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A generic approach for gas turbine adaptive modeling

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Abstract

For gas turbine engine performance analysis, a variety of simulation tools is available. In order to minimize model development and software maintenance costs, generic gas turbine system simulation tools are required for new modeling tasks. Many modeling aspects remain engine specific however and still require large implementation efforts. One of those aspects is adaptive modeling.

Therefore, an adaptive modeling functionality has been developed that can be implemented in a generic component based gas turbine environment. A single component in a system modeling environment is able to turn any new or existing model into an adaptive model without extra coding. The concept has been demonstrated in the GSP gas turbine modeling environment. An object-oriented architecture allows automatic addition of the necessary equations for the adaptation to measurement values. Using the adaptive modeling component, the user can pre-configure the adaptive model and quickly optimize gas path diagnostics capability using experimentation with field data. The resulting adaptive model can be used by gas turbine maintenance engineers for diagnostics.

In this paper the integration of the adaptive modeling function into a system modeling environment is described. Results of a case study on a large turbofan engine application are presented.

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Nomenclature

| | |
|-------|---|
| EGT | Exhaust Gas Temperature |
| FADEC | Full Authority Digital Engine Control |
| GPA | Gas Path Analysis |
| GSP | Gas turbine Simulation Program |
| GUI | Graphical User Interface |
| HPC | High Pressure Compressor |
| HPT | High Pressure Turbine |
| N1 | Low pressure (fan) spool speed |
| N2 | High pressure spool speed |
| NIVR | Netherlands Agency for Aerospace Programmes |
| NLR | National Aerospace Laboratory |
| Ps2.5 | Static Booster Exit Pressure |
| Ps3 | Static HPC Exit Pressure |
| Pt1.3 | Total Fan bypass exit pressure |
| Pt4.5 | Total HPT Exit Pressure |
| Ts3 | Static HPC Exit Temperature |
| Tt4.5 | Total HPT Exit Temperature (EGT) |
| Wf | Fuel flow |



1 Introduction

The last few decades have provided gas turbine performance engineers with increasingly powerful modeling tools. At an early stage, the opportunity was identified to use simulation models for diagnostics purposes, requiring modeling of deterioration and fault effects. Much focus was put on gas path analysis (GPA) methods, linking measured gas path parameter deviations to engine condition. A large number of publications show the development of different GPA approaches including linear GPA [1,2,3], non-linear GPA including adaptive modeling [4,5], neural networks [6,7,8,9,10] and genetic algorithms [11,12,13,14]. Linear and non-linear GPA often employ cycle models to calculate deterioration and fault effects. Adaptive models have an inherent capability to generate deterioration and fault data by adapting to measured engine data that are somehow deviating from the reference engine. Most efforts to apply adaptive modeling for diagnostics have resulted in engine type specific tools [4,5,15,16]. This is due to the fact that many cycle models used as a starting point already are engine specific. Moreover, the optimal configuration of an adaptive model in terms of measured parameters and unknown condition modifiers depends on engine type [15,16].

The Gas turbine Simulation Program GSP was developed with flexibility as a primary objective and has successfully demonstrated the capability to model virtually any gas turbine configuration [17,28]. With the need for improved diagnostics capabilities in many gas turbine operational environments in the Netherlands, a research program was conducted to develop a powerful generic GPA capability inside GSP. The objectives of this research program funded by the Netherlands Agency for Aerospace Programmes NIVR were to be able to:

1. Turn any existing GSP model into an adaptive model.
2. Rapidly configure an effective diagnostics tool for any engine type.

Although GSP was used as environment for implementation, the concept presented can be used in any program with a flexible and generic structure.

2 Adaptive modeling description

2.1 Approach

Most gas turbine cycle models calculate steady state or transient off-design operating points by solving sets of non-linear differential equations. The equation set represents the conservation laws that apply for the specific engine. Truly generic modeling tools such as GSP must somehow automatically build up the equation set during model initialization [17]. The individual gas turbine component models then must be able to add any equation and free state variable to the set that is processed by a separate generic solver. An adaptive model can be represented numerically by just adding a number of equations equal to the number of



measurements to adapt to. To obtain a ‘square’ equation set with a single solution then also an equal number of unknowns must be added representing various engine or component conditions such as efficiency and mass flow deltas or ‘map modifiers’. Naturally, the condition parameter set must include realistic deterioration modes and/or faults with identifiable effects on performance via the gas path.

2.2 Object oriented implementation

Object orientation provides an efficient means to implement functionality common to different modeling elements in a simulation environment. The inheritance principle of object orientation enables the introduction of additional gas turbine component model capabilities in a single ‘ancestor’ component model class [17]. All child classes of that class inherit that capability automatically, without requiring any additional coding. Existing GSP models for example can simply be opened and run with a newer implementation of a component model extended with new modeling capabilities. This convenient mechanism allows the implementation of capabilities required for adaptive modeling in a single component model class, common to all gas path components. The capabilities added are:

1. a list of measurement values corresponding to component performance parameters,
2. a list of condition factors to be multiplied with condition parameters such as efficiencies and map flow rates,
3. an interface to have the user select the measurements and condition factors that are active during ‘adaptive simulation’ mode (the user must be able to quickly change parameter selections in order to evaluate and optimize the adaptive model configuration),
4. user interface elements to present results, such as bar charts to visualize deltas on performance and component condition parameter values.

Although not essential, object orientation clearly provides significant advantages over alternative approaches to implement generic adaptive modeling functions.

2.3 Numerical methods

As explained in the previous sections, the numerical solution of the set of adapted condition factors is simply found by adding the corresponding equations to the equation set that represents the reference engine.

In the adaptive model equations, see equation (1), the upper left section represents the reference engine: f_1 through f_n are the n error equations based on the conservation laws with the unknown states s_1 through s_n . ϵ represents the relative equation tolerance (convergence criterion for the conservation equations) and should be very close to zero (typically 0.0001). f_{m1} through f_{mm} represent the m additional equations added in adaptive modeling mode and simply require a model output parameter to be equal to a specified measurement value. s_{c1} through s_{cm} are the



scalars representing the unknown condition factors that need to be solved for. ε_{m1} through ε_{mm} represent the separate tolerances for the adaptation to the measurement parameters.

$$\begin{array}{ccc|ccc}
 f_1(s_1)+ & \cdots & f_1(s_n)+ & f_1(s_{c1})+ & \cdots & f_1(s_{cm}) & = & \varepsilon \\
 \vdots & & \vdots & \vdots & & \vdots & & \\
 f_n(s_1)+ & \cdots & f_n(s_n)+ & f_n(s_{c1})+ & \cdots & f_n(s_{cm}) & = & \varepsilon \\
 \hline
 f_{m1}(s_1)+ & \cdots & f_{m1}(s_n)+ & f_{m1}(s_{c1})+ & \cdots & f_{m1}(s_{cm}) & = & \varepsilon_{m1} \\
 \vdots & & \vdots & \vdots & & \vdots & & \\
 f_{mm}(s_1)+ & \cdots & f_{mm}(s_n)+ & f_{mm}(s_{c1})+ & \cdots & f_{mm}(s_{cm}) & = & \varepsilon_{mm}
 \end{array} \quad (1)$$

A more compact notation for equation (1) using vector notation is:

$$F(\bar{s}) \leq \bar{\varepsilon} \quad (2)$$

with \bar{s} including both the s and s_c elements and $\bar{\varepsilon}$ including elements equal to the conservation equation tolerance ε and measurement tolerances ε_m .

The measurement equations representing the adaptation constraints for a measurement i are

$$f_{mi} = P_{i\text{mdl}} - P_{i\text{meas}} \leq \varepsilon_{mi} \quad (3)$$

with $P_{i\text{mdl}}$ and $P_{i\text{meas}}$ the adapted and measured values of parameter P_i respectively.

A Newton-Raphson based (or other) solver can be used to iterate towards the solution and at this stage there are no further numerical additions required. The absence of outside iteration loops provides optimal stability and minimal complexity.

3 Application

3.1 Reference models

The objective is to extend an existing gas turbine model with an adaptive modeling capability, without having to interfere with the model itself. In GSP, this can be simply done by drag-and-drop of the adaptive model control component icon (top-left in Figure 1). With adaptive mode turned off, the model represents the reference or baseline engine.

The reference model must be tuned to performance data in order to obtain an accurate baseline. This means matching the model design point to a specific engine operating point data set, usually at high power levels at standard conditions such as maximum take-off thrust for a turbofan engine. If necessary, model parameters can be further fine-tuned to improve the match with available off-design data. Even if component maps are not available and must be scaled from similar public domain maps, errors can be kept small as long as the operating point stays close to the design point. This is the case for example with gas path analysis diagnostics on

maximum take-off power engine pass-off tests at KLM engine overhaul facility Amsterdam (see Case study section).

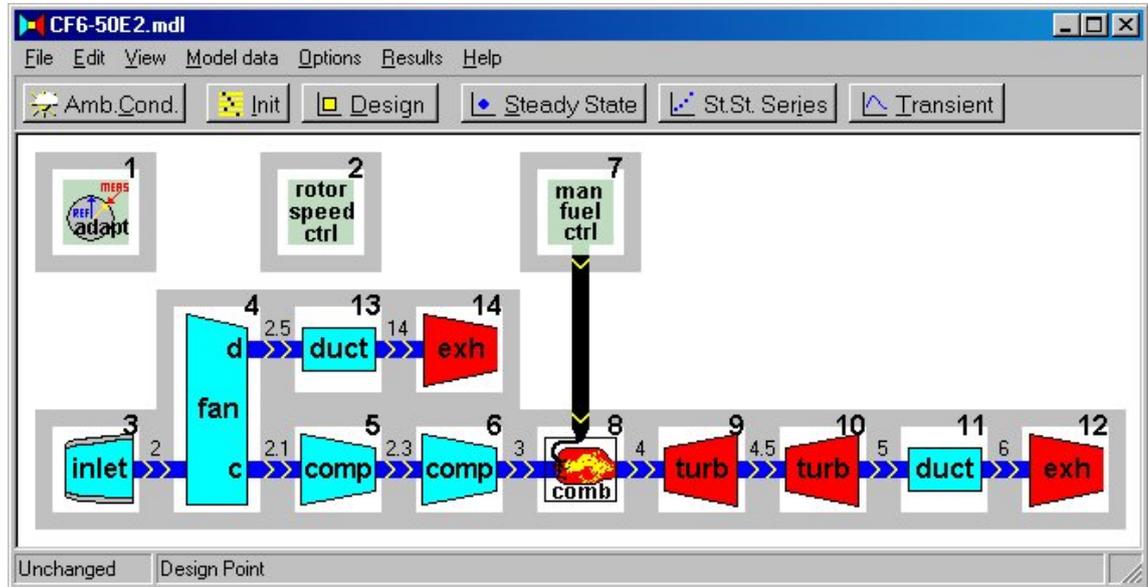


Figure 1 GSP model with (top-left) adaptive model control icon

The accuracy of the reference model match affects the adaptive model simulation process. Reference engine model errors will interfere with the adaptive modeling numerical solution. Therefore, ‘calibration factors’ f_c are introduced, compensating the adaptive model numerics for model errors. Equation (4) shows how a model parameter $P_{I_{mdl\ raw}}$ is calibrated using the ratio of the design point measured and model parameter values.

$$P_{i\ mdl} = P_{i\ mdl\ raw} \cdot f_{ci}$$

$$f_{ci} = \frac{P_{i\ meas\ des}}{P_{i\ mdl\ des}} \quad (4)$$

Normally, if an accurate design point match has been obtained, the f_c factors are very close to 1. The f_c factor calibration method was found to have a significant effect on adaptive model stability and results, even if the f_c factors only deviated 1% from unity. Another important consideration is the source of the data for tuning the reference engine model design point. This source optimally is the same engine test bed under the same calibration settings. Data from a single engine test, well corresponding to the average (new or overhauled) engine performance are usually sufficient to be used for an entire engine fleet and this approach has been used for the case study at KLM. Even better results would be obtained if a range of engine tests would be used and averaged to eliminate measurement scatter effects. Ultimately, the best but also most laborious approach would be to match models to every new engine at the



start of its service life (or time between overhaul) and keep the model for diagnostics for the particular engine. Then engine to engine variation is eliminated and performance deviations will be due to deterioration or faults only. This approach may well be applied in the future in on-wing or remote-wireless continuous engine monitoring systems [18,19,20,21,22]. With the adaptive model continuously running on-board in the FADEC, more interesting opportunities emerge, such as adaptive control logic [23].

3.2 Selection of parameters

The ‘square’ equation set with an equal number of measurements and conditions parameters is the most straightforward approach. However, the number of condition parameters and especially measurements may vary among engine types and applications. Ideally, a large number of accurate measurements is available, covering the gas path conditions at most engine stations, and exceeding the number of condition parameters. In that case, the solution of the ‘over-determined’ equation set would be a minimization problem, for example using a weighted least squares method [1,24]. In most cases however, the number of measurements is limited and often smaller than the number of condition parameters required for a complete representation of engine health including all deterioration and failure modes. Several solutions have been proposed to handle the case of fewer measurements than condition parameters, including multi-point [12,14,25], adding constraints or equations derived from knowledge of the (relations among) deterioration modes [26] or working with optimized selections of condition parameter ‘sub-sets’, equal to the number of measurements. With the latter approach, methods proposed by [12,15,27] can be used to define a measurement and condition parameter set that is best able to isolate specific problems. A method suggested by Ogaji [27] is used in the case study described later in this paper.

Different sets can be used to identify different fault- or deterioration cases. With an adaptive modeling tool that can be rapidly configured, this approach is attractive and therefore has been used in the GSP diagnostics module at this stage. As will be explained in the following sections, the GSP diagnostics component includes a powerful generic GUI, allowing rapid configuration of adaptive models for any GSP modeled gas turbine engine. Results with different sub-selections of both the measurement and condition parameters can be quickly analyzed.

3.3 Measurement uncertainty

The measurement tolerances ε_{m1} through ε_{mm} are independent of conservation law inaccuracy ε and represent measurement specific tolerances for the adaptation equations. The ε_m values are separately user specified corresponding to measurement uncertainty data. Normally, the ε_m values will be larger than ε and can be tuned to obtain optimal results.

With large ε_m values, solutions may be found at the extremes of ε_m margins, which are unrealistic in a sense that the deviation from the reference engine parameter value is ‘ignored’



by the solution. In the future, additional methods may be applied to account for statistical probability distribution of measurement error using weight factors for example. This will allow better representation of measurement error and provide solutions with maximum probability with larger measurement uncertainty margins.

3.4 Standard and adaptive simulation modes

The engine simulation tool only needs to solve the additional equations during adaptive modeling mode. The adaptation of the model can simply be deactivated by replacing the f_m equations (Equation (3)) by

$$f_{mi} = s_{ci} - 1 \quad (5)$$

The result will be a solution with all condition scalars being equal to 1, representing the case of the healthy reference engine. Every adaptive simulation must be preceded by a standard (non-adaptive) simulation to determine the reference engine baseline performance and deltas at the particular operating point. In GSP this is done automatically.

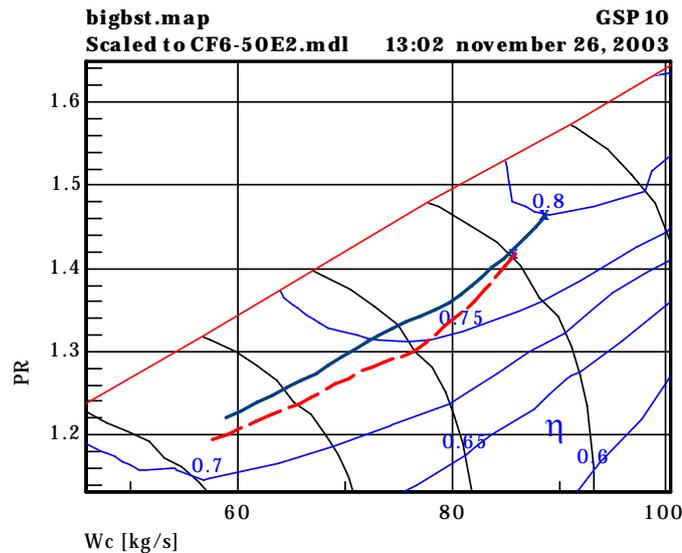


Figure 2 Booster running lines for reference (solid) and deteriorated (dashed) engine (case 1).

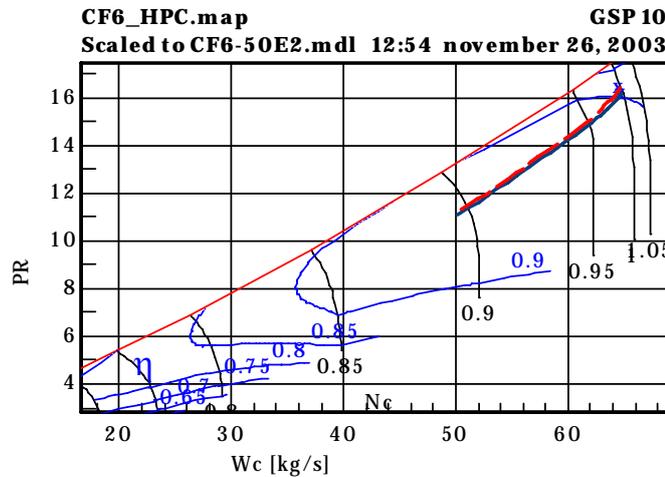


Figure 3 HPC running lines for reference (solid) and deteriorated (dashed) engine (case 1)

Obviously, the ability to use the same model for both performance analysis with the reference engine model and adaptive simulations and diagnostics in the same session, is very convenient. Following a diagnostics session, the performance of the adapted model can be analyzed and directly compared with the reference engine by plotting curves for varying power setting for both cases in simple X-Y graphs and compressor maps for example (see Figure 2 and Figure 3). Figure 2 and Figure 3 represent results of the case study discussed later in this paper.

3.5 Model stability

Large measurement errors may well result in attempts to find engine operating points that are impossible, even with extreme component condition variations. In such cases the conservation equations for mass and energy can simply not be satisfied while simultaneously matching the measured performance parameters. In this case widening the ϵ_m tolerance margins may help to a certain extent, but with large measurement uncertainty (especially scatter) it often is better to omit the particular measurement from the measurement set.

Another problem is multiple solutions. Especially with a small measurement data set the model may adapt with unrealistic condition factors such as very high efficiencies. A slightly different measurement then may have totally different results, indicating there are multiple solutions for the condition vector \bar{s}_c . In this case more measurements are required to 'more tightly' capture engine performance.

In the case study with the twin spool turbofan described later in this paper, at least six parameters were required to obtain realistic results pointing in the right direction. As described in the case study section, the low-pressure section behaves more or less independently from the gas generator. If only a few parameters such as fan duct pressure and fan duct side efficiency are added, results become unstable. It appeared that either the low-pressure (fan and LPT exit)

parameters must be fully omitted or sufficient measurement parameters must be added to unambiguously determine fan and LPT performance.

3.6 User interface

A major challenge is to develop a graphical user interface (GUI) capable to effectively control adaptive models based on any model configuration. For application to virtually any working cycle configuration, a highly flexible concept is required. Several examples of GUIs for GPA exist [16, 21] but these usually are engine specific, so a new approach was required. Generic component based simulation environments usually have a GUI with separate data entry windows for individual component models. In GSP for example, these are accessed by double-clicking the component icons shown in Figure 1. This approach can easily be used for the adaptive modeling capability. However, for adaptive modeling, the focus is on the engine as a system and therefore a separate single interface is required to control all adaptive modeling functions on the system model level. A concept using a tree-view with multiple columns was chosen as the best solution for this.

In GSP, an interface component was inherited from a 'model control component' object class that has access to all other component models. Tree-views are used including all component models as top level elements. The resulting adaptive model control window is accessed via the top left adaptive model component icon in Figure 1 and includes the tab-sheets shown in the following figures with screenshots.

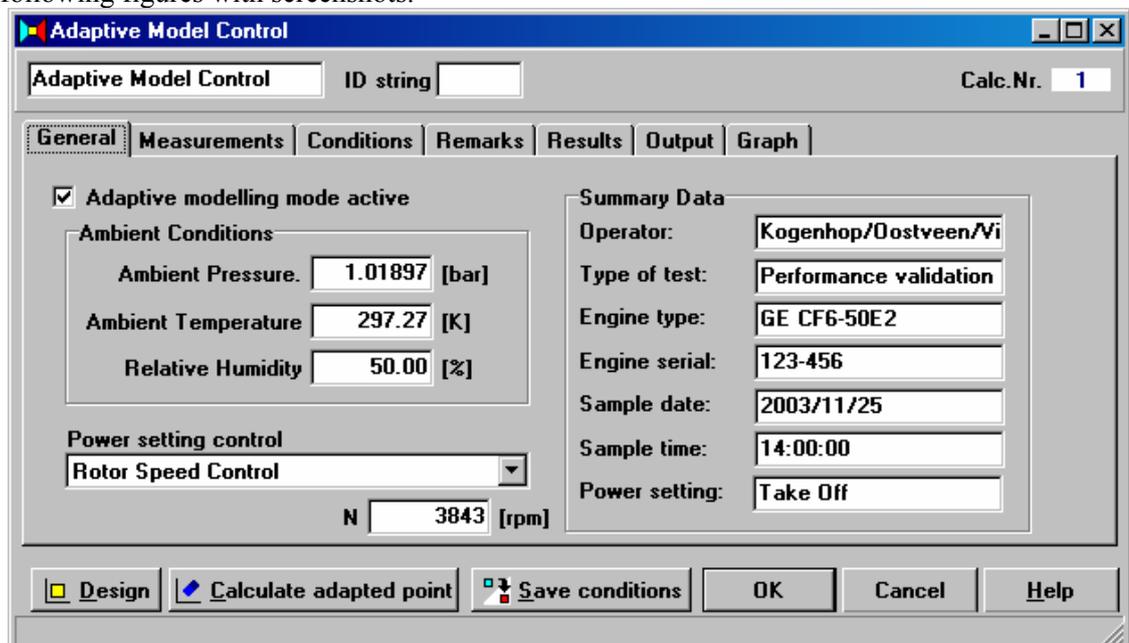


Figure 4 GSP adaptive model control component window

Figure 4 shows the general configuration tab sheet for specification of engine and session reference data, ambient conditions and engine power setting. Depending on the model

configuration, rotor speeds, fuel flow, thrust or other parameters can be specified for power setting.

Two tree-views are defined, one for measurements (Figure 5) and one for the condition parameters (Figure 7):

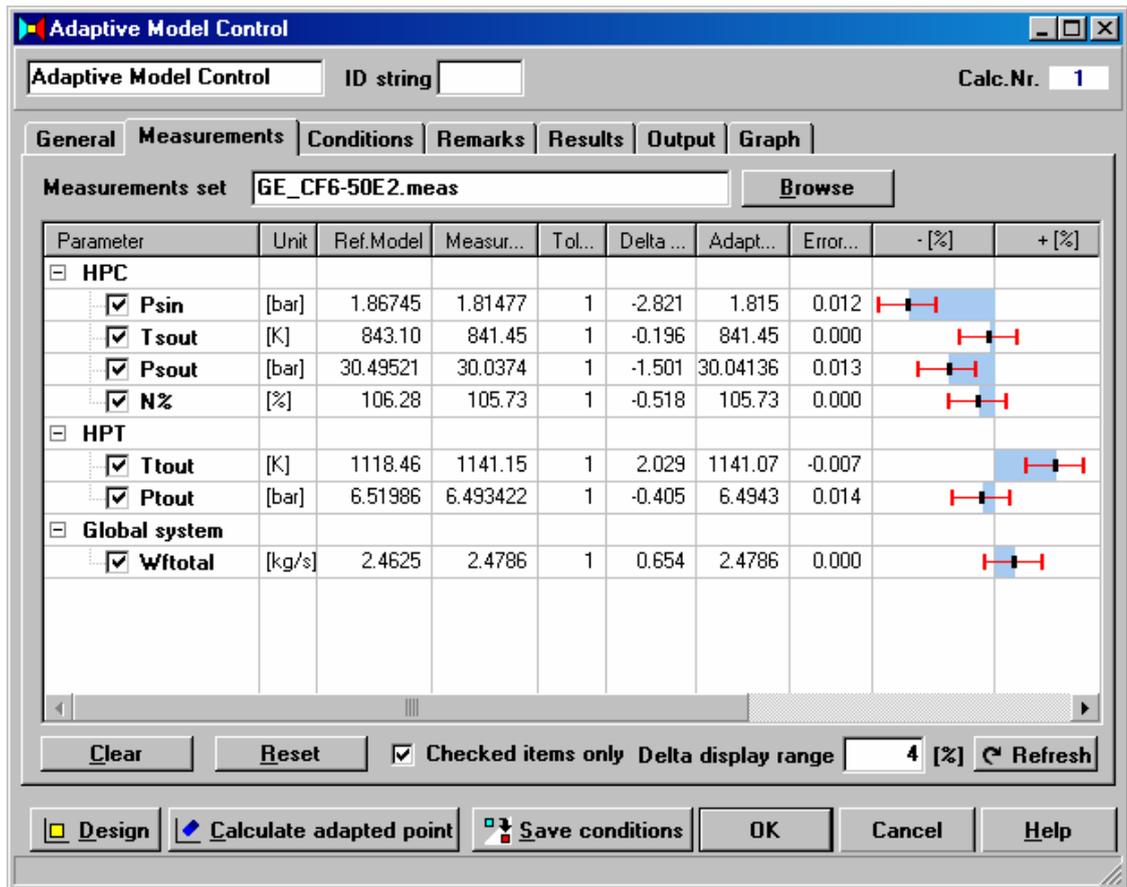


Figure 5 Measurements tab sheet

In the Measurements tree (Figure 5), each component in the tree has sub-elements representing the individual performance parameters that can be used for adaptive modeling. The parameters listed depend on component type. For each parameter, measurement values can be entered and these are compared with reference model calculation results. The check boxes are used to select the set of parameters to adapt to (i.e. the parameters used in the f_m equations). Note that Figure 5 shows the tree-view with an option activated making the unchecked parameters invisible for user convenience. For each parameter, the reference model calculated value, the user specified measured value and tolerance for adaptation (ϵ_m), the calculated delta (reference-measured), the calculated adapted value (should be within tolerance range of measured) and the error (adapted-measured, should be close to zero) are shown. Not displayed are the columns for the design



point calibration factors f_c of equation (5). By scrolling to the right 3 columns with model design and measured design values and the calibration factors are shown.

| Tol. [%] | Delta [%] | Adapted | Error [%] | - [%] | + [%] |
|----------|-----------|---------|-----------|-------|-------|
| 1 | -2.821 | 1.815 | 0.012 | | |

Figure 6 Detail of Measurement tab sheet

The horizontal bars (see detail in Figure 6) indicate measured performance delta (solid blue bar), tolerance for adaptation ϵ_m (red range indicator) and the calculated adapted value (black dot). The latter value must be in the red tolerance range for the modeling system to be accepted as a valid adapted operating point. In Figure 6 a result was found exactly matching the measurement value so the black dot is in the middle of the tolerance range.

| Parameter | Unit | Reference | Adapted | Delta ... | Threshold | - [%] | + [%] |
|--|------|-----------|---------|-----------|-----------|-------|-------|
| Booster | | | | | | | |
| <input checked="" type="checkbox"/> Eta_is | [-] | 1.0000 | 0.9924 | -0.762 | 1 | | |
| <input checked="" type="checkbox"/> Wc | [-] | 1.0000 | 0.9379 | -6.211 | 1 | | |
| <input type="checkbox"/> PR | [-] | 1.0000 | | | | | |
| HPC | | | | | | | |
| <input checked="" type="checkbox"/> Eta_is | [-] | 1.0000 | 1.0068 | 0.677 | 1 | | |
| <input type="checkbox"/> Wc | [-] | 1.0000 | | | | | |
| <input type="checkbox"/> PR | [-] | 1.0000 | | | | | |
| Manual Fuel Control | | | | | | | |
| Combustor | | | | | | | |
| HPT | | | | | | | |
| <input checked="" type="checkbox"/> Eta_is | [-] | 1.0000 | 0.9939 | -0.611 | 1 | | |
| <input checked="" type="checkbox"/> Wc | [-] | 1.0000 | 0.9968 | -0.320 | 1 | | |
| LPT | | | | | | | |
| <input checked="" type="checkbox"/> Eta_is | [-] | 1.0000 | 0.9920 | -0.805 | 1 | | |
| <input checked="" type="checkbox"/> Wc | [-] | 1.0000 | 0.9847 | -1.534 | 1 | | |

Figure 7 Conditions tab sheet

In the Conditions tree (Figure 7) each component has sub-elements representing the individual condition parameters (s_c) that are adapted to match measured performance. The parameters listed depend on component type. The check boxes are used to select the subset of parameters that are allowed to be adapted (i.e. represent the \bar{s}_c vector). Figure 7 shows the tree-view with all possible condition parameters visible (the scroll bar must be used to scroll up and down to cover all components). The horizontal bars indicate the deviations of the condition parameters, thereby providing the gas path diagnostics information. Individual threshold values can be specified to indicate levels beyond which the condition parameter deviation is considered significant. Beyond the thresholds, the bars turn red. The chart can optionally be normalized to the threshold values.

Figure 8 shows the graphical report output of the results with both the performance and the condition parameter deltas.

The information described above can be assembled in a comprehensive diagnostics report to be printed or digitally stored for later reference. Also, event logs are kept to store settings, user comments and results generated during the diagnostics session. The resulting GUI and reporting functions enable the deployment of GSP models as user-friendly diagnostics tools.

4 Results

During development, the adaptive modeling component has been tested and experimented with a variety of engine models for which measurement data were available. It was found that results (stability and realistic result data) are sensitive to both model and measurement inaccuracy. The model accuracy can be improved by better tuning to known data and the use of accurate component maps (rather than maps scaled from generic ones) if available. With the addition of the user measurement tolerance and the design point calibration factors, stability and results were significantly improved.

The user interface was evaluated by several engineers and, after an evolution via several designs, approved as a tool that can be pre-configured to an effective diagnostic aid. The ultimate test was an industrial application as described in the following section.

4.1 Case study

A case study has been performed on an application that is very suitable for gas path analysis diagnostics. At KLM Royal Dutch Airlines CF6 engine maintenance facility, CF6 family engines are overhauled and finally submitted to a 'pass-off test' before being returned into service. GPA is one of the techniques used to diagnose problems indicated by deviating or unacceptable test bed measurement results. Costs could be significantly reduced if more accurate GPA tools than those currently used were available. Therefore, the GSP tool was tested



on a number of cases with CF6-50 engines to assess its potential. Two cases will be described in this section.

First a baseline model was developed and tuned to data measured on an average healthy turbofan engine. This data point corresponds to the GSP design point. In the adaptive model component, the residual design point deviations are stored in the design point calibration factors, to be later used for adaptive modeling mode. Note that the GSP design point is at arbitrary ambient conditions. Power setting in GSP (and on the test bed) is represented by a particular N1 fan rotor speed using the GSP rotor speed controller.

Next, the measurement data of the problem engine under consideration are entered in the particular measurement column in the data entry window shown in Figure 5. In this case either fuel flow or N1 rotor speed can be used to specify power setting (i.e. represent an input parameter). If N1 is chosen then fuel flow can be defined as a measurement parameter and vice versa.

To obtain an optimal measurement set, the parameter offset method as suggested by Ogaji [27] was applied. This method provides a ranking of measurement parameter sensitivities to (1%) component condition parameter offsets. A cycle simulation tool such as GSP can be used to determine the individual sensitivity values. The parameter set should be selected from the top of the sensitivity ranking order. In Table 1 the ordered lists of the 9 measurement parameters available are shown for the two alternative power setting parameters available.

Table 1 Measurement parameter sensitivity rankings

| | Wf = control parameter | N1 = control parameter |
|---|------------------------|------------------------|
| 1 | Ps2.5 | Pt4.5 |
| 2 | Pt4.5 | Ps2.5 |
| 3 | Ts3 | Wf |
| 4 | N1 | N2 |
| 5 | N2 | Tt4.5 |
| 6 | Ps3 | Ps3 |
| 7 | Tt4.5 | Ts3 |
| 8 | FN | FN |
| 9 | Pt1.3 | Pt1.3 |

Although the power setting parameter has an effect on the ranking, the diagnostics end results are not significantly affected by the power setting selection, as may be expected. For the case study, N1 was chosen as power setting parameter since N1 is also the test bed power setting indicator.



Condition parameters were selected using engineering judgement and trial and error. With the powerful GUI, many combinations can be tested very rapidly.

Best results were obtained with the top 7 measurement parameters from Table 1 including Ps2.5 (booster exit), Ps3, Ts3, N2, Tt4.5 (EGT), Pt4.5 and Wf. Extending the set with the remaining number 8 or 9 parameters FN and Pt1.3 did not generate stable and realistic results with any combination of condition parameters. Using 9 parameters including both Pt1.3 and FN prevented the model from finding a solution at all. This is due to the strong correlation between FN and Pt1.3. As a result, the set could not be extended to include fan conditions at this stage due to the limited data for the low pressure system performance. It is expected that with additional measurements such as hot exhaust (station 5) pressure and/or temperature this could well be improved. This will be the subject of future research.

4.2 Case 1

With the 7 parameters described above, a diagnostics session was performed on a CF6-50 engine with a low EGT margin. The engine test indicated an EGT of 23 K over the expected value for a healthy engine but still within acceptance limits. For GPA this means a more difficult case due to the relatively small performance deviation.

Condition factors chosen for this case were booster efficiency and mass flow, HPC efficiency, HPT efficiency and flow capacity and LPT efficiency and flow capacity. As explained above, this set is mainly focused on booster and gas generator health and will not be able to identify fan problems.

Results are shown in Figure 8 depicting a screenshot of the 'Graph' tab sheet of the adaptive model control window. The upper part of the figure depicts the performance deviation relative to the reference engine. The lower part of the figure shows the adaptations needed to fit the base model to the measurement set. As stated above, the performance delta is small, i.e. within 3% for all 7 parameters (including the 23 K EGT delta). The adaptive model calculation indicates the booster to be responsible for the poor performance due to a flow capacity problem. Since the booster has no variable geometry, VSV mis-rigging is ruled out as a cause, leaving at least blow-off valve leakage or tip clearance as candidates for further investigation. This outcome was confirmed after further analysis at KLM, proving the accuracy of the GSP adaptive model to identify engine problems on component level.

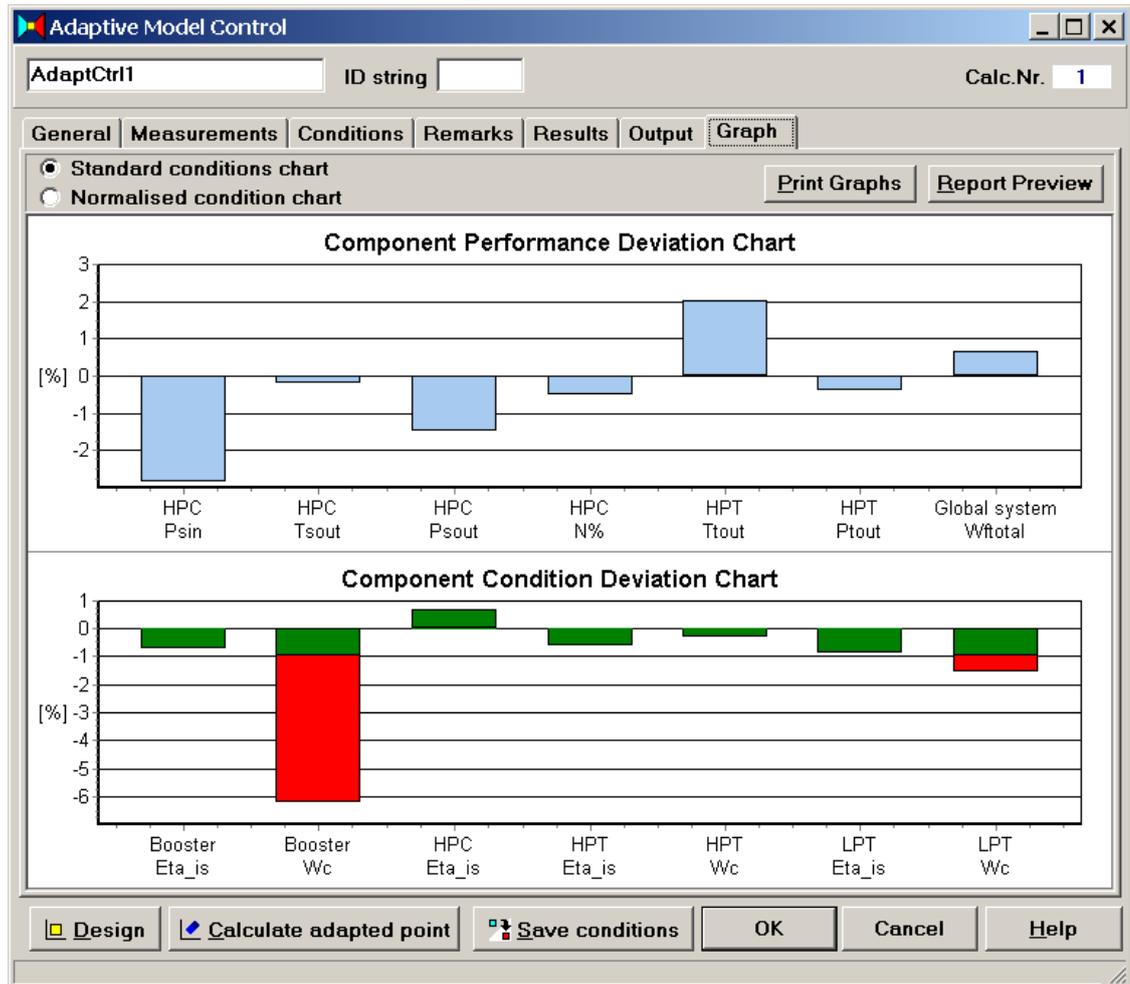


Figure 8 Gas path analysis results chart window, case 1

After a valid diagnostics result has been found the resulting adapted engine model performance can be analyzed. The deterioration deltas are stored in the model and adapted (deteriorated) versus reference engine performance can be compared at various other operating conditions and power settings.

Figure 2 (earlier shown in this paper) shows the calculated booster running lines for the case 1 reference and deteriorated engine in the booster map. A significant shift away from the stall limit is shown as may be expected from the deteriorated booster flow capacity. Figure 3 shows the HPC running line is not significantly affected as may be expected if only the booster condition has changed.

4.3 Case 2

In a second case, an engine was analyzed that was rejected at the performance test after overhaul. The performance test was eventually passed after replacement of the HPC during a second shop visit, although this was not recommended by the available conventional diagnostic



methods. However, the GSP adaptive model indicated an HPC mass flow deficiency (Figure 9), thereby clearly proving its capability to effectively isolate component faults.

Note that the condition set is different from case 1 and includes HPC mass flow instead of booster efficiency. The case 1 set was used first but did not generate realistic results which was caused by the absence of the condition factor responsible for the engine problem. Case 2 demonstrates the benefit of the ability to rapidly evaluate results with different condition parameter sets.

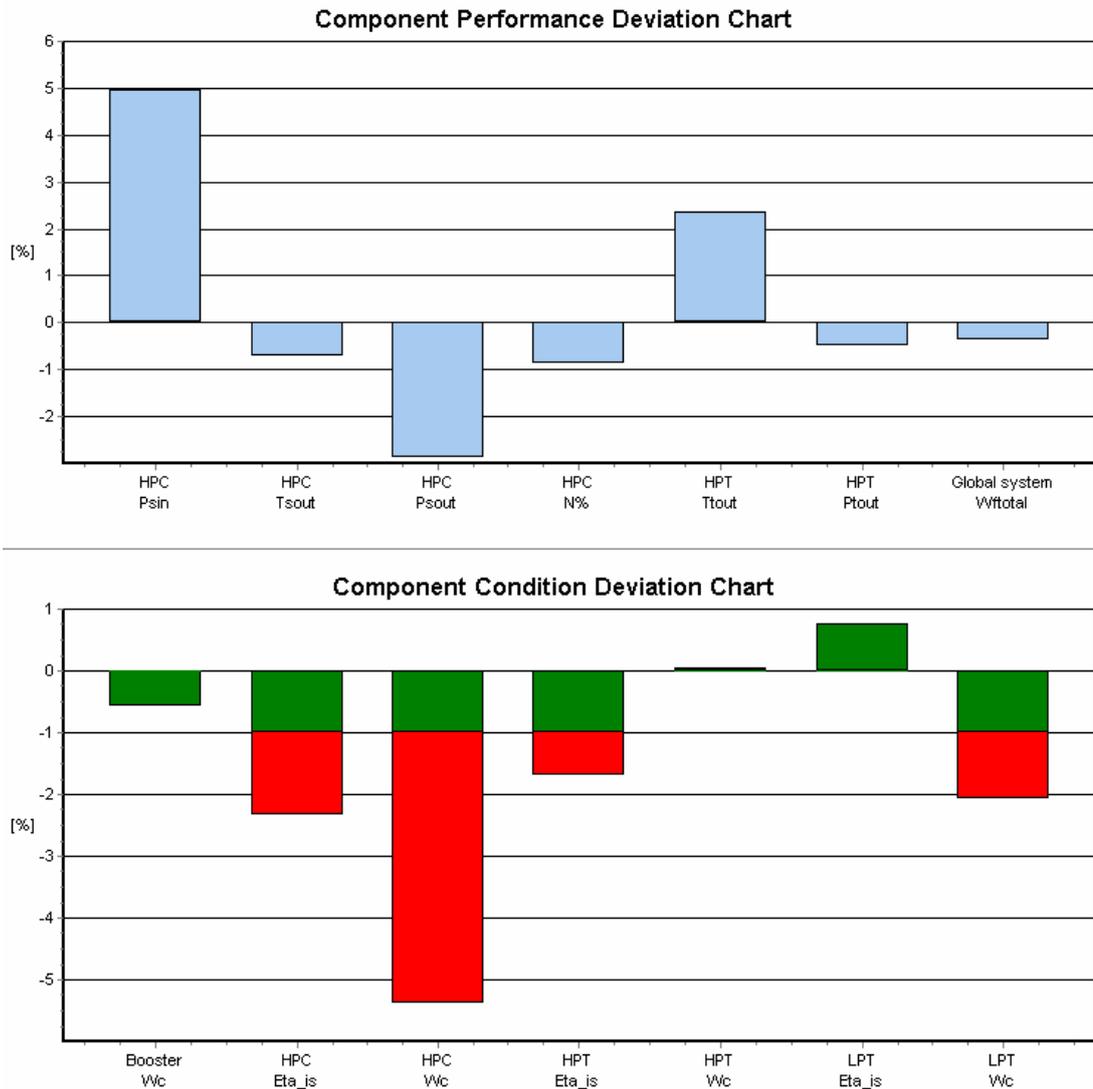


Figure 9 Gas path analysis results case 2



5 Conclusions

Generic gas turbine simulation environments can be extended to generic adaptive modeling tools for diagnostics and gas path analysis of deteriorated engine performance. Critical elements for the extension are

- modeling structure,
- flexibility with regard to the model equations and numerical methods and
- graphical user interface (GUI).

With a flexible object oriented architecture an efficient implementation can be realized and has been demonstrated. New additions to the adaptive modeling system can be easily implemented due to object orientation.

With tree-view elements, a GUI can be developed that adapts to any gas turbine model.

Different combinations of measurement and condition parameter sets can be rapidly evaluated and optimized for specific engines and deterioration types. The different sets can be saved and later activated on request to verify different hypotheses and assumptions with regard to the engine problem.

The approach has been successfully demonstrated in the object oriented gas turbine simulation environment GSP. Component faults were successfully isolated in a number of test cases with a high bypass turbofan engine. The GSP adaptive model control component turns existing GSP models into adaptive models that can be rapidly configured to become powerful user-friendly GPA (gas path analysis) tools.

The adaptation function can be applied to new GSP component models derived from existing using object inheritance. Condition factors and measurement equations can be added for any component model. This means other system models including additional systems such as load compressors and combined cycle components can be included for GPA diagnostics.

The GSP adaptive modeling GUI enables the deployment of GSP models as user-friendly diagnostics tools. A configuration for a specific engine type is currently being validated by maintenance engineers at KLM.

6 Recommendations

Although a flexible concept is working, not all options for powerful GPA with GSP have been explored yet and future work is planned to enhance GSP's adaptive modeling and diagnostic tool capabilities, including:

- application to cases with more measurement data (i.e. including exhaust gas pressure and/or temperature)



- adding a numerical minimization option for cases with more measurements than condition factors
- exploration of feasibility of multi-point GPA
- additional methods to compensate measurement uncertainty (constraints on and relations among condition parameter variations)
- separate GSP adaptive modeling versions with optional hiding of model configuration data entry items to provide a secure and user friendly diagnostics tool at flight line or test bed

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