Trend Monitoring: Crossing the Chasm between Data-driven and Physics-based Approaches

I. INTRODUCTION

Modern development of monitoring capabilities for machines or industrial equipment (collectively called systems) started in the 1960s. Initially, our interest was in the detection and isolation of failures in a system, and it was primarily based on our knowledge of the failure modes and effects of the system [1]. Then the interest was expanded to accommodate the failure so that the system can continue to operate for a period of time until proper maintenance can be performed. Failure accommodation can be accomplished by having redundant hardware; however, hardware redundancy increases cost and weight. A more preferred approach is *software* (or *analytical*) redundancy, which relies on a model to provide the redundant information needed to meet monitoring and safety requirements [2]-[3].

Since the 1990s, prognostics has become the primary focus of monitoring, due largely to the new requirements of autonomic logistics for the Joint Strike Fighter (JSF) [4]. With this new focus, monitoring functions have been increasingly integrated with maintenance planning, maintenance management, and logistics functions; hence, a new generation of capabilities has emerged to provide a complete range of health management functions. These "total" health management functions are often called prognostics and health management (PHM) [5]-[6].

Because the aircraft propulsion system is critical to flight safety and dispatch reliability, engine/propulsion monitoring has led the way in the maturation of PHM capabilities. Several comprehensive surveys of engine monitoring capabilities have been conducted [7]-[9], and a modular framework of handling PHM algorithms has been suggested as shown in Figure 1. This framework can be extended to the entire integrated system like an airplane or a ground or sea vehicle.

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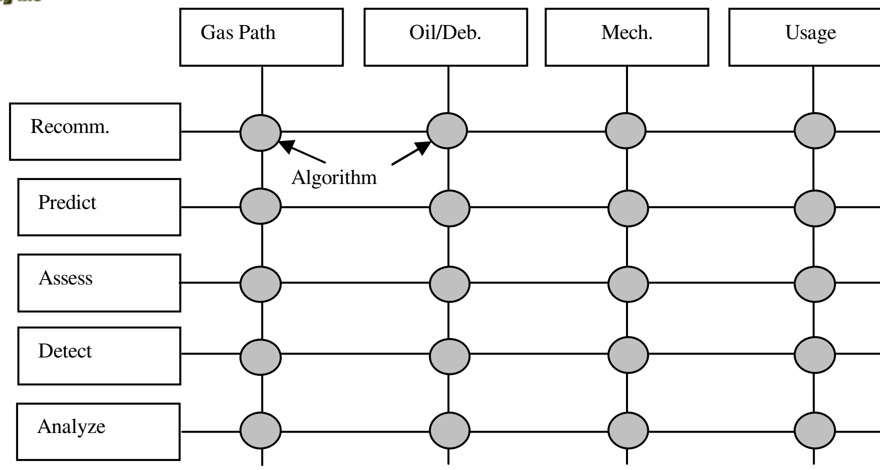

Fig. 1. A framework for PHM algorithms for engines

As the figure illustrates, algorithms are used in a PHM system to analyze data, detect and isolate faults, assess damage and health, predict failures and the remaining useful life (RUL), and recommend maintenance actions. They play the role of extracting information to support decision making at different functional levels. In general, algorithms fall into two broad classes: *data-driven* algorithms and *physics-based* algorithms. Examples of data-driven algorithms are statistical and machine-learning methods. Examples of physics-based algorithms are physics-of-failure models and state equations [10]. Some algorithms combine the attributes of both classes, and they are called hybrid algorithms. Examples of hybrid algorithms include: data-driven corrections to physics-based models, those that combine direct measurements with (hidden) features, and those that combine symbolic information processing (e.g., expert system) with numeric information processing (e.g., artificial neural network). Hybrid algorithms have proven effective in achieving the goal of reducing false alarms and increasing accuracy in corrective actions [11].

II. DATA-DRIVEN TRENDING

Trend monitoring is a systematic way of discovering trends in the data. It is usually performed graphically, because it allows a performance engineer to identify trends in the data more easily. Effective trend monitoring requires that same kinds of data be collected over a period of time. Same kinds of data refer to both the same *set* of data and the same *operating* condition. Using an aircraft engine as an example, take-off and cruise (for commercial engines) are the typical conditions where data are collected for trend monitoring purposes.

A. An Engine Example

An example of graphical presentation of engine trend data is shown in Figure 2. The data are correlated in the 3-D space with the X-Y-Z coordinates corresponding to three measured variables: fan speed (N_1), fuel flow rate (W_f), and exhaust gas temperature (*EGT*), respectively. Furthermore, we see a trend of increasing *EGT* with increasing N_1 or W_f. The question is whether the increase in *EGT* is a normal trend or an *abnormal* trend? A normal trend is one that represents an inherent physical relationship, for instance, the turbine temperature increases with engine fuel flow; whereas an abnormal trend is one that reveals an underlying change or degradation of the engine, for instance, the turbine temperature increases *faster* than what it normally does for the same amount of fuel increase.

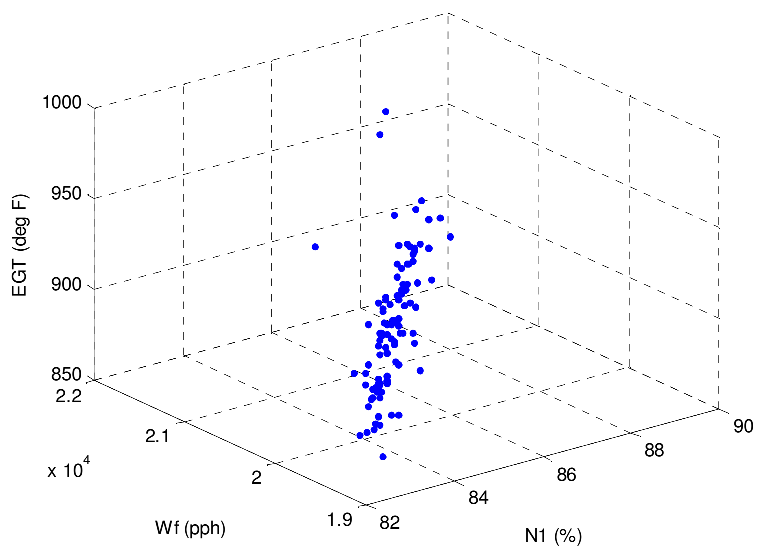

Fig. 2. A 3-D view of three engine variables

In trend monitoring, we are primarily interested in abnormal trends; however, we can not discern any abnormal trend until we know what the normal trends are. This seemingly simple statement can be difficult to realize, because we often do not know all of the normal trends based on the limited measurements we have at hand. Various statistical methods and data analysis techniques have been developed to build normal trends and use then to discover abnormal trends. For instance, Figures 3 shows two different views of the same data in the 3-D view of Figure 1. Through these coordinate transformations, we hope to identify certain data *components* that are more distinctive than others so as to identify similar and dissimilar trends more easily.

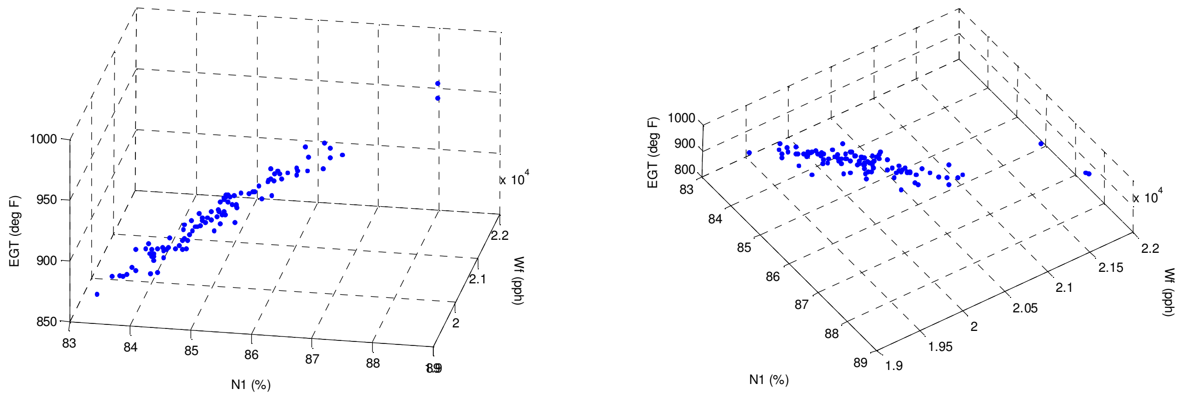

Fig. 3. Two different views of the same engine data

When the number of measured variables exceeds three, graphical presentation of the data becomes impractical. Mathematically we can throw all the time-elapsed data of any dimension (i.e., any number of measured variables) in a hyperspace, $\mathbf{R}^N$, where N is the number of dimensions or variables. Statistically we can even calculate the mean value, the covariance matrix, and other properties for the data that fall in the same cluster in the hyperspace, and use these properties to define normal trends. This concept is the basic premise of the data-driven approach for monitoring.

B. Trend Charts and Thresholds

For each measured variable, we can calculate the mean value and the standard deviation from a sufficiently large collection of data points over time. We can further subtract the mean value from the actual value at each data point as the *difference* from the mean. If we call the mean value a baseline, then each difference value is a *delta* from the baseline. Then a collection of all the deltas for the same variable over time provides a basis for a trend chart.

Figure 4 is an example of the trend charts for the three measured variables described earlier. More data points have been added in these charts to show trends better. Note that these data points on the trend charts are distributed about the horizontal axis (or delta value of zero). Note also that two red lines have been added on each trend chart. These lines represent the thresholds, or the *control limits*, for the chart. The line on the top is called the upper control limit (UCL), and the line on the bottom is the lower control limit (LCL). These control limits trigger alarms or flag faults when points on the chart fall outside the limits, hence a trend chart with control limits is also called a *control chart*. Each data point on a control chart provides a piece of evidence about the state of the operation of the system being monitored.

A statistically motivated threshold value is to multiple the standard deviation that we have calculated from a set of data by an integer number. A typical number is three times the standard deviation (or 3 □).

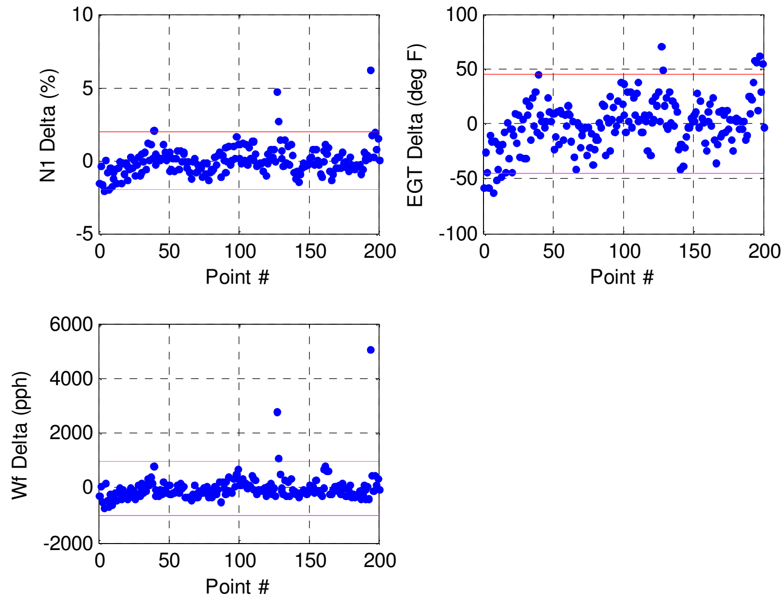

Fig. 4. Trend charts of the same three engine variables

After the baseline, the delta values, and the control limits have been calculated, we can calculate the trend line, which is the best fit of the data points, within a time period of interest, to a straight line. The slope of the trend line indicates how fast the monitored variable will reach a control limit. This predictive feature in trend monitoring is a data-driven approach to prognostics. Figure 5 is an example of the trend line on the EGT trend chart. The trend line shows the predictability of the trend exceeding the UCL.

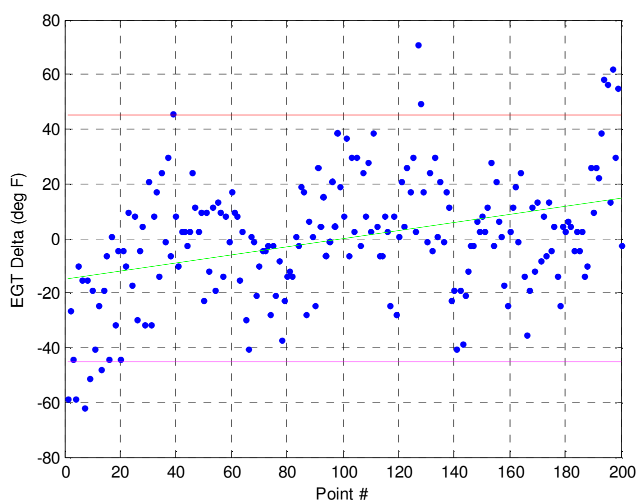

Fig. 5. Trend charts of the same three engine variables

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III. PHYSICS-BASED TRENDING

For complex systems, the number of measured variables easily exceeds 10, hence graphical presentations of data for trend monitoring become impractical. Moreover, the wide range of operating conditions causes the accuracy of the data-driven approach decrease with increasing data dimensions.

To increase the trending accuracy, we like to find a way to inject our knowledge about the system being monitored into the trending method described above. This knowledge is often captured in the form of a model or relationships among some measured variables. Indeed, one of the most practiced ways of applying physical principles to trending is to identify one or a few independent variables among all of the measured variables. After the independent variables are identified, the rest of the dependent variables can be expressed as functions of these independent variables. By doing so, we have effectively reduced the dimension of the hyperspace, and consequently, breaking the original high-dimensional space into several lower-dimensional spaces, which may allow us to identify trends using traditional techniques more easily.

Again, using the engine as an example and from our knowledge of engine performance, we know that the fan speed is directly related to engine thrust and can be selected as an independent variable. By choosing the fan speed as an independent variable, we can now make the other two variables dependent on the fan speed, or as functions of the fan speed. The functional relationships of these two dependent variables with respect to the fan speed are depicted in Figures 6 and 7, and these relationships are the projections of the data points onto the N_1-W_f plane and the N_1-EGT plane, respectively. The green lines on top of the data points in the figures are the linear regression lines excluding the outliers.

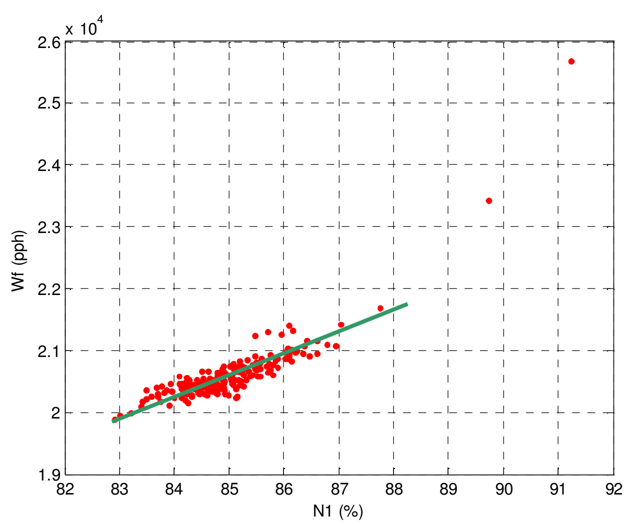

Fig. 6. Fuel flow rate versus N_1

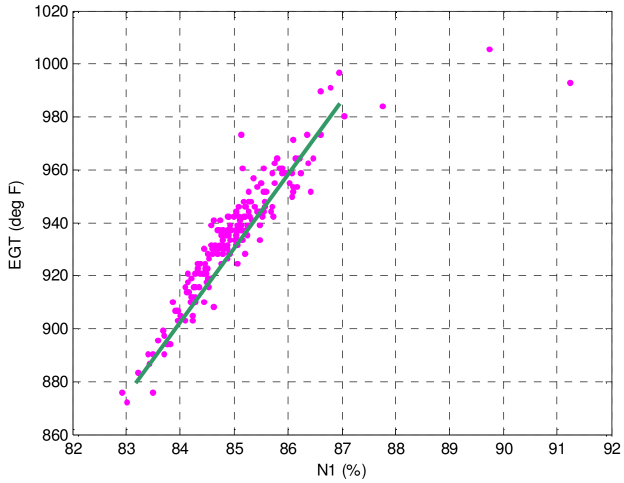

Fig. 7. Turbine temperature versus N_1

Once we have established the functional relationships between the independent and the dependent variables, we can follow the same steps in the data-driven trending method to create control charts for the model-based trending. However, the baselines we should use to calculate delta values are the linear regression lines for each pair of independent-dependent variables.

IV. Mathematical Representation of Trending

The state equation form of a system being monitored is given by [8, 10]

$$\dot{x}_A(t) = A_A x_A(t) + Bu(t) \tag{1}$$

$$y(t) = C_A x_A(t) + Du(t) \tag{2}$$

where $x_A(t)$ is the augmented state variable, and is defined as

$$x_A(t) = [x(t), x_d(t)]^T \tag{3}$$

and the second state variable is the *damage state variable*, $x_d(t)$. Note that these equations represent a system fault model in continuous-time.

In the case of a gradual degradation, the change in degradation state variable is much slower than that of the regular state variable. By applying the *frequency separation principle* and putting our focus on the low-frequency dynamics of the damage state variable, the model of Eqs. (1) and (2) degenerates into a combination of algebraic equation and state equation as follows:

$$0 = Ax(t) + Bu(t) \ , \tag{4}$$

$$\dot{x}_d(t) = A_d x_d(t) + B_d u(t) \ , \tag{5}$$

$$y(t) = C_A x_A(t) + Du(t) \ . \tag{6}$$

These equations form the mathematical basis for using quasi-steady state measurements (or *snap-shot* data) in trending to detect performance degradations.

After the baseline value is defined for each measured variable, the delta value (or residual) can be obtained by

$$\Delta y(t) = z(t) - y_B(t) = y(t) - y_B(t) + v(t) \ . \qquad (7)$$

where z is the measured value of the variable y and v is the measurement noise. An alarm is triggered (or a fault is declared) when the difference exceeds the alarm threshold (from the baseline), i.e.,

$$\Delta y(t) > \gamma_B \ . \qquad (8)$$

To reduce false alarms further, we apply additional rules to the alarm generation logics. For instance, to avoid false alarms due to random, noise-corrupted data, we do not alarm any isolated point that has exceeded the alarm threshold according to Eq. (8).

One thing to note is that Eq. (7)-(8) can be generalized to any state variable of the system, whether it is also a measured output variable or an unmeasured state variable but can be estimated through an observer. By trending the estimated degradation state variable, we can determine the state of degradation and the cause of degradation more directly. The corresponding equations for trending of estimated state variables are

$$\Delta \hat{x}_d(t) = \hat{x}_d(t) - x_{dB}(t) \ . \qquad (9)$$

$$\Delta \hat{x}_d(t) > \kappa_B \ . \qquad (10)$$

Where x_{dB} is the baseline of the degradation state variable, and κ_B is the corresponding alarm threshold.

V. CONCLUSION

A brief description of the traditional data-driven trending method and how it can be modified to increase diagnostic and prognostic accuracy has been given by using examples of a turbine engine. While the principles of traditional trending can be applied to all systems, its effectiveness can be increased by inserting system-dependent, physics-based information. Combining the two methods, in a so-called hybrid model, can produce even better results than either method individually.

ACKNOWLEDGMENT

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