TEMPER—A Gas-Path Analysis Tool for Commercial Jet Engines

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ABSTRACT
Almost from the inception of the gas turbine engine, airlines and engine manufacturers have sought an effective technique to determine the health of the gas-path components (fan, compressors, combustor, turbines) based on available gas-path measurements. The potential of such tools to save money by anticipating the need for overhaul and providing help in work scope definition is substantial, provided they produce reliable results. This paper describes a modern gas-path analysis tool (GE’s TEMPER program), discusses the benefits and problems experienced by current TEMPER users, and suggests promising research areas that may lead to an improved algorithm.

INTRODUCTION
As a result of several factors, the performance of a gas turbine engine gradually deteriorates with time. This deterioration increases the internal operating temperature of the engine and reduces its fuel economy. When the internal temperature reaches a specified limit, the engine must be removed for overhaul. Depending on the cost of fuel and the available temperature margin of the engine, it may be cost effective to overhaul an engine before it reaches its temperature limit. Gas-path analysis is used by airlines to evaluate the performance of an engine and its components. The results may be included in the process to determine overhaul work scope.

Gas-path analysis can be performed using data acquired during routine service on-wing. Gas-path analysis is also accomplished using test cell data obtained during an acceptance run. The on-wing analysis has access to data at some fixed interval. This permits an examination of each new reading in relation to prior readings from the same engine. Deterioration can be recognized as the change in performance from when the engine was new. The objectives of the on-wing analysis are to decide when an engine should be removed for overhaul and what the overhaul work scope should be.

Gas-path analysis based on test cell data is, of necessity, a snapshot evaluation. The engine's and component's performance levels must be inferred from one or more readings that are obtained at a fixed instant in time. Usually, the test cell analysis is based upon an out-bound acceptance run. If the engine satisfies its acceptance limits, there is little interest in the results of the analysis. When the engine fails the acceptance requirement, the data are reviewed to try to determine the minimal rework to correct the problem. Occasionally, an engine removed from service will be run in a test cell to help to define its required work scope.

Most modern gas-path analysis programs use statistical techniques to estimate sensor error. This is desirable because of the limited amount of gas-path instrumentation and the inaccuracy of the available data. The older algorithms did not estimate sensor error. Thus, measurement error was interpreted as component performance by these algorithms. This often produced bizarre results (e.g., an extremely high turbine efficiency coupled with an equally low compressor efficiency). Urban (1980) and Volponi (1982) showed that weighted least squares techniques could be used to reduce the sensitivity to measurement error. Following their lead, modern test cell and on-wing gas-path analysis programs use weighted least squares or a closely related algorithm.

MATHEMATICAL BASIS OF GAS PATH ANALYSIS
To evaluate engine component performance correctly, sensor error must be considered in the analysis. Weighted least squares facilitates the determination of engine state in the presence of sensor error. Weighted least squares is based on a model of the measurement process of the form:

\[ z = h(x) + \nu \]  

1 for Turbine Engine Module Performance Estimation Routine
2 Jet engines are normally tested after overhaul to assure that performance and mechanical requirements are satisfied prior to return to service. This test is known as an acceptance test.
The elements of this equation are:

\[ z \] is the measurement vector consisting of the independent measurements upon which the analysis is based (e.g., core speed, fuel flow). Note that \( z \) has dimension \( p \).

\( x \) is the state vector incorporating those characteristics of the engine expected to vary with time (e.g., compressor efficiency, HP turbine flow function). Other attributes, not expected to change with time, such as nozzle area, are excluded from \( x \). Note that \( x \) has dimension \( n \).

\( h(x) \) is the \( p \times n \) matrix representing the nonlinear effect of the state variables upon the measurements. With no measurement error, \( z = h(x) \) should be precisely true. In the jet engine condition monitoring example, \( h(x) \) is a cycle model.

\( v \) is the vector composed of the random element of the measurement error. Measurement bias is to be included in the model.

For the weighted least squares analysis to succeed, it must be possible to determine the state vector, \( x \), from the available measurements. This requires the dimension of the measurement vector to equal or exceed that of the state vector. Further, it must be possible to choose a subset of \( z \) that yields a unique solution for \( x \). That is, the engine state must be observable from the available measurements.

To avoid difficulties associated with nonlinear optimization, the nonlinear model, \( h(x) \) is replaced by a linear approximation, \( Hx \). The resulting approximation to equation 1 is:

\[ z = Hx + v \] (2)

Several assumptions are made to simplify the mathematics. The measurement error is assumed to be Gaussian, with zero mean. \( R \) is defined to be the covariance matrix of the measurement error:

\[ R = \text{E}(v v^T) \] (3)

where \( \text{E} \) is the expected value operator. The diagonal elements of \( R \) represent the variances of the measurement errors. The off-diagonal elements represent covariance between measurements. Usually, the off-diagonal elements are assumed to be zero.

The state variables, \( x \), are also assumed to be Gaussian. Without loss of generality, their mean can be taken to be zero. \( M \) is defined to be the covariance matrix for the state vector:

\[ M = \text{E}(x x^T) \] (4)

Some off-diagonal elements of \( M \) are expected to be non zero. For example, any mechanism that changes the flow capacity of the fan is almost certain to produce an effect on fan efficiency. However, most off-diagonal elements of \( M \) are assumed to be zero.

The measurement error, \( v \), is assumed to be statistically independent of the engine state, \( x \):

\[ \text{E}(x v^T) = 0 \]

With these assumptions, the objective of the weighted least squares analysis is to determine a "best estimate" of the state of the system given a set of measurements, \( z \). The matrices \( M \) and \( R \), with the assumptions above, allow definition of a Bayesian probability model for the system. A probability density function can be defined for the likelihood that the set of measurements, \( z \), originated from an initial state vector, \( x \). The designation for this probability density function is \( P(x|z) \). It can be shown (Gelb, 1974) that \( P(x|z) \) is a decreasing monotonic function of the quadratic form \( J \), where:

\[ J = \frac{1}{2} \{ x^T M^{-1} x + (z - Hx)^T R^{-1} (z - Hx) \} \] (5)

Minimizing \( J \) with respect to \( x \) will yield the state vector estimate with highest conditional probability. The minimum \( J \) is found by requiring that \( dJ \) be zero for arbitrary \( dx \). Solving this for the optimal solution, \( x_o \), yields:

\[ x_o = (M^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1} z \] (6)

Corresponding to the estimate of the engine state, \( x_o \), is an estimate of the true measurements, \( z_o \). This is computed using equation 2:

\[ z_o = H x_o \]

This is combined with equation 6 to compute the estimated measurement error, \( v_o \):

\[ v_o = \{ I - H (M^{-1} + H^T R^{-1} H)^{-1} H^T R^{-1} \} z \] (7)

The corresponding solution residual, \( J_o \), is obtained by substituting \( x_o \) into equation 5. It can be shown that the expected value of \( J_o \) is \( p/2 \) where \( p \) is the number of independent measurements (Bryson and Ho, 1975). The actual value of \( J_o \) will vary depending upon the ability of the model to fit the observed data. As \( J_o \) increases, it becomes less likely that the assumed statistical model (expressed by the engine model, \( H \), and the covariance matrices, \( M \) and \( R \)) is correct for the particular data sample. When \( J_o \) is much larger than \( p/2 \), it is reasonable to assume that at least one of the statistical assumptions is incorrect.

3 Some of the measurements are used to specify the operating condition of the engine. These include inlet pressure and temperature, fan speed, humidity and the variable geometry position variables. These measurements are not available to the analysis. The remaining measurements are the independent measurements.

4 There are errors in the model. Jet engine cycle models enforce the conservation of mass and energy. The modeling of loss is empirically derived. There are errors in the model. Jet engine cycle models enforce the conservation of mass and energy. The modeling of loss is empirically derived. Some off-diagonal elements of \( M \) are expected to be non zero. For example, any mechanism that changes the flow capacity of the fan is almost certain to produce an effect on fan efficiency. However, most off-diagonal elements of \( M \) are assumed to be zero.

5 In a practical sense, \( v \) will include, in addition to the random measurement errors, the influence of any state variables not included in the state vector, \( x \), and any random imperfections in the model.

6 This requirement can be strengthened in practice to require that the matrix, \( h \), be well-conditioned. If this is not the case, the errors in the state variables can become unacceptably large.

7 It is not unreasonable for there to be a non-zero correlation between measurement errors. This could occur with pressure measurements if several were measured against barometer (gage pressure) and then the same barometric pressure were added to all.

8 This can be achieved by defining \( x \) and \( z \) as deviations from a nominal condition. Thus \( x \) is not the raw measurement value, but is instead the deviation of the measurement from a nominal reference condition, and \( z \) represents the deviation of the state variables from that same nominal point.

9 There could be some correlation as a result of temporal effects; that is, different engine components tend to deteriorate with time and thus their deviation from nominal is positively correlated. This effect is ignored.
PROPERTIES OF THE GAS PATH ALGORITHM

The weighted least squares solution is the expected value for the engine state, given the measurement vector. That is:

$$x_0 = E(x|z)$$

It can be shown that $x_0$ is both the maximum-likelihood and the minimum-variance estimate for $x$ (Bryson and Ho, 1975). Thus, an estimate that properly accounts for measurement error is superior to any estimate that does not acknowledge its presence.

Equations 6 and 7 define the estimate for the state of the engine and the measurement errors as a function of the three matrices $H$, $R$, and $M$. These matrices define the effect of state variables on the measurements, the expected magnitude of sensor errors, and the expected variation of state variables, respectively. The matrices are available before taking any data. They are independent of the analysis results. Therefore, the state and measurement error estimates are linear functions of the input measurement vector, $z$.

Consequently, it is possible to predict the response of the weighted least square algorithm to a specific input. For example, one can input the measurement vector associated with a one percent deterioration in the high-pressure turbine efficiency (with no other deviation present). The weighted least squares solution for this input will, in general, underestimate the change in turbine efficiency. Some of the efficiency change will be attributed to other engine components and to measurement error. This behavior occurs because a solution with small changes to several elements is more probable than a solution with the entire deviation attributed to a single element (the turbine efficiency).

The amount of the underestimate depends on the relative magnitude of the elements of the $M$ and $R$ matrices. If the element of $M$ corresponding to high-pressure turbine efficiency is increased while all other variances are held fixed, the solution will move closer to that of the input. However, as the response to a turbine-efficiency problem is improved, the fidelity of the solution to other problems (e.g., compressor-efficiency deterioration, fuel-flow measurement error) is reduced. Thus, the elements of $M$ and $R$ define the sensitivity of the algorithm to various problems that occur in an engine.

Since the algorithm is linear in $x$, the solution error is proportional to the measurement deviation. If the turbine-efficiency deviation is doubled, the solution error will also be doubled (the percent error remains fixed). Hence, the weighted least squares algorithm provides better results when measurement deviations are small. This is unfortunate since the most interesting cases are those for which the performance of the engine is far from nominal. To address this limitation of the weighted least square algorithm, TEMPER includes a special feature known as "fault logic." The fault logic is used to search for large deviations in component performance, or for large measurement errors, whenever the solution residual is large.

The solution residual, $J_0$, provides the mechanism for recognizing that a specific case is far from nominal conditions.

10 In the classic Kalman filter, the $M$ matrix is updated after each reading is obtained to reflect the increased certainty of the engine state. This update is entirely predictable, and does not depend on the data that were acquired. Furthermore, the $M$ matrix approaches a steady-state value as the number of readings gets large reflecting the reduction in the initial uncertainty of the engine state.

11 As long as no correlation between state variables or measurement errors is present, the solution response is constrained to lie between 0 and 1. With state variable correlation present, it is possible that the solution will overestimate the deterioration in a particular state variable. It is also possible, with correlation, that the estimate will err in the direction of the change.

The expected value for this residual is $p/2$, where $p$ represents the number of independent measurements. TEMPER assumes that $J_0$ follows the Chi-Squared distribution. Figure 1 shows the expected value and the 95% confidence limit for the residual, based on the assumption that $J_0$ obeys the Chi-Squared distribution. The TEMPER fault logic is invoked whenever the residual exceeds the 95% limit.

Figure 1 Weighted Least Squares Solution Residual

ACCEPtANCE TEST GAS PATH ANALYSIS

After overhaul, a jet engine must pass an acceptance test. The test evaluates the thrust level and EGT margin of the engine, and may verify the engine's fuel economy as well. The sensors available for this run are a combination of built-in instrumentation and special sensors available in the test cell (Figure 2). Usually, sensors are single-element probes, subject to significant profile error and to normal measurement noise. Therefore, the weighted least squares algorithm is well suited to the analysis of the test cell data.

Figure 2 Typical Sensors for Gas Path Analysis

12 Actually, $2J_0$ is assumed to obey the Chi-Squared distribution with $p$ degrees of freedom. We are not aware of a proof for this assertion.

13 EGT stands for "Exhaust Gas Temperature." It represents a temperature that is measured at the inlet or discharge of the turbine which is used to assure that the engine hot section is not operated above its metal temperature limit.
The acceptance test consists of a series of discrete readings at a range of power levels. The readings recorded at the highest power levels are compared to performance requirements to evaluate the overhaul. If the engine fails to achieve desired performance, the readings at high power are analyzed to identify the origin of the problem. The data to be analyzed are acquired at a specific instant in time. Consequently, the analysis is a snapshot evaluation of the performance of the engine and its modules.

The original, deterministic algorithms sought the absolute performance of the engine and its modules. They attempted to identify a faulted module by comparing its performance to an absolute standard. There are several difficulties associated with this approach.

Measurement noise distorts the analysis of the performance of the modules.

Measurement bias produces consistent errors in the assessment of modular performance.

Changes to parasitic flows, or other elements not included in the analysis, distort the absolute performance levels for the modules.

The use of an absolute performance standard may lead to unprofitable maintenance by encouraging performance gains that will quickly be lost in service (such as excessively tight clearances in seals and rotating components).

The weighted least squares approach reduces problems associated with measurement noise, but does not address the other difficulties. These other problems are solved by seeking a relative assessment of performance in place of the absolute analysis. Thus, TEMPER seeks to learn how a deficient engine’s modules differ from those of an accepted engine. This is accomplished by comparing data from the specific engine to a model derived from similarly overhauled engines. The effect of consistent measurement bias is eliminated by this approach.

Unrealistic component improvement goals are also avoided by evaluating performance relative to overhauled engines.

The first step in the analysis is to calculate the difference between the independent measurements and the cycle-deck predictions. These differences may be a result of component performance deterioration, measurement noise or measurement bias. The cycle model represents the performance expected from a new production engine. Therefore, it represents a performance level higher than most overhauled engines. Measurement base lines are used to adjust the cycle deck so that it represents the performance exhibited by a typical overhauled engine (including measurement bias). Thus, the next step in the analysis (Figure 3) is to adjust the measurement-to-cycle-deck differences for the base lines.

After the base-line adjustment is made, the modified measurement-to-cycle-deck differences represent two elements. They are:

- module performance differences due to variation in the overhaul process,
- measurement noise.

Several of the available measurements are used to specify the operating point of the engine (Table 1). These include inlet pressure and temperature, humidity, fan speed (to specify engine power level), and variable-geometry settings. These measurements are known as “setting parameters.” The remaining independent measurements form the basis for the gas-path analysis. The cycle model predicts the independent measurements.

The terminology is unfortunate. The term “base line” suggests different meanings to different people. In some cases it is treated as being synonymous with a priori estimate. In other situations, it is interpreted to be the standard against which performance is to be measured. In this latter case, an engine that is better than the base line has been overhauled to exceed the performance requirement. The confusion leads to misunderstanding of the algorithm results. In some instances, it can even cause incorrect determination of the base lines.

Table 1 Typical Jet Engine Measurements for Gas Path Analysis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Availability</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIA</td>
<td>Inlet Total Pressure*</td>
<td>Test Cell</td>
</tr>
<tr>
<td>PSIA</td>
<td>Inlet Static Pressure (Used for Air Flow)</td>
<td>Test Cell</td>
</tr>
<tr>
<td>TIA</td>
<td>Inlet Total Temperature (Also Total Air Temperature)*</td>
<td>Both</td>
</tr>
<tr>
<td>ALT</td>
<td>Pressure Altitude*</td>
<td>On Wing</td>
</tr>
<tr>
<td>XM</td>
<td>Aircraft Mach Number*</td>
<td>On Wing</td>
</tr>
<tr>
<td>HUM</td>
<td>Ambient Humidity (Water to Air Ratio)*</td>
<td>Test Cell</td>
</tr>
<tr>
<td>N12</td>
<td>Fan Rotor Speed*</td>
<td>Both</td>
</tr>
<tr>
<td>PS14</td>
<td>Fan Discharge Static Pressure (Sometimes Total Pressure)</td>
<td>Both</td>
</tr>
<tr>
<td>PS25</td>
<td>High Pressure Compressor Inlet Static Pressure</td>
<td>Both</td>
</tr>
<tr>
<td>T5</td>
<td>High Pressure Compressor Inlet Total Temperature</td>
<td>Both</td>
</tr>
<tr>
<td>N25</td>
<td>Core Rotor Speed*</td>
<td>Both</td>
</tr>
<tr>
<td>VSV</td>
<td>Variable Stator Vane Position*</td>
<td>Both</td>
</tr>
<tr>
<td>VBV</td>
<td>Variable Bypass Valve Position*</td>
<td>Both</td>
</tr>
<tr>
<td>PS3</td>
<td>High Pressure Compressor Discharge Static Pressure</td>
<td>Both</td>
</tr>
<tr>
<td>T3</td>
<td>High Pressure Compressor Discharge Total Temperature</td>
<td>Both</td>
</tr>
<tr>
<td>WF36</td>
<td>Fuel Flow</td>
<td>Both</td>
</tr>
<tr>
<td>TCC</td>
<td>Turbine Clearance Control Position*</td>
<td>Both</td>
</tr>
<tr>
<td>P40</td>
<td>High Pressure Turbine Discharge Total Pressure</td>
<td>Both</td>
</tr>
<tr>
<td>T49</td>
<td>High Pressure Turbine Discharge Total Temperature</td>
<td>Both</td>
</tr>
<tr>
<td>P5</td>
<td>Low Pressure Turbine Discharge Total Pressure</td>
<td>Test Cell</td>
</tr>
<tr>
<td>T5</td>
<td>Low Pressure Turbine Discharge Total Temperature</td>
<td>Both</td>
</tr>
<tr>
<td>FN</td>
<td>Net Thrust</td>
<td>Test Cell</td>
</tr>
</tbody>
</table>

* Parameters used to specify engine operating condition for engine model

4 This terminology is unfortunate. The term “base line” suggests different meanings to different people. In some cases it is treated as being synonymous with a priori estimate. In other situations, it is interpreted to be the standard against which performance is to be measured. In this latter case, an engine that is better than the base line has been overhauled to exceed the performance requirement. The confusion leads to misunderstanding of the algorithm results. In some instances, it can even cause incorrect determination of the base lines.
At this point, the weighted least squares analysis is performed. The analysis estimates the deviation of the performance of the modules from that of an average overhauled engine. It also estimates the magnitude of the measurement noise.

There are several factors that contribute to error in the basic weighted least squares analysis. The weighted least squares analysis is likely to underestimate any pure fault (either measurement error or module performance deviation). The remaining deviation is attributed to other measurement errors and module performance changes. The size of the error is proportional to the size of the actual performance fault.

Another source of error is change to system elements not included in the weighted least squares analysis. For instance, a change in a turbine cooling flow is indistinguishable from the turbine performance fault (affecting both efficiency and flow function). The TEMPER analysis includes consideration of the turbine performance parameters, but does not estimate turbine cooling flow. Any change in turbine cooling flow will be interpreted as if it were a change to the turbine performance parameters.

Measurement error in the setting parameters is not evaluated by the gas-path analysis. These errors will be interpreted as module performance change, or as noise in the independent measurements.

There is no algorithmic way to eliminate these problems. As the number of redundant sensors is increased, the fidelity of the weighted least squares solution is improved. The addition of new sensors to distinguish between turbine performance and cooling flow would permit estimation of additional system elements. This would reduce the tendency to mislabel deteriorated system elements. Redundant setting-parameter sensors can be used to include setting-parameter errors in the analysis. These improvements call for additional sensors. However, large gains are unlikely due to the penalties associated with the additional sensors.

**TEMPER FAULT LOGIC**

Although the problems enumerated above cannot be avoided in all instances, there is a strategy to eliminate an important subset of these problems. It is often possible to identify a single cause for a large deviation from normal behavior. For instance, sensors often exhibit sudden large shifts as a result of some failure mechanism. Foreign object damage or some other mechanism may produce a large shift in a single component, with little effect on the others.

When a large shift in a measurement error or module performance occurs, the statistical assumptions of the weighted least squares analysis are violated. Consequently, the solution residual is very large. When this occurs, it is possible to modify the algorithm to seek a single cause for the large residual. In TEMPER, this alternate strategy is employed whenever the solution residual exceeds the 95% confidence limit.

When the fault logic is invoked, a special weighted least squares analysis is performed to evaluate each possible hardware fault or sensor error. When a particular sensor error is to be evaluated, its standard deviation is increased by a factor of 100. If the large residual of the original solution is due to error in that sensor, the new analysis will return a much lower solution residual. If some other mechanism is at fault, the solution residual will remain nearly unchanged.

A similar technique is applied to seek a large shift in a hardware module. A weighted least squares analysis is performed for each module, with the module's standard deviation increased by a factor of 100. If the performance of the specific module being considered is far from nominal, the solution residual will be returned to the normal range. For hardware modules, it is possible to evaluate a change to efficiency only, to flow capacity only, or a change to both.

The fault search can evaluate system changes not included in the basic gas-path analysis. For instance, a large error in a setting parameter can be detected by adding the setting parameter to a special weighted least squares analysis (with a large standard deviation). If the setting parameter has a large error, this analysis will produce a much lower solution residual. Similarly, a special analysis can be performed to evaluate the possibility that the large residual resulted from a large shift in one of the cooling flows. Any reasonable mechanism for the residual can be evaluated in this way.

The TEMPER fault search performs a weighted least squares analysis for each candidate explanation for the large solution residual. Often, one or more of the solutions will yield a residual that is in the normal range. When this occurs, the best solution is presented in place of the no-fault result. In many situations, no single explanation will account for a large solution residual. Nevertheless, this feature allows TEMPER to analyze an important fraction of highly deteriorated engines. These successes are far more critical than those associated with normal engines. Figure 4 shows a modified flow chart for Test Cell TEMPER including the fault search.

**ON-WING GAS PATH ANALYSIS**

Gas-path measurements are taken regularly during revenue service. Data are acquired at steady-state cruise, either once per flight or at a regular interval (e.g., every four flight hours). The data are analyzed to detect sudden shifts or slope changes that may indicate a problem.

Some airlines purchase expanded instrumentation for their engines to permit analysis of module health based on the cruise data. They hope to use the analysis results to isolate problems identified by trend charts. They also hope to use the data to help define the work scope when the engine is removed for overhaul.

The sensor data are similar to those in the test cell (Table 1) except that inlet static pressure and thrust are not available. The loss of information from these sensors is partly offset by the ability to analyze data obtained at regular intervals over a long period. The time-history element of the data opens the possibility of distinguishing faults based on the timing of their occurrence. Suppose the fuel-flow sensor develops an error and, later, the EGT sensor shifts in the same direction. The knowledge that these events occurred at different times rules out the possibility that they resulted from a common cause. Without this temporal knowledge, it would be tempting to seek a common cause for the two events.

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15 These penalties include cost, weight, reliability and even performance. While some increase in the number of sensors may be desirable, it is likely that the number needed to eliminate all problems with the weighted least squares algorithm would not be cost effective.

16 An example might be a leak in a pressure line.

17 Note that the setting-parameter error is evaluated in the same way as a hardware fault. Thus, it is introduced into the analysis in the same way that a state variable would be added, i.e. as an additional element in . The H matrix must be augmented to include the effect of the setting-parameter error on the measurement deviations.

18 Actually, the selection of a best solution is done using a probability derived from the solution residual. This probability accounts for the degrees of freedom that are associated with the solution residual. It adds a bias towards simpler explanations for the observed deviation.
A snapshot analysis does not provide this memory capability. Some mechanism is needed to carry the solution forward from point to point if the fuel flow shift and the later EGT shift are to be recognized as separate events. The classic means of implementing this memory feature is the Kalman Filter (Sorenson, 1985). On-Wing TEMPER, while not using the Kalman filter directly, mimics the approach in many ways. Specifically, smoothed analysis results for module deterioration and sensor error (called "running base lines") provide an a priori estimate for the analysis of new data. Exponential smoothing is used to smooth the module deterioration and sensor error analysis results (Bowerman and O'Connell, 1979). Exponential smoothing gradually substitutes the new results for the old, using the formula:

\[ x_i = x_{i-1} + \alpha (x_i - x_{i-1}) \]  

where:

- \( x_i \) represents the smoothed value at the \( i \)th time step.
- \( x_{i-1} \) represents the unsmoothed value of the parameter at the \( i \)th time step.
- \( \alpha \) is the smoothing coefficient (typically 0.02 \( \leq \alpha \leq 0.2 \)).

Figure 5 illustrates the result of applying exponential smoothing to a step increase in a parameter.

The only significant way that On-Wing TEMPER is structurally different from Test Cell TEMPER is in the processing of the a priori estimates (Figure 6). The initial base line for On-Wing
TEMPER is derived from the observed performance of newly installed production engines\textsuperscript{19}. This fleet-wide baseline is used for the initial processing of an engine's data. However, the first ten valid readings for an engine are used to modify the fleet baseline for the specific engine\textsuperscript{20}. After this specific baseline is established for the engine, it is used to reprocess the initial readings. The a priori estimate for each new reading is equal to the running baseline from the previous reading.

There is a subtle change in the interpretation of the fault logic in On-Wing TEMPER. In Test Cell TEMPER, the solution residual represents the difference between the reading being analyzed and a fixed reference. In On-Wing TEMPER, the residual is a measure of the deviation of the current reading from the recent past for the engine. A large residual in On-Wing TEMPER is, therefore, an indication of a step change in the data since the last readings. There is a change of emphasis from comparing an engine to a similar class of engines, to comparing an engine to itself. This change increases confidence in the assumptions upon which the fault logic is based.

\textsuperscript{19} Before revenue service data are available, the On-Wing TEMPER baseline lines are derived from the flight test for the aircraft. These original baseline lines often do not adequately represent the performance of engines in service. Often these differences can be traced to the use of different sensors in the flight test. The flight-test engines may not be typical of the performance of later production engines. Thus a sample of newly installed engines is often preferable to the flight-test baseline lines.

\textsuperscript{20} The fleet baseline is expressed in terms of deviations from the engine-cycle model for the independent measurements. The so-called "running baselines" are expressed as smoothed averages for the module performance and sensor error results. Thus, the running baseline lines are applied after the fleet baseline lines have been applied. The running baseline lines are, therefore, a smoothed estimate of the deviation of the engine's performance from a new production engine.

When the fault logic in On-Wing TEMPER identifies a bias shift or a step change to the performance of one of the modules, an alternate process is used to update the running baseline lines. If a measurement fault is identified, the baseline for that measurement's bias is changed to agree precisely with the result from the fault solution. The exponential smoothing process is not applied to that measurement. All other measurements and module performance parameters are treated in the usual way (with exponential smoothing). Similarly, if the fault logic indicates a step change to the performance of one of the engine modules, exponential smoothing is not used for that module performance parameter. Instead, the full change indicated by the fault logic is applied. This approach is taken to reflect the increased certainty associated with a fault solution. It also avoids the need to apply the fault logic repeatedly until the step change has been fully assimilated by the exponential smoothing.

The fault logic may choose a setting parameter or some hardware fault (e.g., cooling flow) for which there is no running baseline. The available baseline lines are updated when this occurs. The special fault is enunciated but no special base line is created. The underlying assumption is that these faults require special maintenance action on the part of the user.

Several specific problems must be addressed when analyzing data acquired during revenue service. Occasionally, readings do not yield a solution with a small residual. Such readings may indicate that the data were taken under unfavorable conditions, or that there was a temporary problem in the data system. If the high residual can be eliminated through use of the fault logic, then a single cause is identified, and the problem may be considered resolved. However, there are instances where the fault logic fails to give a low residual. When this occurs, On-Wing TEMPER does not update the running baseline lines.
practice avoids spurious drift associated with data system problems.

Service experience has indicated that additional precautions are needed to avoid running-base-line drift associated with data system problems. Occasionally, a spike in one or more measurements has been seen for a single reading. In some cases, the fault logic found a feasible solution to the tainted reading that reduced the residual to an acceptable level. When the problem was spurious, the following reading had a problem of approximately the same magnitude with opposite sign (because of the running base line shift). Usually, the fault logic identified the same fault and returned to the pre-spike condition. Occasionally, the second analysis identified a fault different from the first. This can occur if the two faults have similar signatures with small differences leading to the choice of one or the other. To avoid this problem, On-Wing TEMPER now requires corroboration of a fault from a second reading before any running base line changes are implemented.

Another situation requiring special attention is maintenance to the engine while it is installed on wing. Sensors might be changed or some repair procedures (such as water washes) can be performed without removal of the engine. When this occurs, it is desirable to ensure that the gas-path analysis properly interpret any performance changes. To meet this requirement, On-Wing TEMPER allows input of maintenance codes to indicate that certain types of maintenance occurred after the last reading. When maintenance codes are supplied, TEMPER performs a reduced fault search, seeking evidence of a performance change in the repaired item. If the residual for a relevant fault solution is substantially lower than for the no-fault case, the fault solution is used.

Sensor failures are common occurrences in regular service. These failures may be recognized by the data system. TEMPER also tests to confirm whether the sensor is within a reasonable range before using it in an analysis. When a sensor is unavailable for a particular reading, its average (base line) value is used. The standard deviation corresponding to that sensor is increased by a large amount (multiplied by 200) to eliminate the influence of that sensor on the solution. On-Wing TEMPER requires that a sufficient complement of sensors be available to perform modular diagnosis. If too many sensors are unavailable, the modular diagnosis is aborted. The requirements for the performance of a fault search are even more stringent.

When a sensor that was inoperative for a time is repaired, On-Wing TEMPER reintroduces it to the analysis gradually. This gradual return is achieved by scaling the measurement's standard deviation for the first few readings after its repair (Figure 7). The larger standard deviation limits the impact of the sensor on the analysis, and causes its bias to be chosen consistent with the current assessment of engine performance. The scaler is based on the Student t-distribution\(^{21}\) (Burington and May, 1953).

SUGGESTIONS FOR IMPROVEMENT

TEMPER and other comparable algorithms for gas-path analysis represent a clear improvement over the previous, deterministic approaches. Nevertheless, there are still significant problems associated with gas-path analysis of jet engines. To understand these problems, it is important to recognize that the success of the algorithm for engines that meet their performance requirements is of little interest. It is only when an engine fails to achieve its performance requirements that users look to gas-path analysis for help. In this latter case, they hope to obtain a clear indication of the repairs needed to restore the engine to acceptable performance levels.

Often, TEMPER successfully identifies the problem(s). There are a number of success stories where the TEMPER analysis identified a faulted module that either had not been repaired or had been repaired improperly. There have been On-Wing TEMPER analyses that detected a performance shift and successfully isolated the source of the problem. Unfortunately, there are several examples where the gas-path analysis result has been incorrect, leading to expensive and fruitless repairs. One frequently encountered example is where TEMPER identifies a module just repaired as deficient. Only rarely does this result prove to be correct.

Some of the problem can be attributed to the difficulty of interpreting the TEMPER results (Doel, 1991). The information is presented in terms that are more familiar to the gas-turbine-engine performance engineer than to the mechanic. The analysis includes assumptions (such as the constancy of cooling and leakage flows) that are not apparent to the mechanic. Overhaul decisions can be guided by information not included in the gas-path analysis (e.g., module age, repair history, borescope results). In these circumstances, the correct solution may not be discovered until the proper experts examine the data.

There are also circumstances where no amount of review can uncover the difficulty. Sometimes, the measurements point to problems that clearly are not present. Some engines defy all analysis, even detailed tear-down inspections of the individual modules. Sometimes the only solution seems to be to scatter the modules to other engines to eliminate the "cure".

Two experimental improvements have been developed for Test Cell TEMPER. Both are still in the evaluation stage. The first allows simultaneous analysis of the two readings\(^{22}\) normally acquired in the acceptance run. This strategy allows the module performance deviations (efficiency and flow capacity) are identical for both power settings. The measurement errors are allowed to differ for the two readings. Several authors have suggested that the simultaneous analysis of multiple readings increases the information available to the analysis (e.g., Stamatis, et al, 1989). However, it is likely that the efficiency and flow capacity also change with significant changes to operating condition. The take-off and maximum-continuous operating

\(^{21}\) The scale factor represents the effective increase in the standard deviation of the t-distribution based on the small number of samples from which it is derived. The scale factor is equal to the ratio of the 95% confidence range for the given number of degrees of freedom (number of samples minus one) to the corresponding range for the normal distribution (infinite degrees of freedom). The value of 20 for the first reading was chosen arbitrarily (there is no value corresponding to zero degrees of freedom).

\(^{22}\) These readings correspond to the take-off and maximum-continuous power settings. Maximum-continuous thrust is typically about ten percent below take-off.
conditions are close aerodynamically. Hence these changes should be small. The generation of a single result will eliminate inconsistencies between the two readings. It also should improve the analysis of highly deteriorated engines when the fault logic is invoked.

The second experimental change allows use of a deterioration model to improve the a priori estimates. The expected variation of efficiency and flow capacity versus module age is specified in the input. This information is used to alter the predicted values for the independent measurements so the deviations to be analyzed should be smaller. The associated standard deviations are also allowed to vary with age, to reflect the increased uncertainty in the performance of older modules. The use of a deterioration model requires generation of new base lines (that represent the performance of zero-age modules). The basic statistical inputs should also be modified, since the scatter due to module age should now be smaller.

Both improvements are in "Beta Test." The simultaneous two-point analysis is almost certain to improve the ability to interpret test-cell data. The introduction of a deterioration model is less sure to help because of the large amount of additional information which needs to be identified. Neither improvement is likely to be revolutionary.

One possible way of improving the results would be to take advantage of the digital electronic controls on newer gas turbine engines. These controls offer doubly or triply redundant sensors in place of the single probes of earlier engines. The key to achieving the potential associated with the new controls would be to provide the individual sensor values to the gas-path analysis. Having the individual measurements available would increase the amount of redundant information. This should permit choosing statistical inputs that would lessen the tendency to underestimate hardware degradation. Unfortunately, the current practice is to combine the sensor values in the control. Only the average is provided to the ground software.

Another possible vehicle for improvement would be to emphasize the decisions to be made, rather than focusing on the determination of the gas path state (Doel, 1991). This change of emphasis should encourage the algorithm designers to express results in terms the mechanic understands. It also should encourage optimization of the maintenance decisions, instead of module-performance determination. Finally, an emphasis on decisions would encourage consideration of all the information (the gas-path data is only a part) that is relevant to the problem.

There are emerging technologies that could foster improvements to gas-path analysis. Expert-systems techniques offer the possibility of integrating qualitative and quantitative elements of the maintenance decision process (Doel, 1990). Developments in fuzzy logic could offer useful methods to express the uncertainty of the gas-path analysis so that the user receives the appropriate message. Neural networks might offer an alternative to model-based algorithms for fault identification.

It is important to pursue these improvements. With the new engine designs employing features such as counter-rotating and variable-area turbines or "ducted fans", improvements may be needed even to retain the status quo.

SUMMARY

Jet-engine gas-path analysis is used to interpret data acquired from overhaul acceptance tests and from aircraft during routine service. The goal is to isolate performance deficiencies to the faulted modules so that repair can be successfully accomplished. The analysis results are of little interest unless performance is deficient. When this occurs, gas-path analysis results can generate important savings for the user, if they are correct.

Achieving correct diagnosis is difficult, because of the limited instrumentation. Most sensors are single-element probes that do not adequately sample the gas stream. To be effective, a gas-path analysis algorithm must consider sensor error. Modern algorithms use weighted least squares or a similar approach to simultaneously estimate module state and sensor error. These algorithms are a clear improvement over earlier approaches, but their reliability still falls short of user requirements.

Some improvement could be realized if the results were more clearly communicated to the users. Often, inappropriate maintenance is initiated because the mechanic misinterprets the results of the algorithm. If other information such as maintenance history and borescope inspection results were integrated with the gas-path analysis results, better recommendations would be likely. The use of emerging technologies such as expert systems, fuzzy logic and neural networks might generate further gains.

REFERENCES


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23 Age is normally expressed as either flight hours or cycles, but more sophisticated indices are permitted.

24 This situation is more unfortunate than suggested. The value provided to the ground software may be an average of the two or three available probes, or it may be the result of a single probe. The software in the control compares the individual values to each other and to an engine model. The output given to the ground software depends on the outcome of this comparison. In the extreme, it is possible the ground software will receive only the output of the on-board engine model.