used the Bayesian model averaging (BMA) technique to combine results of multiple competing models.

Most of the above methods compare the performance of a gas turbine with that of a brand new one. This comparison is effective as long as the gas turbine is actually new or moderately degraded. If the gas turbine is highly degraded due to the accumulation of usage, however, the degradation masks the symptoms of faults. Consequently, it is harder to distinguish faults from the normal degradation. For industrial gas turbines, which often operate with severe degradation, distinguishing faults from degradation is greatly important in order to prevent hazardous events due to undetected faults. In this paper, the authors examine the offline fault diagnostics method presented in [8], [9] with highly degraded gas turbines and present the modifications made to handle such gas turbines.

## METHODOLOGY

The method presented in this paper is aimed to perform GPA of industrial gas turbines using multiple Bayesian networks. More specifically, the gas turbines of interest are the GE Frame 7FA+e turbines. The Bayesian networks consist of health parameters, sensor biases, and measurements. Each network is tailored to a fault situation. When some measurements become available, the probability distributions of the health parameters and sensor biases are determined.

### Gas Path Analysis

The major health parameters and measurements available for a GE 7FA+e industrial gas turbine are listed in Tab. 1. Let $X$ be a vector of health parameters and $Y$ a vector of measurements. At a steady baseload operating condition, the health parameters and measurements have a functional relationship $f$:

$$Y = f(X) + \varepsilon \tag{1}$$

where $\varepsilon$ is the vector of random error. The relationship $f$ can be linearized at the operating condition and written as

$$Y = AX + \varepsilon \tag{2}$$

where $A$ is the coefficient matrix. This linearized relationship changes as the ambient condition varies. To incorporate the effect of various ambient conditions, each element of $A$ is given as a function of the ambient temperature. $\varepsilon$ in this equation includes not only the random noise but the linearization error as well. When the measurement vector $Y$ is subject to the sensor bias $B$, Eqn. (2) can be written as follows:

$$Y = A(T)X + B + \varepsilon. \tag{3}$$

$Y$ is known in this equation while $X$ and $B$ are unknowns. For the industrial gas turbine of interest, according to Tabl. 1, there are 6 knowns and 10 unknowns. This is an underdetermined problem, which cannot be solved with matrix inversion. Instead, a probabilistic approach using Bayesian Networks is used for this paper.

**TABLE 1.** HEALTH PARAMETERS AND MEASUREMENTS

| Health Parameters | Measurements |
|---|---|
| Compressor flow (CF) | Generator output (DW) |
| Compressor efficiency (CE) | Compressor discharge temperature (CDT) |
| Turbine flow (TF) | Compressor discharge pressure (CDP) |
| Turbine efficiency (TE) | Exhaust gas temperature (TEX) |
| | Fuel flow (WF) |
| | Air flow (WA) |

## Bayesian Networks

A Bayesian network is a directed acyclic graph [13] consisting of nodes and edges as shown in Fig. 1. A node represents a random variable, and an edge shows probabilistic dependency between two variables. When two nodes are connected with an edge, the node from which an edge emanates is called a *parent*, and the other a *child*. A node without any parent is called a *root* node. Each node requires a probability distribution conditioned by its parents. The probability distribution of a root node is called the *prior* distribution. A child has a conditional probability distribution (CPD). When some nodes in the Bayesian network become known, the probability distributions of the other nodes can be updated using inference algorithms. If Child C is instantiated and the probability of Parent A is of interest, it can be calculated from the following equations using Bayes' theorem and marginalization:

$$p(A,B|C) \propto \frac{p(C|A,B)p(A)p(B)}{p(C)} \tag{4}$$

$$p(A|C) \propto \int \frac{p(C|A,B)p(A)p(B)}{p(C)} dB \tag{5}$$

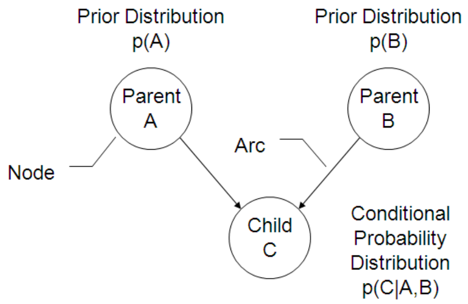


**FIGURE 1.** A SIMPLE BAYESIAN NETWORK

Although Eqns. (4) and (5) are derived upto proportionality, they still can be determined with the fact that any proper probability distribution integrates to one.

To conduct GPA derived in the previous section using a Bayesian network, the dependencies between the health parameters, sensor biases, and measurements as given as Eqn. (3) are transformed to a graph as shown in Fig. 2. Whereas each health parameter affects all measurements, each sensor bias affects only its corresponding measurement. However, a bias in CDP or TEX can affect all other measurements as well because they are used for controlling the industrial gas turbine. To complete this Bayesian network, each node needs its probability distribution. Let us assume that the conditional probability of $Y$ given $X$ and $B$, $p(Y|X,B)$, follows a multivariate normal distribution $N(\mu,\tau)$ where $\mu$ is the mean vector and $\tau$ the precision matrix. If the mean of the random error $\varepsilon$ is assumed to be zero, the mean vector $\mu$ is written as

$$\mu = AX + B. \tag{6}$$

The precision matrix $\tau$ can be either a known constant or a variable. When $\tau$ is considered as a variable, a prior probability distribution has to be assigned to it. The health parameter $X$ is assumed to be any value in the range of interest. It is also assumed that no particular value is more likely than others in the range. This notion can be expressed with a uniform distribution $U(a,b)$ where $a$ and $b$ are the lower and upper boundaries. With the same reason the bias $B$ is assumed to follow a uniform distribution as well. Choice of prior probability distributions will affect the sensitivity and accuracy of diagonsis from the Bayesian network.

## Multiple Model Approach

The Bayesian network shown in Fig. 2 has all major health parameters and sensor biases. It is so general that it can be used in any fault situations. On the other hand, it is not as precise as the Bayesian network tailored to the particular fault situation it is trying to diagnose. For example, consider a gas turbine whose

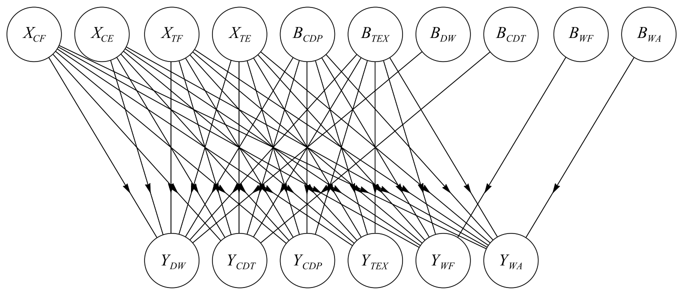


**FIGURE 2**. BAYESIAN NETWORK FOR GE 7FA+E GAS TURBINES

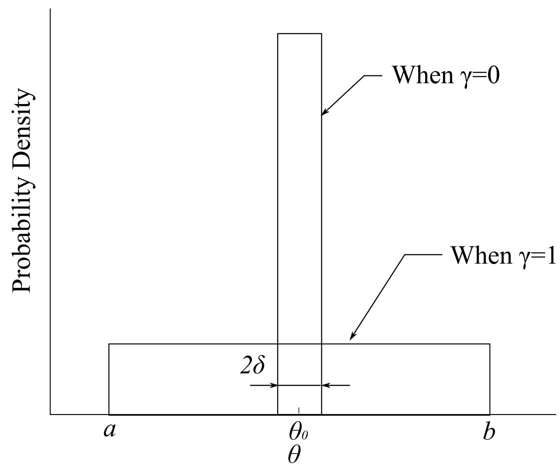


**FIGURE 3**. SPIKE AND SLAB DISTRIBUTION

sensors are working properly. The Bayesian network tailored to this gas turbine is the one without all the bias nodes. This tailored Bayesian network results in more precise results than the general one. On the other hand, this tailored network cannot be general. If it is used in other fault situations, it will result in wrong solutions.

To resolve this generality and preciseness issue, a multiple model approach is proposed in [8]. Depending on the fault situation, some of the health parameters and sensor biases are necessary in the network, and the others are not. As the fault situation changes, the necessary and unnecessary nodes change as well. To implement the inclusion and exclusion of a node numerically, a mixture of two uniform distributions is assigned to $X$ and $B$. Let us refer to the union of $X$ and $B$ as $\theta$. The mixture is referred to as the *spike and slab* distribution [14] and shown in Fig. 3. The mixture ratio is controlled by an auxiliary binary variable $\gamma$ associated to $\theta$. When $\gamma$ is zero, $\theta$ follows the spike, which is centered at a prescribed value. The spike is so thin that $\theta$ is nearly deterministically the prescribed value. When $\gamma$ is one, $\theta$ follows the slab, which bounds the range of interest. In contrast to the previous case, $\theta$ can be any value in the range and has to be included in the network.

When the total number of the health parameters and sensor biases is $n$, $2^n$ different networks can be built using all possible subsets of the health parameters and sensor biases. Categorical variable $M$ is introduced to represent these $2^n$ network models. Unless there is a sufficient reason to favor one model over another, it is reasonable to use a non-informative prior [15]; each model is equally probable. Thus, a categorical distribution with $2^n$ categories is assigned to the model variable $M$ such that the probability of $M$ being a particular model $m$ is as follows:

$$p(m) = \frac{1}{2^n}. \tag{7}$$

The assumption of equally probable models is equivalent to assigning

$$p(\gamma = 0) = p(\gamma = 1) = 0.5. \tag{8}$$

$M$ and $\gamma$ are added to the network in Fig. 2, and the resulting Bayesian network is shown in Fig. 4. Once $Y$ is instantiated, i.e., some measurements become available, the probabilities of other nodes can be updated. The posterior probability of $\theta$, $p(\theta|Y)$, can be expanded using marginalization as follows:

$$p(\theta|Y) = \sum_{m\in M} p(\theta|Y,m)p(m|Y). \tag{9}$$

$p(\theta|Y,m)$ is the posterior of $\theta$ when the model variable $M$ is equal to $m$. $p(m|Y)$ is a number between zero and one, and the summation of $p(m|Y)$ over all models is equal to one. Therefore, Eqn. (9) is merely the average of the posterior of $\theta$ from each model, $p(\theta|Y,m)$, using the model posterior $p(m|Y)$ as a weighting factor. Calculating the posterior of $\theta$ using Eqn. (9) is called *Bayesian model averaging* [16]. Equation (9) can be further derived using Bayes' rule as follows:

$$\begin{aligned} p(\theta|Y) &= \sum_{m\in M} \frac{p(Y|\theta,m)p(\theta|m)}{p(Y|m)} p(m|Y) \\ &= \sum_{m\in M} p(Y|\theta,m)p(\theta|m)\frac{p(m)}{p(Y)} \\ &\propto \sum_{m\in M} p(Y|\theta,m)p(\theta|m)p(m), \end{aligned} \tag{10}$$

where $p(m)$ is the prior probability of the model variable $M$ being a particular model $m$. Because $\theta$, $Y$, and $M$ constitute a serial

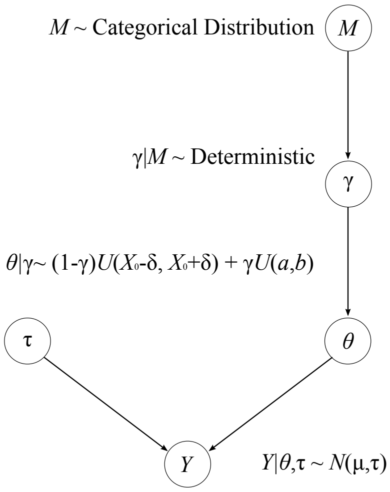


**FIGURE 4**. MULTIPLE BAYESIAN NETWORKS IN SINGLE GRAPH

connection, and $\theta$ is in the middle of the serial connection, $Y$ is independent of $M$ given $\theta$ [13]. Therefore, the first factor in Eqn. (10) can be written as

$$\begin{aligned} p(Y|\theta,m) &= p(Y|\theta) \\ &= \int_{\tau} p(Y|\theta,\tau)p(\tau)d\tau. \end{aligned} \quad (11)$$

The second factor $p(\theta|m)$ can be written using marginalization as follows:

$$p(\theta|m) = \sum_{\gamma\in\{0,1\}} p(X|\gamma)p(\gamma|m). \quad (12)$$

A degree to which each model is supported by data is determined by the model posterior $p(M|Y)$, which can be expressed with the CPDs using Bayes' rule and marginalization as follows:

$$\begin{aligned} p(M|Y) &\propto p(Y|M)p(M) \\ &\propto \int_{\theta} p(Y|\theta,M)p(\theta|M)d\theta \\ &\propto \int_{\theta} p(Y|\theta)p(\theta|M)d\theta. \end{aligned} \quad (13)$$

$p(Y|\theta)$ and $p(\theta|M)$ are given in Eqns. (11) and (12), respectively. Public domain software WinBUGS [17] is used for calculating Eqns. (10) and (13).

## Unresolved Issues

The Bayesian multiple model approach has been proven effective when the machines it is analyzing are new and clean and do not have significant degradation [9]. Table 2 below shows the results of using the Bayesian multiple model approach on data representing a new and clean gas turbine with a compressor flow fault. The model with compressor flow variable with a slab distribution best matches the data with a probability of 30%. The probability of this model is distinctively higher, at least five times than the others.

**TABLE 2**. MODELS WITH HIGHEST PROBABILITY - NEW AND CLEAN WITH COMPRESSOR FLOW FAULT

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 513 | 30.08 | 30.08 | ✓ | | | | | | | | | |
| 641 | 6.70 | 36.78 | ✓ | | ✓ | | | | | | | |
| 545 | 5.58 | 42.35 | ✓ | | | | ✓ | | | | | |
| 577 | 5.45 | 47.80 | ✓ | | | ✓ | | | | | | |
| 521 | 4.85 | 52.65 | ✓ | | | | | | ✓ | | | |
| 517 | 4.00 | 56.65 | ✓ | | | | | | | ✓ | | |
| 673 | 2.60 | 59.25 | ✓ | | ✓ | | ✓ | | | | | |
| 514 | 2.38 | 61.63 | ✓ | | | | | | | | | ✓ |
| 705 | 2.20 | 63.83 | ✓ | | ✓ | ✓ | | | | | | |
| 529 | 1.95 | 65.78 | ✓ | | | | | ✓ | | | | |

As the unit operates over time, the compressor flow, compressor efficiency, and turbine efficiency decrease because of component degradation while the turbine flow increases as a result of the increase of the turbine nozzle flow area. Figure 5 shows the general expected gas turbine component degradation in the context of Bayesian multiple model approach. If the spike distribution is centered around one, the model that represents the degraded turbine is one where the compressor flow, compressor efficiency, turbine flow, and turbine efficiency have slab distributions. As more variables have have non-informative prior, diagnoses using such model becomes less accurate with a significantly lower confidence. Table 3 shows the results of using the Bayesian multiple model approach on data representing a degraded gas turbine with a compressor flow fault. Compared with the new and clean diagnosis from Tab. 2, no model is distinctively more likely than others. Moreover, the model that represents the actual status of the turbine, model 961, has the second highest probability. Compressor discharge pressure appears frequently in the diagnoses because it is highly confounded with compressor flow and turbine efficiency.

Table 4 shows the results of Bayesian model averaging (BMA) using Eqn. (9) for the cases on a new and clean machine and a degraded machine. The results for $X_{CF}$, $X_{CE}$, $X_{TF}$, and $X_{TE}$ for all these cases are shown compared with the expected values , new and clean for the first case and degraded for the second case. The expected values of sensor biases are zero. For both cases, the -2% shift in CF was correctly estimated. However,

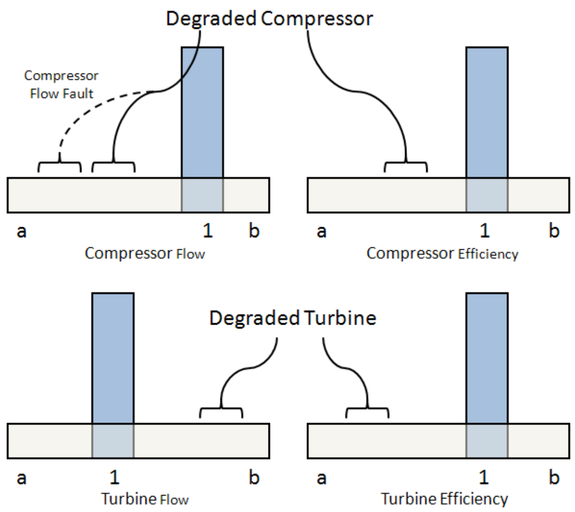


**FIGURE 5**. DEGRADED GAS TURBINE IN BAYESIAN MULTIPLE MODEL CONTEXT

**TABLE 3**. MODELS WITH HIGHEST PROBABILITY - DEGRADED WITH COMPRESSOR FAULT

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 737 | 7.40 | 7.40 | ✓ | | ✓ | ✓ | ✓ | | | | | |
| 961 | 6.68 | 14.08 | ✓ | ✓ | ✓ | ✓ | | | | | | |
| 609 | 6.63 | 20.70 | ✓ | | | ✓ | ✓ | | | | | |
| 709 | 6.22 | 26.93 | ✓ | | ✓ | ✓ | | | | ✓ | | |
| 613 | 5.08 | 32.00 | ✓ | | | ✓ | ✓ | | | ✓ | | |
| 741 | 3.50 | 35.50 | ✓ | | ✓ | ✓ | ✓ | | | ✓ | | |
| 745 | 3.43 | 38.93 | ✓ | | ✓ | ✓ | ✓ | | ✓ | | | |
| 969 | 3.30 | 42.23 | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | |
| 865 | 3.13 | 45.35 | ✓ | ✓ | | ✓ | ✓ | | | | | |
| 993 | 2.75 | 48.10 | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |

BMA on a unit with large degradation detected a shift in TF and TE from expected. Moreover, the confidence of the diagnosis decreases significantly with standard deviations on some variables increased by a factor of five. Thus, as the unit degrades in time, the accuracy and confidence of the diagnosis decreases.

For a new and clean gas turbine, without any prior information it is valid to assume that the health parameters are equal to one and that none of the sensors is biased, and the spike distribution is located accordingly. However, a highly degraded gas turbine operates outside of the spike region even when the gas turbine is not experiencing any fault. The inaccurate diagnosis with low confidence is due to the use of slab distributions on multiple variables.

In addition, the diagnosis cannot differentiate between degradation and fault. Figure 5 shows that both a compressor with either normal degraded flow or with a fault that causes a reduction in the airflow lie in the slab region. From the perspective of the Bayesian multiple model diagnostics, the same model represents both cases. The fault may not be detected, and the gas turbine may be kept operating without any maintenance action. The value of the diagnosis is greatly diminished.

**TABLE 4**. SUMMARY OF DIAGNOSIS

| Delta From Expected | | Bayesian Model Averaging - New & Clean Gas Turbine | | Bayesian Model Averaging - Degraded Gas Turbine | |
|---|---|---|---|---|---|
| | Units | Delta | Std Dev | Delta | Std Dev |
| CF | % | -1.90 | 0.20 | -2.00 | 0.60 |
| CE | % | 0.00 | 0.30 | 0.10 | 1.10 |
| TF | % | 0.10 | 0.60 | -1.00 | 1.20 |
| TE | % | 0.00 | 0.30 | 1.30 | 1.50 |
| BCDP | % | 0.06 | 0.27 | 0.28 | 0.98 |
| BTEX | F | 1.00 | 4.90 | 0.00 | 6.64 |
| BDWATT | % | 0.00 | 0.33 | -0.03 | 0.72 |
| BCDT | F | -0.18 | 1.80 | 0.63 | 5.62 |
| BWF | % | 0.00 | 0.10 | 0.00 | 0.34 |
| BWA | % | 0.00 | 0.58 | 0.00 | 0.22 |

## Proposed Solution

One of the strengths of Bayesian networks is its flexibility to allow the integration of other observations into the algorithm to enhance or improve its diagnosis. As an engineer performs diagnostics on a gas turbine, other observations are available which may either change the perspective of the engineer or allow the engineer to eliminate certain potential faults. Such observations can be, but are not limited to, a fleet or unit degradation model, historical data, sensor calibration reports, vibration data, or physical observations on the gas turbine. To address the previously discussed issues, this paper proposes the integration of other observations into the Bayesian multiple model scheme in order to improve the diagnosis confidence. This paper will focus on the integration of a degradation model via onsite monitoring or historical data and sensor calibration reports into the Bayesian multiple model diagnostic algorithm for gas turbines.

**Bring In More Information.** By integrating a degradation model, the prior assumptions of the component performance are changed such that the diagnosis method only needs to detect deviations from the expected performance. Figure 6 shows the general expected gas turbine component degradation in the context of Bayesian multiple model diagnostics when a degradation model is integrated. The spike distribution shifts from being centered around one to being centered around the expected level of component degradation. This is analogous to changing the perspective such that a diagnosis is made in comparison with a normaly degraded gas tubine instead of a new and clean unit.

There have been attempts to build physics based models of component degradation. However, the attempts had limited success in terms of accuracy. This limitation leads to empirical based techniques of which there are two general concepts: fleet based or unit based model. A fleet based model incorporates all, or a subset, of the historical data of a fleet, potentially including fired hours, variation in operation type, and variation in operating environment. These models provide a broad high level estimate of the degradation, but often can have large uncertainties [18]. When an event occurs for which diagnostics is required, the engineer would input the known operating hours as well as the operating environment, and the model would output a estimate of the component degradation with a confidence bound. From the perspective of Bayesian multiple model approach, this estimate would represent the spike distribution for each component as shown in Fig. 6.

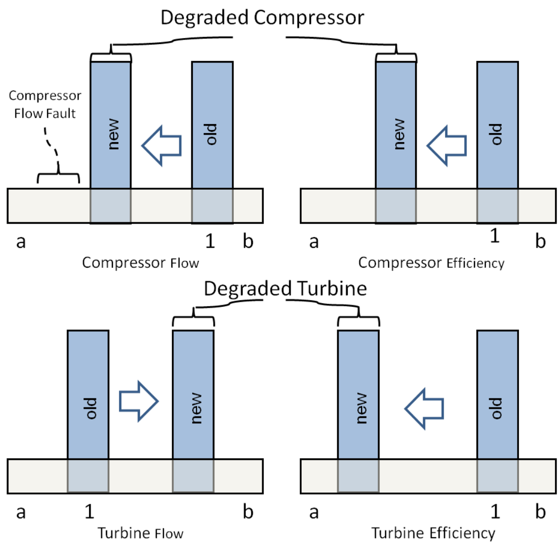


**FIGURE 6**. DEGRADED GAS TURBINE IN BAYESIAN MULTIPLE MODEL CONTEXT WITH SHIFT IN SPIKES

A unit based model can be developed using similar techniques as the fleet based model or using a filtering technique such as a Kalman filter [19]. The sources of the uncertainty in the filtering based model are reduced to sensors and the model, with the large unit-to-unit variation eliminated. When an event occurs for which diagnostics is required, the engineer would input the last known 'healthy' data point as the probabilistic estimate of the component degradation.

**Reduction of Number of Models.** In addition to integrating degradation models which shift the estimate of the spike distribution of health parameters, there are observations about the 'health' of the sensors that can be integrated. In its previous form, the Bayesian multiple model approach tests whether each and every sensor has a bias. However, observations can be made by engineers which would lead the engineer to trust a given sensor measurement, or quantify what the bias is. Often, calibration reports are available to engineers on certain sets of sensors. Analogous to the integration of degradation models, these calibration reports provide an estimate on the magnitude of the bias in each sensor. Also, by integrating sensor calibration reports when available, the diagnostic method does not need to test for the presence of an unknown systemic bias on a given sensor. From the Bayesian multiple model perspective, the inclusion of calibration reports has a two-fold effect on a given sensor measurement: 1) Shift of the spike distribution and 2) elimination of the need for a slab distribution.

## TEST CASES

The developed method is applied to two test cases which show the advantages of using a degradation model and sensor calibration reports. The measurements in the following situations are simulated using the Gas Turbine Performance (GTP) software developed at GE [20]. A notional turbine with a significant number of fired hours is used for the test cases. An approximate model of the component health parameters as a function of fired hours was used to model the degradation [21]. As the number of fired hours increases, the confidence bound of the predicted value of the health parameters increases as a result other unmodeled operation parameters [18]. When a health parameter has a value of one, this means that the performance of the corresponding component is the same as a new and clean unit. All sensor biases are expressed as percentages of the values at the design condition except for the temperature sensor biases, which are in deviation from design condition.

### Highly Degraded Unit With Compressor Flow Fault

In this case, there is a compressor flow fault of 2%. Hence the value of the compressor flow is 2% less than the value obtained from the degradation model. All the other components are assigned values based on a highly degraded turbine. This case is not indicative of actual situations seen in the field, but it provides a good measure of the changes to the diagnosis as a degradation model is integrated. The analysis is carried out with ten data points. To capture the effect of daily temperature variation, each data point represents the performance of the gas turbine at a different ambient temperature.

Table 5 shows the results of this test case of a highly degraded gas turbine with a compressor flow fault with the degradation model. Model 513 is the most probable with a probability of 23.45%, which is distinctively higher than the others. Indeed, it is the right diagnosis because model 513 has a slab distribution on only $X_{CF}$ and represents the actual fault case. This is a significant improvement from the case without a degradation model in Tab. 3. The inclusion of the degradation model increases the confidence in the most probable model by a factor of three in this case.

**TABLE 5**. MODELS WITH HIGHEST PROBABILITY - WITH DEGRADATION MODEL

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 513 | 23.45 | 23.45 | ✓ | | | | | | | | | |
| 577 | 8.08 | 31.53 | ✓ | | | ✓ | | | | | | |
| 641 | 7.25 | 38.78 | ✓ | | ✓ | | | | | | | |
| 521 | 5.08 | 43.85 | ✓ | | | | | | ✓ | | | |
| 545 | 4.85 | 48.70 | ✓ | | | | ✓ | | | | | |
| 517 | 3.45 | 52.15 | ✓ | | | | | | | ✓ | | |
| 673 | 3.45 | 55.60 | ✓ | | ✓ | | ✓ | | | | | |
| 585 | 2.85 | 58.45 | ✓ | | | ✓ | | | ✓ | | | |
| 769 | 2.78 | 61.23 | ✓ | ✓ | | | | | | | | |
| 529 | 2.15 | 63.38 | ✓ | | | | | ✓ | | | | |

Table 6 shows the results of Bayesian model averaging (BMA) using Eqn. (9) for the cases without and with a degradation model. The table also shows the results of running the "truth" model (model 513) which had only a spike distribution on $X_{CF}$. Since the "truth model" represents the actual case, the results from running only this model should provide the highest levels of confidence as shown in the standard deviation values. The results for $X_{CF}$, $X_{CE}$, $X_{TF}$, and $X_{TE}$ for all these cases are shown compared with the expected values from the degradation model. The expected values of sensor biases are zero. For all the three cases, the -2% shift in CF was correctly estimated. However, BMA without the degradation model detected non-neglibible shifts in TF and TE. By including the degradation model, the estimated shifts in TF and TE became neglibible. Moreover, the confidence of the diagnosis increased significantly with standard deviations on some variables reduced by a factor of five. Thus, by integrating a degradation model in a Bayesian network of a highly degraded gas turbine, the network can detect both the presence of and the magnitude of a CF fault while reducing the chances of making incorrect diagnoses.

## Highly Degraded Unit With CDP Sensor Bias

After the implementation of the degradation model, the advantage of the sensor calibration report is demonstrated in this case. Here instead of a CF fault, there is a CDP sensor bias

**TABLE 6**. SUMMARY OF COMPRESSOR FAULT DIAGNOSIS

| Delta From Degraded Expected | | Bayesian Model Averaging - No Degradation Model | | Bayesian Model Averaging - With Degradation Model | | Model 513 With Degradation Model "Truth" | |
|---|---|---|---|---|---|---|---|
| | Units | Delta | Std Dev | Delta | Std Dev | Delta | Std Dev |
| **CF** | % | -2.00 | 0.60 | -1.90 | 0.20 | -2.00 | 0.10 |
| **CE** | % | 0.10 | 1.10 | 0.00 | 0.20 | 0.00 | 0.10 |
| **TF** | % | -1.00 | 1.20 | -0.10 | 0.50 | 0.00 | 0.10 |
| **TE** | % | 1.30 | 1.50 | 0.10 | 0.70 | 0.00 | 0.20 |
| **BCDP** | % | 0.28 | 0.98 | 0.00 | 0.46 | 0.00 | 0.06 |
| **BTEX** | F | 0.00 | 6.64 | 0.00 | 4.03 | 0.00 | 0.57 |
| **BDWATT** | % | -0.03 | 0.72 | 0.00 | 0.43 | 0.00 | 0.11 |
| **BCDT** | F | 0.63 | 5.62 | 0.49 | 1.63 | 0.90 | 1.07 |
| **BWF** | % | 0.00 | 0.34 | 0.00 | 0.18 | 0.00 | 0.06 |
| **BWA** | % | 0.00 | 0.22 | 0.00 | 0.66 | 0.00 | 0.06 |

of 2%. All the other variables are assigned values based on a highly degraded turbine. Since the CDP measurement is used to control the gas turbine, an unknown bias in CDP would cause a shift in the performance of the gas turbine. This case will highlight how the Bayesian multiple model approach can be used to aid the engineer doing performance analysis in differentiating an unknown sensor bias from a gas turbine fault. To illustrate this point, three sub cases were analyzed: no sensor calibration information available, calibration reports for all sensors except CDP, and calibration reports for all sensors. When available, the calibration reports indicated no bias in all the sensors other than CDP and a 2% bias in CDP. The second sub case, although not completely realistic, demonstrates how the diagnosis improves as models are removed from the network. Similar to the degradation model example, the third sub case will demonstrate how a shift in the spike distribution of a sensor improves the diagnosis. For all three sub cases it was assumed that there were 10 data points available for each.

Tables 7 illustrates the results of the sub case when no sensor calibration information is available. In this case, the Bayesian network correctly finds that model 33, which has a slab distribution for $B_{CDP}$ and spike for all others, is the most probable model. The probability of the most probable model is 23.78% which is slightly more than two times greater than the second most probable model which has both a spike distribution for both $B_{CDP}$ and TF. Given that all the models with sensor biases other than CDP have low probabilities, it can be assumed that these sensors can be trusted. This assumption is analogous to sensor calibration reports on those sensors indicating no biases.

Table 8 illustrates the results of the sub case where calibration reports for all sensors except the CDP sensor are available. Similar to the case with no sensor information, the Bayesian network correctly finds that model 33, which has a slab distribution for $B_{CDP}$ and spike for all others, is the most probable model with a likelihood of 49.25%. This model is now three times more likely than the second most likely model which again has both a

**TABLE 7**. MODELS WITH HIGHEST PROBABILITY - NO SENSOR INFORMATION KNOWN

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 33 | 23.78 | 23.78 | | | | | ✓ | | | | | |
| 161 | 11.00 | 34.78 | | | ✓ | | ✓ | | | | | |
| 97 | 6.83 | 41.60 | | | | ✓ | ✓ | | | | | |
| 41 | 4.53 | 46.13 | | | | | ✓ | | ✓ | | | |
| 105 | 3.73 | 49.85 | | | | ✓ | ✓ | | ✓ | | | |
| 37 | 3.55 | 53.40 | | | | | ✓ | | | ✓ | | |
| 545 | 3.23 | 56.63 | ✓ | | | | ✓ | | | | | |
| 49 | 3.13 | 59.75 | | | | | ✓ | ✓ | | | | |
| 225 | 2.60 | 62.35 | | | ✓ | ✓ | ✓ | | | | | |
| 169 | 1.98 | 64.33 | | | ✓ | | ✓ | | ✓ | | | |

spike distribution for both $B_{CDP}$ and TF. However, the probability of this model as well as that of the third most likely model, which has again has both a spike distribution for both $B_{CDP}$ and TE, both increase by around 6% from their values in the previous sub case. To verify the presence of a TF or TE fault, the gas turbine has to be shut down, and the casing has to be opened, which is a quite expensive job. Instead, the performance engineer can simply request a calibration report on the CDP measurement.

**TABLE 8**. MODELS WITH HIGHEST PROBABILITY - ALL SENSOR INFORMATION EXCEPT CDP KNOWN

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 33 | 49.25 | 49.25 | | | | | ✓ | | | | | |
| 161 | 16.38 | 65.63 | | | ✓ | | ✓ | | | | | |
| 97 | 13.13 | 78.75 | | | | ✓ | ✓ | | | | | |
| 545 | 6.00 | 84.75 | ✓ | | | | ✓ | | | | | |
| 225 | 3.50 | 88.25 | | | ✓ | ✓ | ✓ | | | | | |
| 289 | 3.35 | 91.60 | | ✓ | | | ✓ | | | | | |
| 673 | 2.13 | 93.73 | ✓ | | ✓ | | ✓ | | | | | |
| 417 | 1.55 | 95.28 | | ✓ | ✓ | | ✓ | | | | | |
| 609 | 1.53 | 96.80 | ✓ | | | ✓ | ✓ | | | | | |
| 353 | 1.50 | 98.30 | | ✓ | | ✓ | ✓ | | | | | |

As the calibration report on the CDP sensor becomes available, the performance engineer runs the Bayesian network again to refine its solution. Consider the calibration report indicating a 2% bias in the CDP measurement. To accommodate this information, the spike distribution of CDP bias was shifted to 2%. Because the CDP bias is already considered in its probability distribution, the “truth” model for this case is the one with a spike distribution for every variable. Table 9 illustrates the result from the case when the calibration information of all sensors is available. The Bayesian network correctly finds, again, the truth model with the highest probability, which is increased by 7.3% from the case where no CDP information was known. In addition to the increased confidence of the right diagnosis, the Bayesian network finds a TF fault less likely by 6.25% compared with the previous case making the most likely model now four times more likely than the second most likely model. The probability of a TE fault remains nearly same. With the sensor calibration report included in the analysis, along with the degradation model, the diagnosis becomes much more confident from about 7% in Tab. 3 to 56% in Tab. 9.

**TABLE 9**. MODELS WITH HIGHEST PROBABILITY - ALL SENSOR INFORMATION KNOWN

| Model Number | Probability | Cumulative Probability | Variables With Slab Distribution | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $X_{CF}$ | $X_{CE}$ | $X_{TF}$ | $X_{TE}$ | $B_{CDP}$ | $B_{TEX}$ | $B_{DW}$ | $B_{CDT}$ | $B_{WF}$ | $B_{WA}$ |
| 1 | 56.55 | 56.55 | | | | | | | | | | |
| 65 | 13.55 | 70.10 | | | | ✓ | | | | | | |
| 129 | 10.13 | 80.23 | | | ✓ | | | | | | | |
| 513 | 6.28 | 86.51 | ✓ | | | | | | | | | |
| 257 | 3.93 | 90.44 | | ✓ | | | | | | | | |
| 193 | 3.48 | 93.92 | | | ✓ | ✓ | | | | | | |
| 577 | 1.95 | 95.87 | ✓ | | | ✓ | | | | | | |
| 641 | 1.30 | 97.17 | ✓ | | ✓ | | | | | | | |
| 321 | 0.93 | 98.10 | | ✓ | | ✓ | | | | | | |
| 385 | 0.55 | 98.65 | | ✓ | ✓ | | | | | | | |

Table 10 shows the results of Bayesian model averaging (BMA) using Equation (9) for the CDP bias sub cases when no sensor information was available and when all sensor calibration information was available. The table also shows the results of running the ”truth” model (model 1) which did not test for the slab distribution for all sensor biases and shifted the CDP bias spike to the biased value. Since the ”truth” model represents the actual case, the results from running only this model should provide the highest levels of confidence as shown in the standard deviation values. The results for CF, CE, TF, and TF for all these cases are shown compared with expected values from a degradation model. The expected values of sensor biases were 0, except for the CDP bias for the 2nd and 3rd sub case which expected a 2% bias in CDP. All three sub cases detect a large bias in CDP. However, the sub case with no sensor information known had a significantly lower confidence in the diagnosis of the CDP bias. Additionally there was a small TF fault detected in this case. The confidence of the diagnosis with all sensor information known is very close to the sub case of the ”truth” model. This example shows that by integrating a calibration in a Bayesian network of a highly degraded gas turbine, the network can detect both the presence of and the magnitude of a CDP bias while reducing the likelihood of incorrect diagnosis.

**TABLE 10**. SUMMARY OF CDP DIAGNOSIS

| Delta From Degraded Expected | | Bayesian Model Averaging - No Sensor Information Known | | Bayesian Model Averaging - All Sensor Information Known | | Model 1 With Degradation Model "Truth" | |
|---|---|---|---|---|---|---|---|
| | Units | Delta | Std Dev | Delta | Std Dev | Delta | Std Dev |
| **CF** | % | 0.00 | 0.30 | 0.00 | 0.20 | 0.00 | 0.10 |
| **CE** | % | 0.00 | 0.50 | 0.00 | 0.10 | 0.00 | 0.10 |
| **TF** | % | 0.10 | 0.40 | 0.00 | 0.20 | 0.00 | 0.10 |
| **TE** | % | 0.00 | 0.50 | 0.00 | 0.30 | 0.00 | 0.20 |
| **BCDP** | % | 1.86 | 0.49 | 0.00 | 0.06 | 0.00 | 0.06 |
| **BTEX** | F | 0.00 | 1.92 | 0.00 | 0.58 | 0.00 | 0.57 |
| **BDWATT** | % | 0.00 | 0.41 | 0.00 | 0.12 | 0.00 | 0.11 |
| **BCDT** | F | 0.16 | 1.52 | 0.00 | 1.22 | 0.00 | 1.18 |
| **BWF** | % | 0.00 | 0.11 | 0.00 | 0.06 | 0.00 | 0.06 |
| **BWA** | % | 0.00 | 0.11 | 0.00 | 0.06 | 0.00 | 0.06 |

## CONCLUSIONS AND FUTURE WORK

This paper presents the advantages of using additional information such as a degradation model and a sensor calibration report in the offline fault diagnostics process for industrial gas turbines in a steady state. The cases analyzed include a gas turbine with a compressor flow fault and a gas turbine with a CDP sensor bias. The present method successfully detects and identifies the magnitudes of the compressor flow fault and the CDP sensor bias with a limited number of data points. As the compressor degrades over time, it is sensible to analyze the diagnostics from the perspective of where it is expected to operate instead of analyzing from the stand point of a new and clean gas turbine. The results indicate that the confidence of the diagnosis is greatly improved when a degradation model is used. With the help of a degradation model, we can clearly differentiate between a fault and degradation in the gas turbine. Further, using a sensor calibration report reduces the number of models to be tested and hence the results show an improvement in the confidence of the analysis.

The future scope of the research includes enhancing the accuracy of the diagnostics by testing it for other fault situations and sensor biases. In addition to verifying the performance on other computer simulated fault cases, future work will focus on validating the diagnostic performance on real-life cases. A challenge here is identifying cases where a known fault or event has occurred. Potential validation cases for an industrial gas turbine could be events such as a compressor water wash or a hot gas path outage. In addition to verification and validation tests, the fidelity of the model can be enhanced, by including secondary flow faults in the analysis. This would allow engineers to study the sensitivity of the secondary flow assumptions in the diagnostics. The addition of secondary flows in the analysis may require integrating other data such as vibration data and wheel space temperatures. Since the multiple Bayesian network approach is so flexible, it can leverage new tools, methods, and sensors developed for the state-of-the-art gas turbines, to enhance the diagnostics.

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