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Multiple-Point Adaptive Performance Simulation Tuned to Aeroengine Test-Bed Data

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Adaptive simulation technology enables the calibration of a performance simulation code to a given in-service gas turbine and provides correct prediction of its performance. This is a fundamental prerequisite for reliable gas-path diagnostics and performance health monitoring. In this paper, a new offdesign performance adaption algorithm is introduced. Cranfield University's consolidated engine performance simulation code PYTHIA is enhanced with the capability of offdesign performance adaptation to model available field data. The software minimizes, via a genetic algorithm, an objective function that measures the error between an initial engine model output and the real engine data by varying some characteristics' scaling factors. In this study, a multiple-point adaptation procedure was applied to a two-shaft aeroengine. This generated an optimized engine model that minimized its deviations from a set of test-bed data. The adapted model was then tested against different real data, resulting in an average error, over 8 measured parameters, of less than 0.35%.

Nomenclature

a	=	weighting factor
ETA	=	isentropic efficiency
K	=	number of measurement
$N1$	=	relative low-pressure shaft speed, %
$N2$	=	relative high-pressure shaft speed, %
n	=	number of offdesign points
OF	=	objective function
P	=	pressure, atm
$\mathbf{P}$	=	measurable performance-parameter vector
PR	=	pressure ratio
SF	=	scaling factor
T	=	temperature, K
$\mathbf{u}$	=	ambient and operating-condition vector
WAC	=	corrected mass flow rate, kg/s
$\mathbf{X}$	=	component-characteristics vector

Subscripts

amb	=	ambient
DP	=	design point
ETA	=	isentropic efficiency
N	=	relative shaft speed
OD	=	offdesign
PR	=	pressure ratio
WAC	=	corrected mass flow rate, flow capacity
0	=	design point
6	=	low-pressure compressor exit
8	=	high-pressure compressor exit
11	=	high-pressure turbine exit
15	=	outlet fan turbine exit

Superscript

def	=	default

I. Introduction

THE capability of modeling and accurately predicting aeroengine performance is recognized to be an asset for both engine manufacturers and users. This Introduction discusses how adaptive simulation techniques can be advantageous for both parties, even if from different perspectives.

For original engine manufactures (OEMs), a reliable performance simulation contributes to a more cost-effective engine development and health monitoring. Although for the purpose of engine development, a generic performance simulation model (representative of a family of engines) is suitable, in the case of performance health monitoring, an engine model (which is tuned to the specific operating engine) is necessary. This allows minimizing the intrinsic deviations between the generic (engine fleet) simulation model and the operating engine that are caused by the not-negligible performance differences that characterize any production line (engine-to-engine variation).

Another point of view can be given for aeroengine operators. The accuracy of the prediction is highly dependent on the quality of engine design data and empirical component information such as component characteristic maps. Such information is normally the exclusive property of engine manufacturers and only partially disclosed to engine users. Consequently, intrinsic deviations between the simulation and the operating engine may exist due to lack of engine component characteristic information.

Equally of interest to both engine manufacturers and operators is the fact that these deviations between the simulation and the operating engine, if not reduced to an acceptable minimum, can result in misleading gas-path diagnostics (GPD) analyses [1,2]. GPD is used in health monitoring to identify the component(s) responsible for performance deterioration and to quantify the deviations of each component performance parameters (typically efficiencies and flow capacities of compressors and turbines) from a baseline condition represented by the simulation model. These deviations, when the engine is clean (not degraded), have to be small; otherwise, these simulation biases will have a disastrous impact on the GPD assessment. As a matter of fact, given that the nonlinear behavior of the thermodynamic performance of a gas turbine varies the component performance parameters, an initial simulation bias or deviation between simulation and operating engine does not result in a constant bias on the GPD assessment, but may produce significant

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errors in the diagnostics evaluation. A prompt and secure identification of a fault in gas turbine components typically results in considerable time and cost savings and therefore is highly desirable by OEMs and operators. In this context, adaptive simulation techniques play a key role in providing a performance simulation code (initially implemented with the best available gas turbine performance simulation technique) calibrated to a given in-service gas turbine. This enables correct prediction of its performance.

Therefore, adaptive simulation technology has been developing over the years. Roth et al. [3,4] and Li et al. [5] describe methods based on performance matching to test data at the design point. Nevertheless, an adaptation at the design point does not guarantee a simulation model adapted in a relevant offdesign range. Therefore, other methods based on offdesign adaptation were implemented and described by Stamatis et al. [6], Lambiris et al. [7], and Kong et al. [8].

The focus of this paper is on the improvement of engine offdesign (OD) performance predictions that was achieved by introducing a multiple-offdesign-point adaptation algorithm. A genetic algorithm was used to calculate the optimal set of scaling factors, associated with the best match between real and simulated values of some selected measurements. The results presented in this paper are based on real test-bed data for the engine under investigation.

II. Aims and Objectives

The aim of the work described in this paper was to develop and test an adaptive simulation algorithm able to calibrate a given initial engine model to multiple sets of test-bed data of a specific in-service engine. This initial model was assumed to be as close as possible to a fleet's average engine model. The accuracy of the initial model plays a key role in achieving a satisfactory final result and contributes to reducing the convergence time of the algorithm. Therefore, much effort was invested in developing the initial model using in-house experience and public-domain data.

The objectives of the work were therefore as follows:

1) Implement an adaptive simulation algorithm that is capable of providing a highly representative engine model obtained by tuning an initial model. The quality of the initial model is characterized by the deviations between simulated and measured gas-path parameters with the influence inclusion of measurement uncertainties due to the limited availability of the OEM's information.

2) Test the procedure with real data to enhance the confidence in the method.

3) Implement and test a multiple-offdesign adaptation procedure, aiming at further reducing the residual errors across the operating range of interest, in comparison with the model adapted only at one offdesign point.

III. Methodology of Offdesign Performance Adaptation

The adaptive simulation algorithm described in this paper was designed to calibrate given component characteristic maps. The algorithm acts on defined independent parameters' scaling factors to minimize the error between the modeled measurement vector **P** and the in-service data. The aim is to achieve high accuracy in a limited operating range of interest. The steady-state-performance modeling problem of calculating the dependent (measurable) performance-parameter vector **P** as a function of the ambient and operating-condition vector **u** and the independent component-characteristics vector **X** can be analytically expressed by means of Eq. (1):

$$\mathbf{P} = f(\mathbf{X}, \mathbf{u}) \tag{1}$$

The adaptive simulation algorithm identifies the optimal set of independent component-characteristics vector **X** that minimizes the objective function OF defined by Eq. (2). This function represents the difference between a set of measured parameters $\mathbf{P}_{\mathrm{M}}$ (which is the target) and the simulated measurements **P** for a given operating condition **u**:

$$\mathrm{OF} = \sum_{i=1}^{K} a_i \left| \frac{P_i - P_{M_i}}{P_{M_i}} \right| \cdot 100 \tag{2}$$

where Pi are the simulated measurements and a_i are weighting factors that could be used to take into account the measurement uncertainty of the individual parameters and relative importance of the parameters.

The minimization of the OF (and therefore the estimation of the most appropriate vector **X**) is achieved in this work via a pertinent genetic algorithm. The algorithm is such that the optimal vector **X** identifies a set of compressor-map scaling factors that are then applied to the successive offdesign performance calculations.

A. Compressor-Map Scaling

Compressor-characteristic maps store the information needed for the prediction of engine offdesign performance. PYTHIA, like most of the gas turbine performance simulators, offers a library of default compressor-characteristic maps that are suitable to different compressors. Each of these maps can be scaled and made suitable for a particular engine of interest. A reference point on the compressor-characteristic map (point DP_0 in Fig. 1 with $N = 0.0$, $\mathrm{WAC} = 0.0$, $\mathrm{ETA} = 0.0$, and $\mathrm{PR} = 1.0$) is chosen as the center of the scaling procedure. The level of scaling of any point on the speed lines is determined by the value of the scaling factors and the distance between the point and the center. The value of the scaling factors is defined by the initially unknown values of the actual compressor design parameters (N_{DP}, $\mathrm{PR}_{\mathrm{DP}}$, $\mathrm{WAC}_{\mathrm{DP}}$, and η_{DP}) and the value of the parameters (N_{DP0}, $\mathrm{PR}_{\mathrm{DP0}}$, $\mathrm{WAC}_{\mathrm{DP0}}$, and η_{DP0}) corresponding to the chosen design point on the default map. The design point chosen for performance simulation for a particular engine can be an operating point with detailed knowledge and may not be the same as that chosen by engine manufacturer:

$$\mathrm{SF}_{N,\mathrm{DP}} = \frac{N_{\mathrm{DP}}}{N_{\mathrm{DP0}}} = 1.0 \tag{3}$$

$$\mathrm{SF}_{\mathrm{PR,DP}} = \frac{\mathrm{PR}_{\mathrm{DP}} - 1}{\mathrm{PR}_{\mathrm{DP0}} - 1} \tag{4}$$

$$\mathrm{SF}_{\mathrm{WAC,DP}} = \frac{\mathrm{WAC}_{\mathrm{DP}}}{\mathrm{WAC}_{\mathrm{DP0}}} \tag{5}$$

$$\mathrm{SF}_{\mathrm{ETA,DP}} = \frac{\mathrm{ETA}_{\mathrm{DP}}}{\mathrm{ETA}_{\mathrm{DP0}}} \tag{6}$$

The scaling factors need then to be applied to the whole default compressor-characteristic maps with Eqs. (7–10) to make them representative of the behavior of the compressor of interest. An example of this scaling procedure is shown in Figure 1.

$$N' = N^{\mathrm{def}} \tag{7}$$

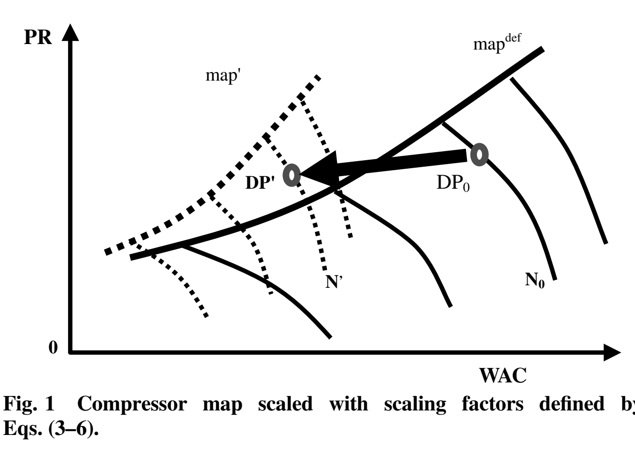

Fig. 1 Compressor map scaled with scaling factors defined by Eqs. (3–6).

$$\mathrm{PR}' = \mathrm{SF}_{\mathrm{PR,DP}} \cdot (\mathrm{PR}^{\mathrm{def}} - 1) + 1 \tag{8}$$

$$\mathrm{WAC}' = \mathrm{SF}_{\mathrm{WAC,DP}} \cdot \mathrm{WAC}^{\mathrm{def}} \tag{9}$$

$$\mathrm{ETA}' = \mathrm{SF}_{\mathrm{ETA,DP}} \cdot \mathrm{ETA}^{\mathrm{def}} \tag{10}$$

where the indices def and prime refer, respectively, to default and DP adapted maps.

Once default compressor maps $\mathrm{map}^{\mathrm{def}}$ are chosen and scaled to represent the behavior of the compressors, the accuracy of offdesign performance predictions is heavily dependent on how close the default maps scaled at the design point are to those of real engine compressor maps. An additional improvement to improve the accuracy of the engine model can be achieved with a successive offdesign adaptation.

B. Scaling Factors for Offdesign Adaptation

Once the default compressor maps are chosen and scaled using the design-point (DP) scaling factors as described previously, map′ can be used in the engine offdesign performance predictions. With design-point performance adaptation techniques, such as those proposed by Li et al. [5], the required accuracy of design-point performance prediction can be achieved. However, the difference between the actual compressor maps and the DP adapted compressor map′ may still be large, and the offdesign performance prediction errors may be unacceptable for gas-path diagnostics. To reduce the offdesign performance prediction errors, the speed lines on the compressor maps need to be adapted (relocated) by using observed offdesign performance measurements.

The design point on the compressor map′ is chosen as a reference point. The adaptation of the speed lines in this study is based on a linear offdesign scaling technique, considering that an engine performance behaves almost linearly near its design point. A proper selection of one set of observed offdesign performance measurements near the design point would satisfy the offdesign performance adaptation, although more points ensure better accuracy, as will be discussed in the next section.

In this study, a definition of offdesign scaling factors that directly refers to offdesign conditions close to the design condition has been introduced. The scaling of a compressor PR–WAC map with offdesign adaptation is shown in Fig. 2, in which map″ represents map′ after the OD adaptation, and the new offdesign scaling factor for the corrected mass flow rate is defined as follows:

$$\mathrm{SF}_{\mathrm{WAC,OD}} = \frac{\mathrm{WAC}_b - \mathrm{WAC}_{\mathrm{DP}}}{\mathrm{WAC}_a - \mathrm{WAC}_{\mathrm{DP}}} \tag{11}$$

where DP, the design point chosen as the reference point for the OD adaptation, remained fixed during the offdesign adaptation; a is a point on a speed line of the map′ before offdesign adaptation; and b is a new position of the point a on the same speed line after the offdesign adaptation, initially unknown.

Similarly, offdesign scaling factors for pressure ratio and isentropic efficiency can be expressed as

$$\mathrm{SF}_{\mathrm{PR,OD}} = \frac{\mathrm{PR}_b - \mathrm{PR}_{\mathrm{DP}}}{\mathrm{PR}_a - \mathrm{PR}_{\mathrm{DP}}} \tag{12}$$

$$\mathrm{SF}_{\mathrm{ETA,OD}} = \frac{\mathrm{ETA}_b - \mathrm{ETA}_{\mathrm{DP}}}{\mathrm{ETA}_a - \mathrm{ETA}_{\mathrm{DP}}} \tag{13}$$

The offdesign scaling factor for the rotational speed lines is set to 1.0, as defined in Eq. (14), to calibrate and relocate them as described previously:

$$\mathrm{SF}_{N,\mathrm{OD}} = \frac{N_b}{N_a} = 1.0 \tag{14}$$

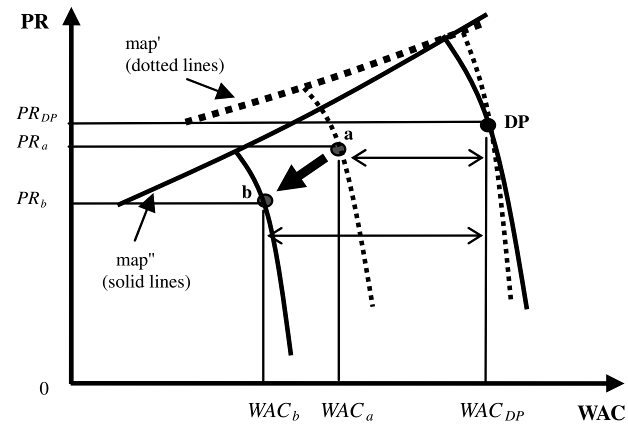

Fig. 2 Offdesign scaling of compressor map.

Therefore, for a given set of offdesign scaling factors, the characteristic parameters of an adapted compressor map″ can be expressed by Eqs. (15–18). The new position in the OD adapted map″ of any point on the map′ is determined by the value of the scaling factors and the distance between the point and the reference point DP:

$$\mathrm{WAC}'' = \mathrm{WAC}_{\mathrm{DP}} + (\mathrm{WAC}' - \mathrm{WAC}_{\mathrm{DP}}) \cdot \mathrm{SF}_{\mathrm{WAC,OD}} \tag{15}$$

$$\mathrm{PR}'' = \mathrm{PR}_{\mathrm{DP}} + (\mathrm{PR}' - \mathrm{PR}_{\mathrm{DP}}) \cdot \mathrm{SF}_{\mathrm{PR,OD}} \tag{16}$$

$$\mathrm{ETA}'' = \mathrm{ETA}_{\mathrm{DP}} + (\mathrm{ETA}' - \mathrm{ETA}_{\mathrm{DP}}) \cdot \mathrm{SF}_{\mathrm{ETA,OD}} \tag{17}$$

$$N'' = N' \tag{18}$$

Note that such offdesign scaling of the maps′ is linear in nature, and this is consistent with the focus of the adaptive approach, which is the improvement of offdesign performance prediction accuracy around the design point. Such linearity may lead to a significant modification of the map in the area far from the design point (low-speed line area); consequently, the adapted performance model using adapted compressor maps″ may lose prediction accuracy at certain offdesign operating conditions far from the design condition. However, accurate offdesign performance prediction around the design point is of crucial importance for gas-path diagnostics if the design operating point is chosen as the nominal diagnostic operating point.

C. Offdesign Adaptation: Procedure and Genetic Algorithms

The objective of the offdesign performance adaptation is to estimate an optimal set of offdesign scaling factors using Eqs. (11–13). A flowchart of the offdesign performance adaptation procedure is illustrated in Fig. 3, in which a genetic algorithm (GA) is used to minimize the objective function. The sets of compressor offdesign scaling factors are optimized during the iterations, ensuring the best match of the simulated performance to the real offdesign performance. Once the objective function reaches its minimum, the best set of offdesign scaling factors is obtained and can be used to produce more accurate offdesign performance predictions around the operating condition at which the optimization was carried out.

Compared with conventional optimization methods, GA offers several unique features: It combines elements of directed and stochastic search techniques, avoiding local minima of the objective function to the benefit of identifying the absolute minimum. In addition, no derivatives are required, and so nonsmooth functions can be optimized. Because of these features, a real-coded GA [9] was chosen in this study, although it is generally known to be

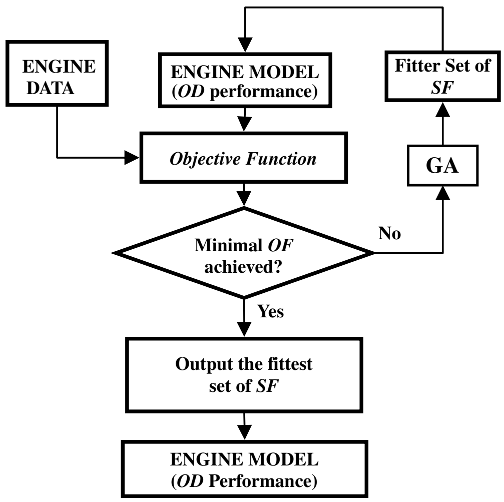

Fig. 3 Procedure of offdesign performance adaptation.

computationally more expensive than conventional optimization methods.

A genetic algorithm normally uses three GA operations in the searching process: reproduction (or selection), crossover, and mutation. Along with the three conventional GA operators just mentioned, an *elitism* operation [10] was used in this study. With this operation, the worse strings in the GA population of any generation are replaced with better strings generated by the three conventional GA operations, and a fitter GA population is produced in the following generation. Therefore, it is ensured that the average fitness of the whole population will improve from one generation to the next.

The numbers of crossovers and mutations in each generation of the GA search are determined by the probabilities assigned to these operators. The probability of crossover was set at 35%, and the probability of mutation was set at 30% for preliminary adaptation calculations.

The accuracy of the results and the speed of the search depend on the number of maximum GA generations used and the size of the population. A higher number of maximum generations with larger size of population are beneficial to a more accurate solution, but lead to a more computationally intensive solution. A tradeoff among these parameters must typically be carried out.

D. Multiple-Operating-Point Adaptation

The procedure described previously is aimed at calculating an optimal set of DP and OD scaling factors that provide the most accurate performance prediction in a given operating range around the DP condition. Multiple-operating-point (MOP) adaptation allows the use of multiple-offdesign test points in the offdesign performance adaptation process to get better adaptation of offdesign performance. The definition of the OF is modified to reflect that, and therefore Eq. (2) becomes

$$\mathrm{OF} = \left[\sum_{j=1}^{n}\sum_{i=1}^{K} a_{ij}\left|\frac{P_{ij}-P_{M_{ij}}}{P_{M_{ij}}}\right|\cdot 100\right]\cdot\frac{1}{n} \tag{19}$$

where $K \cdot n$ is the total number of dependent parameters involved in the multiple-operating-point adaptation, which include the K measurable parameters taken across the engine at the n operating conditions, and the meaning of all other symbols remains unchanged.

The next section will show how, in an operating range of interest, the simulation accuracy improves by introducing the MOP adaptation, when compared with the single point OD adaptation results.

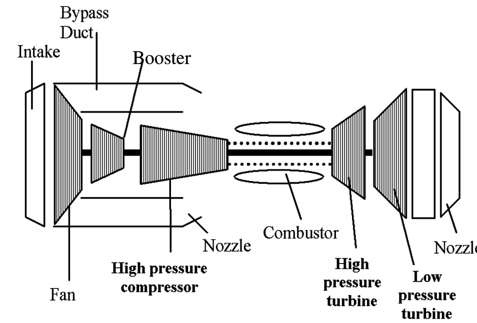

Fig. 4 Model engine configuration.

IV. Applications

A. Engine and Parameters Involved

The adaptive simulation algorithm was applied to an in-service 2-spool aeroengine (Fig. 4) for which test-bed data were available. For confidentiality reasons, most of the relevant raw data and engine information are not published in this paper; instead, normalized data and results are provided.

An engine model was generated using Cranfield University's PYTHIA gas turbine performance and diagnostics software. The core of PYTHIA is TURBOMATCH [11], FORTRAN-based gas turbine performance simulation software that has been validated over many years at Cranfield University.

Table 1 shows the environmental and power-setting parameters used to set the engine model operating condition. The power-setting parameter is the percentage of low-pressure shaft speed with reference to the shaft speed at rated maximum continuous thrust. Table 2 shows the list of $K = 8$ dependent measurable parameters that were available from the test-bed data.

In the range of offdesign operating conditions of interest (see Table 3) for this work, the turbines and the nozzle are choked or nearly choked. On the other hand, the performance of the compressors can vary significantly. Therefore, the adaptive algorithm considers the following key elements of the compressor-characteristic maps as independent or to-be-adapted parameters: 1) corrected mass flow rate WAC, 2) pressure ratio PR, and 3) isentropic efficiency ETA.

B. Problem Definition: Test-Bed Data

In this study, six sets of test-bed data for different power settings and at given environmental conditions were available. These data were used in part to set up the adapted models and in part as test cases (TC). In other words, three data sets were used as the 1) baseline DP condition, 2) first offdesign condition OD1, and 3) second offdesign condition OD2. Table 3 shows the three sets used to set up the

Table 1 Environmental and power-setting parameters

No.	Symbol	Performance parameters	Unit
1	T_{amb}	Ambient temperature	K
2	P_{amb}	Ambient pressure	atm
3	N1	Relative low-pressure shaft speed	%

Table 2 Measurable performance parameters

No.	Symbol	Performance parameters	Unit
1	FF	Fuel flow rate	kg/s
2	N2	Relative high-pressure shaft speed	%
3	T6	Low-pressure compressor exit total temperature	K
4	T8	High-pressure compressor exit total temperature	K
5	T11	High-pressure turbine exit total temperature	K
6	T15	Outlet fan exit total pressure	atm
7	P6	Low-pressure compressor exit total pressure	K
8	P8	High-pressure compressor exit total pressure	atm

Table 3 Test-bed data operating conditions

No.	Symbol	Unit	DP	OD1	OD2
1	T_{amb}	K	282.42	282.48	282.63
2	P_{amb}	atm	0.9887	0.9887	0.9887
3	N1	%	0.9147	0.8594	0.8040

adapted models, and Tables 3 and 4 show the following analysis being carried out:

1) Undertake a DP adaptation of a generic engine model using DP data (DP adapted model).

2) Undertake a single-OD adaptation for the first condition: namely, OD1 (adaptation at OD1).

3) Undertake a single-OD adaptation for the second condition: namely, OD2 (adaptation at OD2).

4) Undertake a multiple-OD adaptation using the OD1 and OD2 data (multiple-OD model).

5) Test the preceding 4 models with the available different combinations of 6 sets of data (DP, OD1, OD2, TC1, TC2, and TC3).

V. Analysis of Results

The results that follow represent the deviations between the 4 adapted engine models and the test-bed data. The offdesign adapted models were obtained by scaling the compressor maps of the three compressors to minimize the objective functions in Eqs. (2) and (19). The values of the OF for the adapted models used in this work are listed in the last row of Table 5. Equation (2) represents the sum of the percentage deviations between the models and the data for all 8 measurable parameters. In Table 5, these equations were also used to calculate the error summation for each model. The model adapted only at DP shows increasing error with the decrease of $N1$. The models adapted with offdesign adaptation show that the error reduces in the operating condition (OD1) in which the adaptation took place.

Table 4 Test-bed data operating conditions

No.	Symbol	Unit	TC1	TC2	TC3
1	T_{amb}	K	282.42	282.34	283.43
2	P_{amb}	atm	0.9887	0.9886	0.9885
3	N1	%	0.8938	0.8831	0.8275

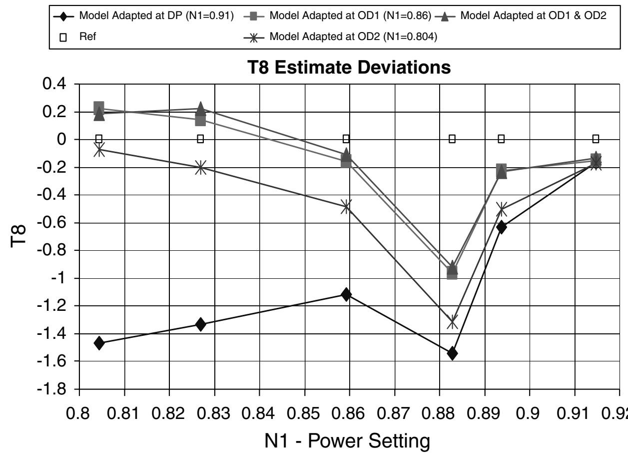

Fig. 5 Deviations in T8 between the values from the adapted models and the test-bed data.

A better representation of the adaptation error is the average error calculated with Eq. (20) over the 8 selected measurements:

$$\text{average error} = \left[\sum_{i=1}^{K}\left|\frac{P_i - P_{M_i}}{P_{M_i}}\right|\cdot 100\right]\cdot\frac{1}{K} \tag{20}$$

where Table 6 shows the values of average errors of each model at the 6 considered operating conditions. Note that the values of error that all 4 models show at the condition TC2 are not in trend with the other values; the errors are surprisingly higher. It is the authors' opinion that the TC2 data were corrupted by high levels of measurement error that can also be observed in Figs. 5–8. The error for all models associated with TC2 is always not in trend with the others.

Figures 5–7 show a selection of estimate deviations between the test data and the outputs from the 4 models, respectively, for T8, T11, and P6.

A diagram that summarizes the behaviors of the 4 models is represented in Fig. 8 and Table 6. It shows the average error between the simulated and the test-bed data over the 8 parameters estimated for all cases examined. It confirms the following:

1) The model adapted at DP is capable of accurately simulating the test data taken at operating conditions ($N1$ values) close to the point of adaptation. The average error increases at a lower power setting, reaching a maximum value of 2.27% at $N1 = 0.80$.

Table 5 Error summation over the 8 measurements listed in Table 2

Case		Error summation [Eq. (2) or (19)]			
Reference	N1	Adapted DP	Adapted OD1	Adapted OD2	Adapted OD1 and OD2
DP	0.9147	1.86	1.80	1.90	1.63
TC1	0.8937	6.38	2.24	4.00	2.28
TC2	0.8829	10.65	7.68	9.01	7.69
OD1	0.8593	10.53	1.72	3.79	1.60
TC3	0.827	13.14	3.97	2.67	2.78
OD2	0.8044	18.18	4.96	1.28	2.21
OF		1.86	1.72	1.28	1.91

Table 6 Average errors over the 8 measurements listed in Table 2

Case		Average error [Eq. (20)]			
Reference	N1	Adapted DP	Adapted OD1	Adapted OD2	Adapted OD1 and OD2
DP	0.9147	0.23	0.22	0.24	0.20
TC1	0.8937	0.80	0.28	0.50	0.28
TC2	0.8829	1.33	0.96	1.13	0.96
OD1	0.8593	1.32	0.21	0.47	0.20
TC3	0.827	1.64	0.50	0.33	0.35
OD2	0.8044	2.27	0.62	0.16	0.28

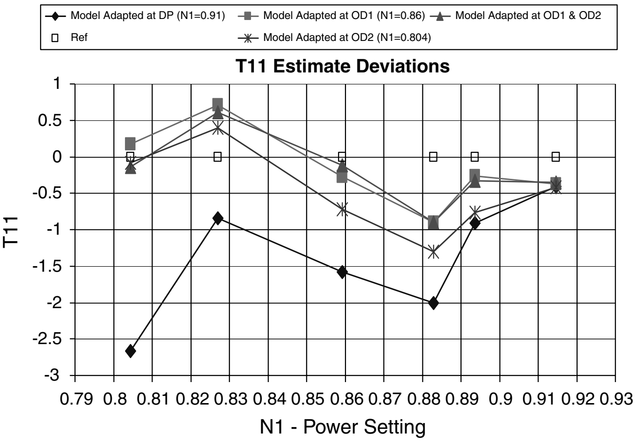

Fig. 6 Deviations in T11 between the values from the adapted models and the test-bed data.

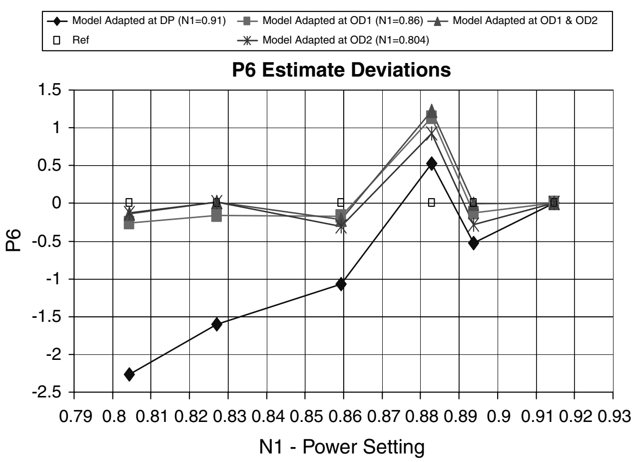

Fig. 7 Deviations in P6 between the values from the adapted models and the test-bed data.

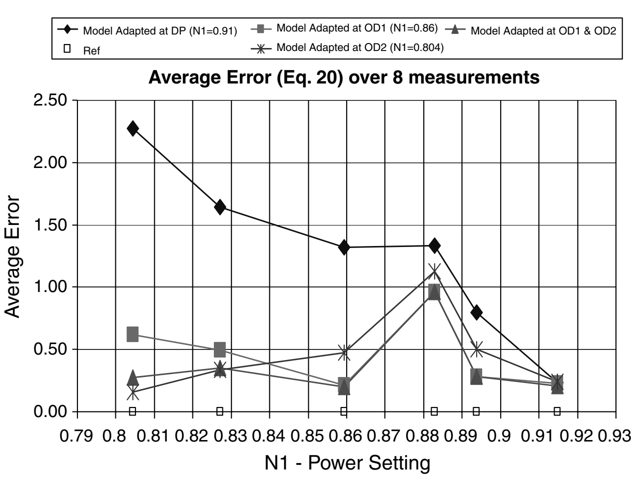

Fig. 8 Average error between the adapted models and the test-bed data, calculated over 8 measurements.

2) For the models adapted only at OD1 ($N1 = 0.8593$) or at OD2 ($N1 = 0.80$), a remarkable improvement (excluding TC2 from the analysis) is shown around the operating conditions in which the adaptation was applied.

3) The highest level of accuracy is achieved with the model adapted at both OD1 and OD2: multiple-point adaptive simulation. The average error on the 8 parameters is always smaller than 0.35% (excluding TC2).

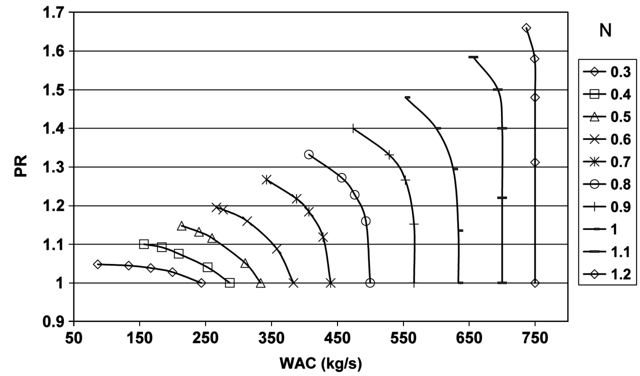

Fig. 9 Default fan map for (PR–WAC).

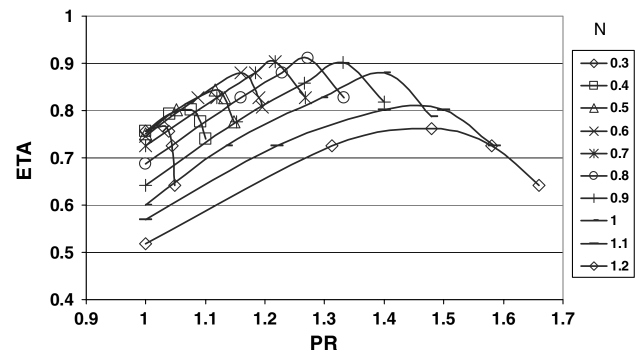

Fig. 10 Default fan map (ETA–PR).

The modification of compressor maps plays an important role in the performance adaptation, and two steps of scaling were involved in the scaling. In the first step, due to the unknown actual compressor maps of the engine, a default compressor map shown in Figs. 9 and 10 was chosen for the fan, the booster, and the high-pressure compressor to start the engine performance simulation. Because of that, the range of the compressor-characteristic parameters (PR, WAC, and ETA) of the map are very different from those of the three compressors, and so the maps are scaled based on the actual compressor design parameters using Eqs. (3–10), and the obtained DP scaling factors for the three compressor maps are shown in Table 7. As an example of the scaling, the scaled map for the fan is shown in Figs. 11 and 12 (solid lines).

In the second step of the map modification (i.e., the offdesign performance adaptation), the three compressor maps are modified

Table 7 DP scaling factors for the three compressor maps

Parameters	Fan	Booster	High-pressure compressor
$SF_{PR,DP}$	0.588	0.698	0.553
$SF_{ETA,DP}$	1.369	0.807	1.207
$SF_{WAC,DP}$	0.617	0.536	1.151

Table 8 Obtained OD scaling factors for the three test cases

Parameters		Fan	Booster	High-pressure compressor
TC1	$SF_{PR,OD}$	0.890	0.887	0.872
	$SF_{ETA,OD}$	0.864	0.849	1.074
	$SF_{WAC,OD}$	0.810	0.855	1.308
TC2	$SF_{PR,OD}$	1.252	1.094	0.753
	$SF_{ETA,OD}$	0.840	0.866	1.371
	$SF_{WAC,OD}$	0.934	0.898	0.899
TC3	$SF_{PR,OD}$	0.588	0.698	0.553
	$SF_{ETA,OD}$	1.369	0.807	1.207
	$SF_{WAC,OD}$	0.617	0.536	1.151

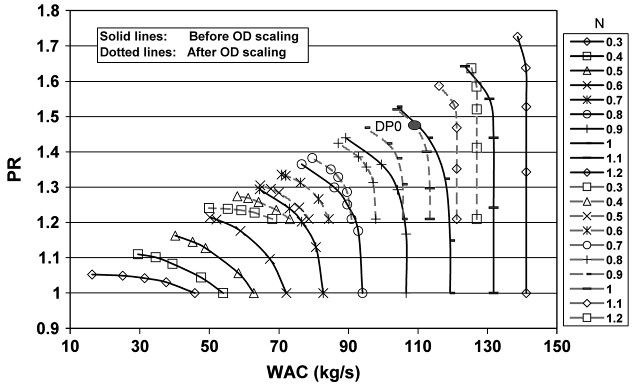

Fig. 11 Comparison of scaled fan maps (PR–WAC).

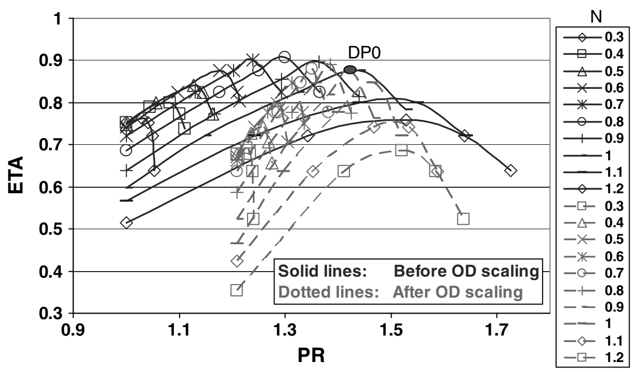

Fig. 12 Comparison of scaled fan maps (ETA–PR).

further with the OD scaling factors defined in Eqs. (11–18). The obtained OD scaling factors for the three test cases are shown in Table 8. As an example of the OD scaling of the compressor maps, Figs. 11 and 12 show a comparison between maps before and after OD adaptation for the fan in the test case TC3. The maps may be modified significantly to match the offdesign test data.

The test cases show that by using the developed offdesign performance adaptation method, it is possible to tune an engine performance model to match offdesign performance test data when actual engine compressor maps are not available.

VI. Conclusions

Accurate offdesign performance prediction in a defined operating range is very important in many applications of gas turbine performance analysis such as gas-path diagnostics. In this paper, a new definition of offdesign scaling factors is introduced to modify compressor maps and a novel multiple-point-offdesign performance adaptation method is described. On the basis of the work presented in the paper, the following conclusions can be made:

1) Although based on linear compressor-map scaling, the method has proven to have the capability to improve the accuracy of engine performance models in the vicinity of specified design conditions, provided that a detailed gas-path measurement of engine offdesign performance around the design condition is available.

2) Models adapted at one OD point (in addition to the DP adaptation) require a more careful tuning of the adaptation procedure in which the selection of the OD points for adaptation plays a very important role in determining the quality of the adapted model. The improvement of model accuracy achieved across an offdesign operating range using one point offdesign adaptation is significant in the test case.

3) Multiple-offdesign adaptive simulation offers the opportunity to improve the prediction accuracy even further in the vicinity of the design point, but requires more measurement information and more effort in tuning the model.

4) Because of the linear nature of the adaptation approach, the adapted performance model may loss prediction accuracy or even provide worse prediction for certain offdesign points far from the design point. Therefore, it should preferably be used in the vicinity of the engine design point.

5) The application of this technique to a civil aero gas turbine showed that the developed offdesign performance adaptation is effective and able to provide promising results, with an average error smaller than 0.35% in predicting the 8 measurable parameters in the test case.

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