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DOI:

[10.1016/j.apenergy.2014.08.115](https://doi.org/10.1016/j.apenergy.2014.08.115)

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Document Version

Peer reviewed version

Citation for published version (Harvard):

Tsoutsanis, E, Meskin, N, Benammar, M & Khorasani, K 2014, 'A component map tuning method for performance prediction and diagnostics of gas turbine compressors', *Applied Energy*, vol. 135, pp. 572-585. <https://doi.org/10.1016/j.apenergy.2014.08.115>

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Checked for eligibility: 08/01/2018

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A component map tuning method for performance prediction and diagnostics of gas turbine compressors

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Abstract

In this paper, a novel compressor map tuning method is developed with the primary objective of improving the accuracy and fidelity of gas turbine engine models for performance prediction and diagnostics. A new compressor map fitting and modelling method is introduced to simultaneously determine the best elliptical curves to a set of compressor map data. The coefficients that determine the shape of the compressor map curves are analyzed and tuned through a multi-objective optimization scheme in order to simultaneously match multiple sets of engine performance measurements. The component map tuning method, that is developed in the object oriented Matlab Simulink environment, is implemented in a dynamic gas turbine engine model and tested in off-design steady state and transient as well as degraded operating conditions. The results provided demonstrate and illustrate the capabilities of our proposed method in refining existing engine performance models to different modes of the gas turbine operation. In addition, the excellent agreement between the injected and the predicted degradation of the engine model demonstrates the potential of the proposed methodology for gas turbine diagnostics. The proposed method can be integrated with the performance-based tools for improved condition monitoring and diagnostics of gas turbine power plants.

Keywords: Component map, Model adaptation, Performance prediction, Gas turbine, Condition monitoring

Highlights

- A method for fitting rotated elliptical curves to compressor performance map data is presented.
- The proposed fitting method is integrated into a dynamic model of a gas turbine.
- The performance of the method is tested in steady state and transient conditions of gas turbine.
- The proposed method is used to diagnose compressor fouling from transient data.

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- The maintenance cost attributed by the accuracy of the proposed method is assessed as compared to other methods.

Nomenclature

Symbols

a	semi-major axis of an ellipse
A	matrix of elements α
b	semi-minor axis of an ellipse
f	flow rate
g	generic form of map's sub/coefficients
m	corrected mass flow rate
\dot{m}	mass flow rate
\dot{m}'	mass flow rate from plenum
n	total number of operating points per speed line
N	corrected shaft rotational speed
p	pressure
p'	pressure from plenum
P	power
q	total number of speed lines
sm	surge margin
T	temperature
T'	temperature from plenum
\mathbf{u}	ambient and operating conditions vector
x	coordinate of an ellipse in x-axis
\mathbf{X}	component characteristics vector
y	coordinate of an ellipse in y-axis
\mathbf{Y}	measurement vector

Greek

α	element of matrix A
Γ	mass flow capacity
ϵ	average prediction error
η	isentropic efficiency
θ	angle of rotated ellipse

π pressure ratio
 σ spread, smooth parameter

Subscript

act actual
amb ambient
 c compressor
cl clean
 d diffuser
deg degraded
des design point
 f fuel
 i order of the polynomial, number of the speed lines
inj injected
 j number of the operating points
max maximum
pred predicted
 pt power turbine
r reference engine
s steady state
surge surge point
 t turbine
tr transient
w weighted
0 fixed coordinate, $\theta=0$
2 compressor inlet
3 compressor exit
4 combustor exit
5 turbine exit
6 power turbine exit
7 exhaust

1 **1. Introduction**

2 Gas turbine performance simulation, diagnosis and prognosis are strongly dependent on detailed under-
3 standing of the engine component behavior. Typically the behavior of an engine component is represented

4 by performance maps which are the Original Equipment Manufacturer's (OEM) proprietary design infor-
5 mation. At the off-design conditions, the quality of engine component maps is vital for the accuracy of gas
6 turbine performance and diagnostic models. Special interest is given to compressors since they can generate
7 various operational problems such as surge, stall and flutter, although their operating line is determined
8 by the turbine characteristics. Maps can also be determined by flow analysis schemes such as the Stream
9 Line Curvature (SLC) method [1] or high fidelity Computational Fluid Dynamics approaches (CFD) if the
10 geometry of the compressor is known.

11 Gas turbine users do not have access to the context of such maps and their involvement is only limited
12 to the use of tailored to customer decks for performance computations. The above limitations have recently
13 motivated gas turbine research community to explore alternative methods [2],[3],[4] for representing the
14 compressor maps in order to improve the accuracy of the performance prediction.

15 Some researchers have focused on the map representation itself, while others have implemented compres-
16 sor map methods further in performance models of gas turbines. Kurzke [5] introduced auxiliary coordinates
17 (beta lines), having no physical significance, which are superimposed in order to address the non-uniqueness
18 and ill-conditioning issues of the compressor map shapes. Jones *et al.* [6] and Sethi *et al.* [7] introduced
19 quasi-physics-based backbone compressor mapping approaches. The work by Drummond and Davison [8]
20 examined the shape variance of the compressor maps for a wide range of compressor shapes and related
21 them to the physical processes. A promising data-based method for the component performance which uses
22 Back Propagation Neural Networks (BPNN) has been developed by Yu *et al.* [2]. The general regression
23 neural networks (GRNN) and Multi Layer Perception (MLP) approaches that have been suggested by M.
24 Gholamrezaei and K. Ghorbanian [9] provide good prediction of the compressor map shape. The accuracy
25 and performance of the above methods depend on the quality and quantity of the available engine data from
26 the engine manufacturers or the engine users.

27 One of the most commonly used methods involves scaling and shifting the shape of a similar compressor
28 map through optimization techniques such that it matches the targeted engine measurements. Such a
29 scaling method was proposed by Kong *et al.* [10] on the assumption that the implemented map has a very
30 similar shape to the actual map. A combined hybrid approach that was developed by Kong *et al.* [3] takes
31 advantage of Genetic Algorithms (GA) for determining the coefficients of the polynomials used in the system
32 identification method. Recently Li *et al.* [4] have suggested a unique set of scaling coefficients for each line
33 of the constant speed and efficiency to capture nonlinear effects. This method yields a higher accuracy than
34 the traditional scaling methods at operating points away from the design point of the engine.

35 Although the advantages and benefits of the above approaches in engine performance prediction are
36 extensive, the trade-offs between key parameters such as the operating range, accuracy, complexity and
37 computational time are still debated and worth further investigation. Data-based approaches such as Neural
38 Networks (NN) [2, 9] and GA [10, 11] might provide improved prediction accuracy with the compressor map

39 data and/or engine measurements; however they suffer from the extensive training and non-uniqueness of
40 the solution, respectively. On the other hand, in diagnostics systems and approaches both GA and NN can
41 be designed to be robust due to performing prior signal processing operations [12]. Since transient data
42 are normally acquired online at reasonably high rates the former methods cannot be used effectively when
43 integrated into a dynamical engine model. This is specially the case for real-time performance prediction of
44 a gas turbine. Therefore, it is essential to develop a robust, formally validated, generic and computationally
45 efficient approach for representing a compressor map that when empowered with model adaptation will be
46 able to predict a gas turbine's performance at off-design steady state and transient conditions.

47 In this paper, a compressor map generation method for improving the accuracy of the gas turbine
48 performance prediction and diagnostics is developed. In contrast to the earlier work [13], where the shape of
49 a compressor map was expressed by mathematical equations of an ellipse with fixed center and no rotation,
50 this study proposes a more sophisticated and accurate approach by considering rotation of the ellipses
51 and transformation of its coordinates. This method is integrated into a dynamic engine model that is
52 developed in the Matlab/Simulink environment. The dynamic engine model itself and its validation against
53 the gas turbine simulation software PROOSIS [14] were the subject of our earlier work [15]. Moreover, the
54 application is not only tested to the steady state off-design operation [16], but is also extended to transient
55 operation for healthy and degraded conditions. Finally, a simplified techno economic assessment based on
56 the work of Aretakis *et al.* [17] is carried out for evaluating the effects that the accuracy of our method have
57 on the cost of gas turbine maintenance when the compressor is degrading.

58 2. Methodology

59 Axial compressor performance maps are used in the gas turbine thermodynamic models for estimation
60 of key component parameters such as the pressure ratio π_c , the corrected mass flow rate $m_c = \left(\frac{\dot{m}_c \times \sqrt{T_2}}{p_2}\right)$
61 and the isentropic efficiency η_c at several corrected rotational speeds N . A typical compressor map available
62 from the literature [18] has been digitized and reproduced as shown in Fig. 1. Generating compressor maps
63 for low speed regions, that is below 50% of the corrected rotational speed, is another research topic that has
64 been addressed by other researchers [6], [19] and is beyond the scope of this study.

65 The objective of map generation approaches is to determine mathematical expressions that could accu-
66 rately capture the shape of the map. This is performed by relating the corrected mass flow rate m_c and the
67 isentropic efficiency η_c with the pressure ratio π_c and the corrected rotational speed N , i.e. $m_c = f(\pi_c, N)$
68 and $\eta_c = g(m_c, N)$. Another way of expressing the efficiency $\eta_c = h(\pi_c, N)$ is by expressing it as a function
69 of the pressure ratio π_c , which is beneficial for high rotational speed lines that are almost vertical. A detailed
70 description of our proposed method follows in the next subsections.

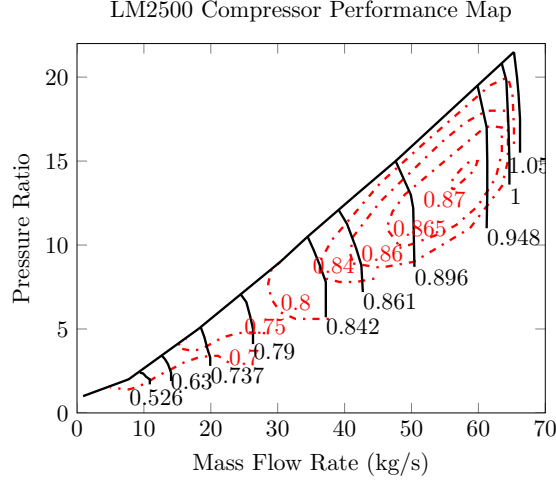


Figure 1: Compressor performance map as reproduced from [18].

71 2.1. Map Fitting

72 The process of map fitting commences with a reference map that is available either from the open
 73 literature or constructed from the operational data. Having the reference compressor map, the objective
 74 is to fit the available data with a single mathematical expression, which should be of the same form for
 75 every speed line. The accuracy of the fitting procedure depends on several factors, such as the complexity
 76 of the mathematical model chosen, the quality of the data, the threshold of the tolerance criterion and the
 77 objective function that is used in the optimization, if any. Several maps from the literature have been used
 78 to test the validity of the proposed method but due to space limitations in this work we will only present
 79 the accuracy of the method as it is applied to the compressor map shown in Fig. 1. After an extensive
 80 review of several methods (polynomials, neural networks [2],[9], etc.) for representing the pressure ratio π_c
 81 and the efficiency η_c as a function of m_c and N , the most mathematically robust approach is determined
 82 where each line belongs to an elliptic curve. The equation, adjusted for the π_c versus m_c map, is given by

$$\left(\frac{m_{c_0} - x_0}{a_{\pi_c}}\right)^2 + \left(\frac{\pi_{c_0} - y_0}{b_{\pi_c}}\right)^2 = 1 \quad (1)$$

83 where a_{π_c} and b_{π_c} denote the semi-major and the semi-minor axes of the ellipse, respectively. In addition
 84 m_{c_0} and π_{c_0} denote the corrected mass flow rate and the pressure ratio when the ellipse is fixed at (x_0, y_0) ,
 85 which represents the center coordinates of the ellipse, respectively. Taking into consideration that each
 86 ellipse is free to rotate, at an angular value of θ_{π_c} , the new coordinates of the ellipse (m_c, π_c) are now given
 87 by

$$m_c = m_{c_0} \cos(\theta_{\pi_c}) - \pi_{c_0} \sin(\theta_{\pi_c}) \quad (2)$$

$$\pi_c = m_{c_0} \sin(\theta_{\pi_c}) + \pi_{c_0} \cos(\theta_{\pi_c}) \quad (3)$$

88 Similarly for the efficiency the governing equation is given by

$$\left(\frac{m_{c_0} - x_0}{a_{\eta_c}} \right)^2 + \left(\frac{\eta_{c_0} - y_0}{b_{\eta_c}} \right)^2 = 1 \quad (4)$$

89 where a_{η_c} and b_{η_c} denote the semi-minor and the semi-major axes of the ellipse, respectively, and m_{c_0} and
 90 η_{c_0} denote the corrected mass flow rate and the efficiency. Once again, rotating the ellipse at an angle of
 91 θ_{η_c} yields the compressor's isentropic efficiency η_c as

$$\eta_c = m_{c_0} \sin(\theta_{\eta_c}) + \eta_{c_0} \cos(\theta_{\eta_c}) \quad (5)$$

92 where eq. (2) is used to determine m_c since the range of the corrected mass flow is identical for both π_c vs.
 93 m_c and η_c vs. m_c maps.

94 The start and the end of the map generated for each speed line are limited according to the variation of
 95 each coefficient with respect to the corrected rotational speed N . The distribution of the points at which
 96 the surge occurs $\pi_{c_{surge}}$ is expressed as a 2nd order polynomial function of the corrected rotational speed N ,
 97 as follows:

$$\pi_{c_{surge_i}} = aN_i^2 + bN_i + c \quad (6)$$

98 where a, b, c are the coefficients of the equation and i denotes the corresponding speed line of the surge point
 99 $\pi_{c_{surge}}$. Assuming a constant surge margin sm of 20%, the maximum pressure ratio $\pi_{c_{max}}$ of each speed line
 100 is then given by:

$$\pi_{c_{max_i}} = \left(\frac{\pi_{c_{surge_i}}}{(1 + sm)} \right) \quad (7)$$

101 This surge limiter prevents the speed lines from exceeding their corresponding maximum pressure ratio.

102 Three approaches of varying complexities have been proposed for fitting the π_c versus m_c map data with
 103 the following assumptions on the ellipses, namely

104 **Approach 1.** Center at $(0, 0)$ and no axes rotation,

105 **Approach 2.** Center at $(0, 0)$ and rotation of the axes at an angle of θ ,

106 **Approach 3.** Center at (x_0, y_0) and rotation of the axes at an angle of θ .

107 Similar approaches are considered for the η_c versus m_c map apart from the first one, where x_0 is assumed
 108 to be the mid point of each curve as follows:

109 **Approach 1.** Center at $(x_0, 0)$ and no axes rotation.

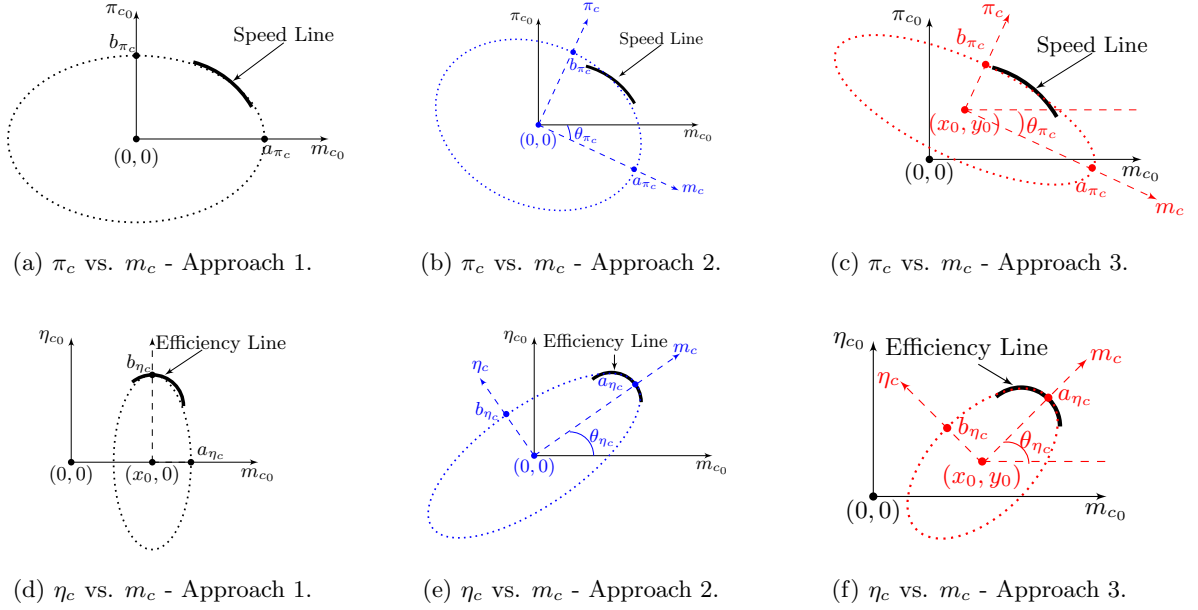


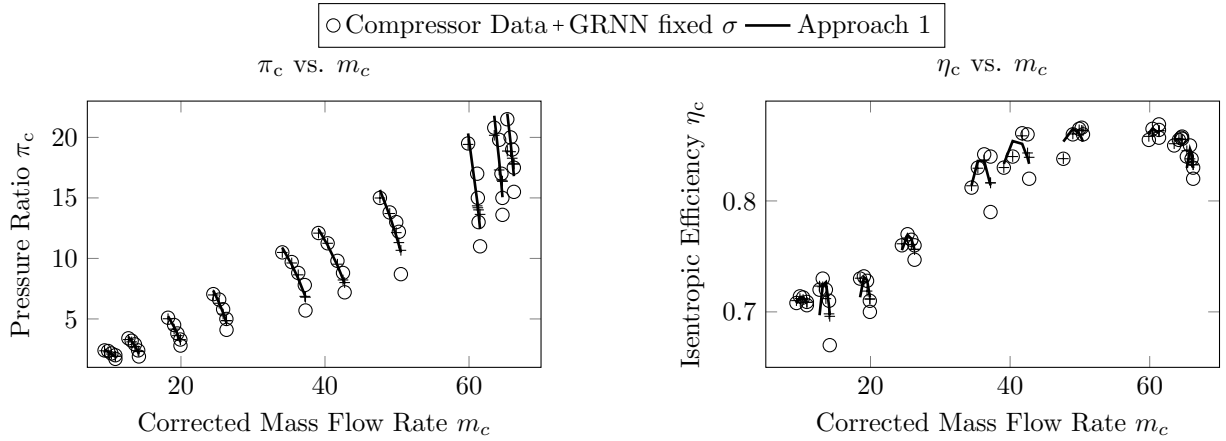
Figure 2: Elliptical curve parameters for various fitting approaches.

110 **Approach 2.** Center at $(0, 0)$ and rotation of the axes at an angle of θ ,

111 **Approach 3.** Center at (x_0, y_0) and rotation of the axes at an angle of θ .

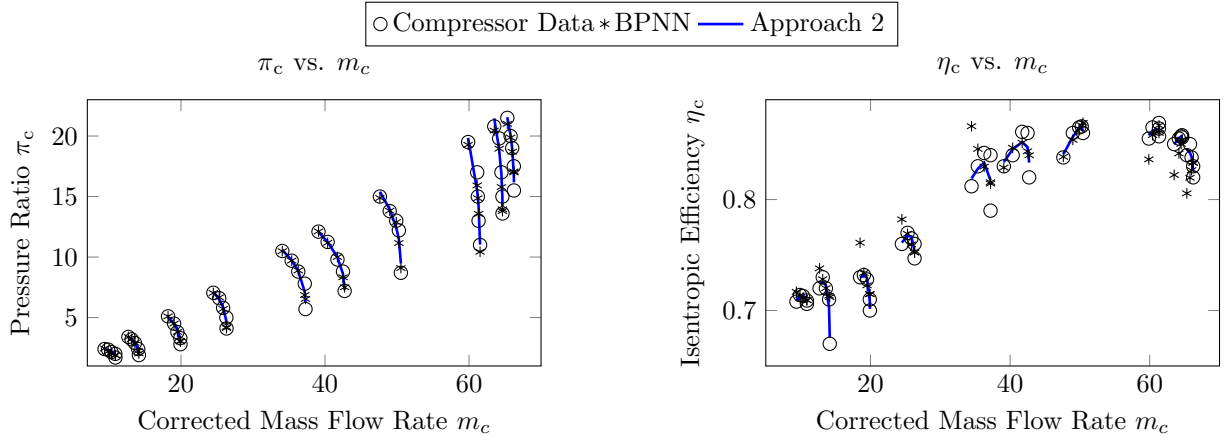
112 A graphical illustration of the suggested elliptical curve fitting approaches along with the important pa-
 113 rameters of eqs. (1)-(5) is shown in Fig. 2. Furthermore, a family of the compressor map fitting approaches as
 114 suggested by Gholamrezaei and K. Ghorbanian [9], and Yu *et al.* [2] are implemented according to the same
 115 objectives. The fitting methods employed here are the GRNN approach with constant and variable spreads
 116 σ [9] and a typical BPNN method [2]. The GRNN approach [9] and the BPNN method [2] have been tested
 117 by implementing the Matlab's GRNN functions and the NN toolbox [21], respectively. The value of each
 118 coefficient for the Approaches 1, 2 and 3 has been determined by integrating the above elliptical functions
 119 in one of the Matlab's minimization algorithms (specifically the `fminsearch` [21]). The initial conditions for
 120 these coefficients did not require any expert knowledge and could be easily set based on the elliptical curve
 121 properties as shown in Fig. 2. The application of the proposed and available methods for the selected map
 122 is shown in Fig. 3.

123 It is observed from Figs. 3a and 3b that the Approach 1 yields similar results as in the GRNN method
 124 with constant spread σ . When approaching the high corrected rotational speed N region, the accuracy
 125 of both methods decreases and they are not accurately capturing the curvature of each speed line. In the
 126 second group of fitting approaches, as shown in Figs. 3c and 3d, Approach 2 is more accurate than Approach
 127 1 and the BPNN fitting method. Once again, at the high rotational speed N region the BPNN performance
 128 is not as accurate; nevertheless it is more accurate than Approach 1 and GRNN with fixed spread.



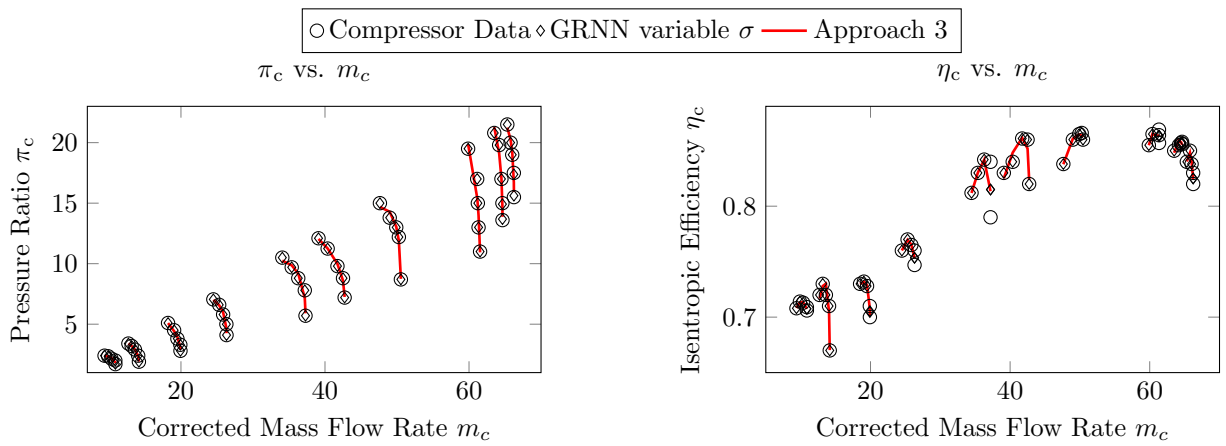
(a) π_c -Fitting (Approach 1 and GRNN fixed σ).

(b) η_c -Fitting (Approach 1 and GRNN fixed σ).



(c) π_c -Fitting (Approach 2 and BPNN).

(d) η_c -Fitting (Approach 2 and BPNN).



(e) π_c -Fitting (Approach 3 and GRNN variable σ).

(f) η_c -Fitting (Approach 3 and GRNN variable σ).

Figure 3: Compressor performance map fitting methods.

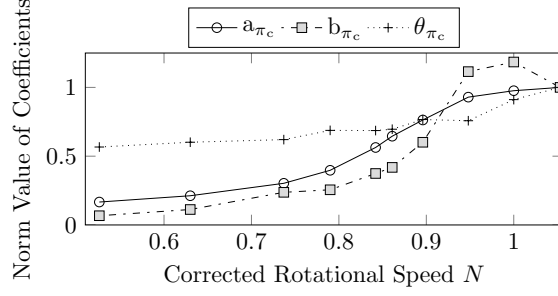


Figure 4: Variation of the proposed map fitting coefficients as a function of the corrected speed N for the π_c versus m_c map.

129 It is evident from the final group of fitting approaches that are shown in Figs. 3e and 3f, that Approach
 130 3 provides a very good agreement with the compressor map data; as does the GRNN method with variable
 131 spread. We are now in a position to evaluate the above proposed approaches in terms of their computational
 132 cost and fitting performance given that they have different complexities. The common parameters of each
 133 ellipse in all the proposed approaches are a and b . In addition, the angles θ_{η_c} and θ_{π_c} of the rotated ellipses
 134 are employed in both the Approaches 2 and 3. The third approach has also the center coordinate parameters
 135 (x_0, y_0) and Approach 1 has an additional parameter x_0 for the efficiency map. The only important parameter
 136 to be computed in both GRNN methods is the spread or the smoothing parameter σ .

137 All the above parameters or coefficients should be expressed as functions of the corrected rotational
 138 speed N . This process results in a number of sub-coefficients depending on the type of the function. The
 139 propagation of the coefficients with respect to N should be captured by smooth and simple functions that
 140 will not give rise to ill-conditioned extrapolation affecting the accuracy of the targeted optimization solution.
 141 Each coefficient of the suggested elliptical approach is now expressed as a polynomial function of the corrected
 142 rotational speed in the generic form as

$$g(N) = g_1 N^i + \dots + g_i N + g_{i+1} \quad (8)$$

143 where g denotes as one of map coefficients and i denotes the order of the polynomial function. For instance,
 144 in the second approach, the coefficient a_{π_c} is now expressed as

$$a_{\pi_c}(N) = a_{\pi_{c1}} N^3 + a_{\pi_{c2}} N^2 + a_{\pi_{c3}} N + a_{\pi_{c4}} \quad (9)$$

145 which is a 3rd order polynomial with a total number of 4 sub-coefficients. In Approach 2 where the coefficients
 146 for the pressure map ($a_{\pi_c}, b_{\pi_c}, \theta_{\pi_c}$) are expressed as a function of the speed, as shown in Fig. 4, this results
 147 in 13 sub-coefficients for the π_c versus m_c map.

148 The above process is performed for all the three proposed fitting approaches using the Matlab's curve
 149 fitting toolbox. The total number of the sub-coefficients for each proposed approach along with the fitting

150 errors of the available methods are tabulated in Table 1. For the GRNN method with a constant spread
 151 this parameter can be expressed as a linear function of the corrected rotational speed N with only two
 sub-coefficients, i.e. $\sigma = \sigma_1 N + \sigma_2$. The qualitative evaluation and comparison of the above compressor map

Table 1: Evaluation of various compressor map fitting methods.

Method	Coefficient	Coefficient as $f(N)$	Sub- coefficients	No of Sub-coef.	Fit Error m_c, η_c (%)
App.1 [13]	$a_{\pi_c}, b_{\pi_c},$ $a_{\eta_c}, b_{\eta_c}, x_{0\eta_c}$	Polynomial	$a_{\pi_{c1\dots4}}, b_{\pi_{c1\dots4}},$ $a_{\eta_{c1\dots4}}, b_{\eta_{c1\dots4}}, x_{0\eta_{c1\dots4}}$	20	6.5, 0.89
App. 2	$a_{\pi_c}, b_{\pi_c}, \theta_{\pi_c},$ $a_{\eta_c}, b_{\eta_c}, \theta_{\eta_c}$	Polynomial	$a_{\pi_{c1\dots4}}, b_{\pi_{c1\dots5}}, \theta_{\pi_{c1\dots4}},$ $a_{\eta_{c1\dots3}}, b_{\eta_{c1\dots4}}, \theta_{\eta_{c1\dots3}}$	23	2.9, 0.54
App. 3	$a_{\pi_c}, b_{\pi_c}, \theta_{\pi_c},$ $x_{0\pi_c}, y_{0\pi_c}, a_{\eta_c}, b_{\eta_c},$ $\theta_{\eta_c}, x_{0\eta_c}, y_{0\eta_c}$	Polynomial & Splines	$a_{\pi_{c1\dots8}}, b_{\pi_{c1\dots9}}, \theta_{\pi_{c1\dots10}},$ $x_{0\pi_{c1\dots13}}, y_{0\pi_{c1\dots9}}, a_{\eta_{c1\dots10}},$ $b_{\eta_{c1\dots8}}, \theta_{\eta_{c1\dots12}}, x_{0\eta_{c1\dots14}},$ $y_{0\eta_{c1\dots7}}$	100	2.2, 0.41
BPNN [2]	-	-	-	-	3.8, 1.41
GRNN constant σ [9]	σ	Linear	$\sigma_{1\dots2}$	2	6.5, 0.71
GRNN variable σ [9]	σ	-	-	-	0.5, 0.24

152 fitting methods highlight several trade-offs among their performance, robustness and further implementation
 153 in gas turbine models. Generally, the GRNN with fixed spread parameter is a good candidate along with
 154 the Approach 1, since they are able to extrapolate data in a compressor map, but both suffer in terms
 155 of accuracy. Approach 3 yields the most accurate results among the proposed elliptical fitting approaches
 156 due to the fact that there is freedom in changing the center coordinates of the ellipses and simultaneously
 157 rotating them. The distribution of the Approach 3 coefficients, as a function of N , is highly nonlinear and
 158 only high order polynomials and spline curves are capable of capturing effectively this nonlinear distribution.
 159 This results in the use of 100 sub-coefficients for the Approach 3 as opposed to 23 that are required for the
 160 Approach 2 although their differences are not significant in both the pressure ratio and the efficiency maps.
 161 Approach 2 has a fitting error of 2.9% for m_c which may be considered high to allow for an accurate
 162

163 prediction given that for diagnostic purposes one examines faults greater than 1%. However, this fitting
164 error refers to the accumulated deviation from all the points of the reference map. This implies that the
165 average fitting error in Approach 2 for m_c is 0.044% corresponding to each one of the 50 data points. The
166 GRNN with variable spread provides excellent results, however it has the same disadvantage as Approach
167 3 in terms of its implementation in a gas turbine model, since the distribution of the spread parameter as
168 a function of the speed is highly nonlinear to allow for reliable extrapolation. The excessive parameters
169 corresponding to the GRNN with the variable spread has motivated the development of the rotated GRNN
170 (RGRNN) and MLP approaches as presented in [9]. While accuracy is improved by the latter methods, the
171 RGRNN is limited to represent compressor curves for which data are available. On the other hand, further
172 implementation of the MLP approach in a dynamic adaptive engine model for performance prediction and
173 diagnostics remains to be investigated.

174 The above comparison is made in order to emphasize that although certain methods will always, inde-
175 pendent of the map shape, outperform others in fitting the compressor map data, this goal is not the only
176 measure for a successful gas turbine performance prediction and diagnostic scheme. The well-conditioned
177 interpolation, extrapolation and the ability of the map fitting algorithms to account for the degradation
178 factors are far more important and crucial than their absolute accuracy that is expressed in terms of the
179 fitting error criterion.

180 Therefore, we have concluded that Approach 2 is selected to be implemented for the engine performance
181 prediction by its integration in a gas turbine model. This decision is justified by the fact that Approach
182 2 yields a good balance between the accuracy that is obtained and the complexity of the mathematical
183 expressions capturing the variations of each coefficient with respect to the speed. The analytical methodology
184 enables one to formally control the compressor map shape in a nonlinear manner, so that the corresponding
185 map generation method can replace simple lookup tables and/or externally linear-scaled maps in an engine
186 model. Another advantage of our proposed fitting method, due to the analytical nature of the expressions
187 employed for representing an ellipse, is the fact that initial values of the coefficients (a, b, θ) can be selected
188 without any empirical knowledge of the desired maps.

189 2.2. Gas Turbine Engine Model

190 The proposed compressor map fitting method is now integrated into a dynamic model of a two shaft
191 industrial gas turbine that is developed in Matlab/Simulink environment and validated with PROOSIS [14].
192 The engine model that is developed consists of a compressor, a combustor, a compressor turbine and a power
193 turbine as shown in Fig. 5. The components are represented by a set of suitable component maps from
194 PROOSIS, although the compressor map that is used is the one shown Fig. 1.

195 The engine simulations performed consist of two modes, the steady state and the transient. Steady
196 state simulations are performed for a scheduled variation of the rotational speed N and through an iterative

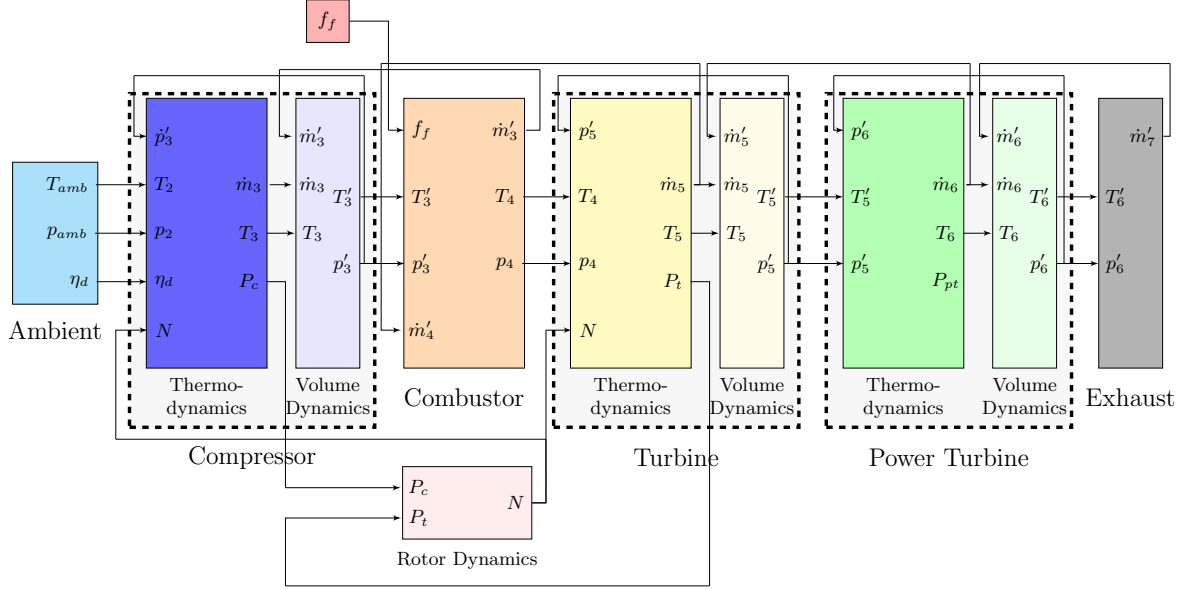


Figure 5: Engine model layout in Simulink (for definition of the variables refer to the Nomenclature section).

197 method, that selects key component parameters (i.e. mass flow rate \dot{m} , Turbine Entry Temperature (TET),
 198 etc.) for satisfying the mass flow and the work compatibility laws, where the model converges to the steady
 199 state condition. From the converged steady state condition, the values of temperatures at the compressor,
 200 combustor, compressor turbine and the power turbine exits, namely, T_3, T_4, T_5, T_6 , are passed onto the
 201 transient model's plenum volumes as initial conditions.

202 The transient simulation, based on the Inter Component Volume (ICV) method [20], commences from
 203 the last known converged steady state condition of the model with the variation of the control vector which
 204 is the fuel flow f_f . As can be observed from the engine layout shown in Fig. 5 plenums are introduced
 205 between various components to account for all the flow imbalances to occur in these volumes. These mass
 206 imbalances are used to evaluate the rate of the pressure increase to the engine and hence calculate the
 207 values of the pressures at the compressor, turbine and the power turbine plenum exits, namely, p'_3, p'_5, p'_6 .
 208 The difference between the power required by the compressor P_c and the power extracted from the turbine
 209 P_t at any given time instant yields an estimate of the rotor acceleration, and hence the rotor speed N . The
 210 process is repeated for the next time interval until the end of the simulation time is reached. The developed
 211 engine model in the Simulink, an object oriented environment, can be easily adapted to any kind of gas
 212 turbine configuration. A detailed description of the model used for this application can be found in our
 213 earlier work in [15].

214 2.3. Model Adaptation

215 Model performance adaptation is concerned with the inverse performance analysis where engine compo-
 216 nent characteristics are tuned until they reproduce the measured engine behavior at the same environmental
 217 conditions and throttle setting. Generally the engine behavior, assuming no measurement noise or bias, is
 218 expressed as follows:

$$\mathbf{Y} = f(\mathbf{X}, \mathbf{u}) \quad (10)$$

219 where \mathbf{Y} denotes the engine performance vector consisting of the measurements such as the pressure and
 220 the temperature at different engine gas path locations, namely $\mathbf{Y} = [p, T]$. The component characteristic
 221 vector \mathbf{X} includes non-measurable quantities such as the corrected mass flow and the efficiency, namely
 222 $\mathbf{X} = [m_c, \eta_c]$ and \mathbf{u} denotes the ambient and the operating conditions vector consisting of ambient conditions
 223 and a parameter called *handle* of the engine model which acts as input to the model for engine performance
 224 simulations, namely $\mathbf{u} = [p_{amb}, T_{amb}, handle]$. Depending on the simulation approach selected, the *handle*
 225 can be either useful power output from the power turbine P_{pt} , TET, corrected rotational speed N or any
 226 other quantity.

227 The measured engine behaviour is represented either by the field data of a service engine or through
 228 simulations of a different engine model. For conducting testing of our proposed method, the *reference engine*
 229 is an engine model that uses the compressor performance map of Fig. 1. In contrast to the map generation
 230 procedure that is employed by the *engine model*, the *reference engine* employs the map of Fig. 1 as simple
 231 lookup tables for determining the corrected mass flow rate and the isentropic efficiency of the compressor.

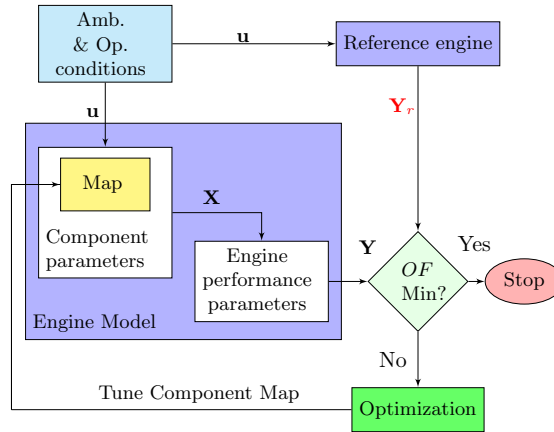


Figure 6: Flow chart of adaptive performance simulation.

232 The adaptive simulation algorithm that is depicted in Fig. 6 attempts to tune the component charac-
 233 teristics vector \mathbf{X} so that the difference between the performance vector of the *engine model* \mathbf{Y} and the

234 reference engine \mathbf{Y}_r is minimized. For this study, the difference between the predicted \mathbf{Y} and the observed
 235 \mathbf{Y}_r measurements can be evaluated by means of an Objective Function (OF) that is defined as follows:

$$OF = \|\mathbf{A}\|_F = \sqrt{\sum_{i=1}^q \sum_{j=1}^n |\alpha_{i,j}|^2} \quad (11)$$

$$= \sqrt{\sum_{i=1}^q \sum_{j=1}^n \left| \frac{\mathbf{Y}_{i,j} - \mathbf{Y}_{r_{i,j}}}{\mathbf{Y}_{r_{i,j}}} \right|^2} \quad (12)$$

236 where n denotes the total number of operating points corresponding to q number of different corrected
 237 rotational speed lines. The Frobenius norm $\|\mathbf{A}\|_F$ of an $m \times n$ matrix A is defined as the sum of the
 238 absolute squares of its elements $\alpha_{i,j}$. The element $\alpha_{i,j}$ denotes the difference between the predicted $\mathbf{Y}_{i,j}$ and
 239 the measurable performance vector $\mathbf{Y}_{r_{i,j}}$, divided by $\mathbf{Y}_{i,j}$. Since the above adaptive performance simulation
 240 covers multiple operating points, the objective function was modified to accommodate for such a feature.
 241 The number of the measured parameters to be matched depends on the test case itself, however for this
 242 work all the measured parameters are used in a single optimization problem.

243 The criterion OF is minimized by implementing one of the Matlab's built-in nonlinear unconstrained
 244 optimization algorithms [fminsearch] [21], which is an implementation of the Nelder Mead algorithm [22].
 245 This algorithm is most effective in exploring the neighborhood of the starting point and converging to a
 246 local minimum of OF . However, mathematically multiple solutions might be possible since the algorithm
 247 employed here might not always provide the global minimum of OF . This limitation is addressed by initially
 248 matching the operating points that are close to the design point of the engine and then moving further away
 249 from the design point. Another measure taken to address the former limitation is to set the optimization
 250 without any constraints on the sub-coefficients values in order to increase the search space. The last criterion
 251 for successful optimization is that convergence of the solution should occur before reaching the maximum
 252 number of iterations. The above steps ensure that the solution obtained is the global minimum of the OF .

253 It should be emphasized that the proposed method assumes the existence of an initial map shape. There
 254 is no similarity or closeness requirement between the initial map selected for the engine model and the
 255 unknown compressor map of the reference test engine. This is supported by the fact that the method is
 256 capable of regenerating any shape of the compressor map since the map curves are analytically controlled.
 257 The number of the sub-coefficients utilized has to do only with the fidelity by which a compressor map
 258 shape is generated and is not related to the number of gas path measurements that are to be matched. The
 259 adaptation procedure is now described as follows:

- 260 1. Select an initial compressor map from the open literature or any other available source.
- 261 2. Scale the map linearly so that the compressor map parameters at 100% of their nominal value
 262 $(m_{cmap}, \eta_{cmap}, \pi_{cmap})$ satisfy the design point performance of the reference engine $(m_{cdes}, \eta_{cdes}, \pi_{cdes})$.

- 263 3. Fit the elliptical curves to the linear scaled initial map in order to determine the coefficients $a_{\pi_c}, b_{\pi_c},$
264 $\theta_{\pi_c}, a_{\eta_c}, b_{\eta_c}, \theta_{\eta_c}.$
- 265 4. Express the coefficients with respect to the corrected rotational speed N and determine the values of
266 the 23 sub-coefficients. Note that one may choose to match a map shape that is uniformly smooth and
267 not so mathematically challenging as the one shown in Fig. 3 in order to utilize high order polynomials
268 for expressing several map coefficients. This is something that is facilitated by the optimizer since the
269 algorithm has the freedom to assign zero values to the sub-coefficients, and therefore reduce the order
270 of the polynomials.
- 271 5. Integrate the map fitting equations along with the sub-coefficients of the initial scaled map in a gas
272 turbine engine model.
- 273 6. Utilize the gas path measurements of a reference engine and let the adaptation process tune the sub-
274 coefficients to generate an adapted map for matching all the measurements. Note that before the
275 adaptation process is employed the simulated engine measurements will have significant deviations
276 from those of the reference engine, and in some cases convergence of the engine model might not be
277 possible before invoking the optimization process.
- 278 7. The final adapted map is a compressor map that is capable of generating the same results as the gas
279 path measurements available. The generated map is only an approximation to the unknown map since
280 there are many uncertainties such as measurement noise, humidity, etc., that are not accounted for.

281 Specifically, for the case studies examined in this paper the initial values of the sub-coefficients are
282 determined by the fitting procedure performed earlier to a typical reference compressor map. These are
283 passed onto the compressor map generation procedure as shown in Fig. 7, along with the measured corrected
284 rotational speed N_r , in order to determine the coefficients of the map $(a_{\pi_c}, b_{\pi_c}, \theta_{\pi_c}, a_{\eta_c}, b_{\eta_c}, \theta_{\eta_c})$. Once the
285 coefficients are calculated, the pressure ratio π_{c_r} , which is a known measurable parameter of the reference
286 engine, is used for determining the corrected mass flow m_c by solving eqs. (1), (2) and (3). The corrected
287 mass flow m_c is then used in the same manner as in π_{c_r} to calculate the compressor's isentropic efficiency
288 η_c from eqs. (4), (5).

289 Both m_c and η_c form the component characteristics vector \mathbf{X} which is then used in the remaining ther-
290 modynamic computations of the engine model. The key optimization parameters, such as the number of
291 iterations and the tolerance criterion are specified accordingly. Once the optimization process converges, the
292 new set of sub-coefficients are passed onto the engine model. The developed algorithm can be executed both
293 for external and internal adaptive simulations. In case of internal adaptive simulation, the optimization of
294 sub-coefficients takes place simultaneously with the iterative computation of the compatibility thermody-
295 namic equations of the engine model.

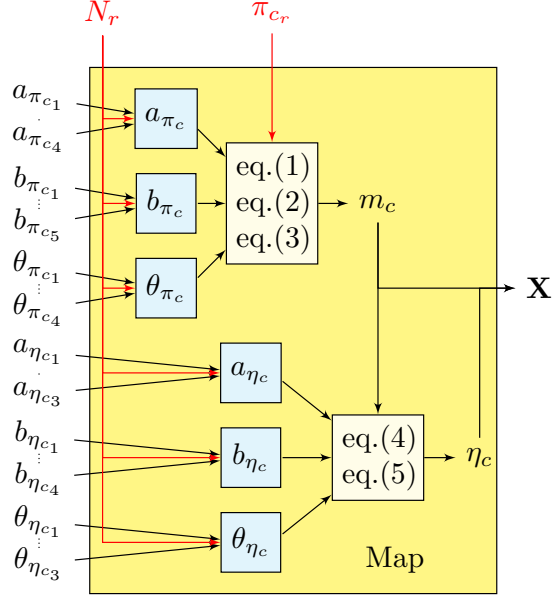


Figure 7: Flow chart of compressor map generation.

296 The data driven nature of the proposed method implies that the accuracy of the map generated depends
 297 on the number of operating points that are available from an engine with an unknown map. However, it
 298 should be noted that the generated map is an accurate representation of the unknown map mainly for the
 299 region for which the data points are available. This implies that a map can be generated even when a small
 300 number of operating points or a set of points distributed in the same speed line are available. The remaining
 301 area of the generated map can be considered as a reasonable estimate of the unknown map according to the
 302 extrapolation capabilities of the method. The ideal case will be when the targeted operating points cover a
 303 wide area of the map. In such a case the generated map is a more accurate representation of the unknown
 304 map.

305 2.4. Adaptive Diagnostics

306 An additional feature of the model adaptation is that it can be applied not only for performance
 307 simulation but also for gas turbine diagnostics. Below we employ the model adaptation scheme for per-
 308 forming engine diagnostics as shown in Fig. 8. The component vector \mathbf{X} consists of mass flow capacity
 309 $\Gamma_c = m_c/m_{c_{des}}$ and isentropic efficiency η_c . Compressor degradation of the reference engine is repre-
 310 sented by the deviation of these parameters from their healthy values, i.e. $\Delta\Gamma_{c_{inj}} = 100(\Gamma_{c_{deg}} - \Gamma_{c_{cl}})/\Gamma_{c_{cl}}$,
 311 $\Delta\eta_{c_{inj}} = 100(\eta_{c_{deg}} - \eta_{c_{cl}})/\eta_{c_{cl}}$. The above deviations injected to the reference engine form the deviation
 312 vector $\Delta\mathbf{X}_{inj}$.

313 Consequently, the reference engine will operate at degraded conditions and will produce a new set of
 314 degraded measurable parameters $\mathbf{Y}_{r_{deg}}$. The task of the adaptation scheme in this case is to determine the

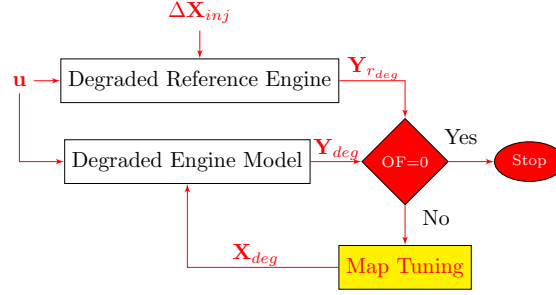


Figure 8: Flow chart of engine model adaptive diagnostics.

315 rate of the degradation that is injected in the *reference engine*, by tuning the component map of the *engine*
 316 *model* as described earlier. Therefore, the *engine model* matches the targeted degraded measurements of
 317 the *reference engine*, by a new set of components parameters that form the degraded vector \mathbf{X}_{deg} . The
 318 earlier adaptation of the model is in fact a training phase for fault diagnosis since it acts as the reference
 319 point for the engine healthy condition. Therefore, the difference between the degraded and the healthy set
 320 of component vectors ($\mathbf{X}_{deg}, \mathbf{X}_{cl}$) determines the severity of the degradation

$$\Delta \mathbf{X}_{pred_{i,j}} = 100 \left(\frac{\mathbf{X}_{deg_{i,j}} - \mathbf{X}_{cl_{i,j}}}{\mathbf{X}_{cl_{i,j}}} \right) \quad (13)$$

321 In order to assess how effective the prediction results are a diagnostic index (DI) is defined as follows

$$DI = 100 \left(\frac{1}{1 + \epsilon} \right) \quad (14)$$

322 where ϵ is the average error in terms of the characteristic vector \mathbf{X} which is the output of the compressor
 323 map. **In contrast to the gas path analysis (GPA) index used in the GPA methods [23], the one utilized**
 324 **here assesses the effectiveness of the prediction based on the output of the compressor map which forms the**
 325 **characteristic vector \mathbf{X} . Consequently, the accuracy by which a map is tuned to meet the degraded gas path**
 326 **measurements is evaluated according to**

$$\epsilon = \frac{\sum_{i=1}^q \sum_{j=1}^n \left(\frac{\Delta \mathbf{X}_{pred_{i,j}} - \Delta \mathbf{X}_{inj_{i,j}}}{\Delta \mathbf{X}_{inj_{i,j}}} \right)}{qn} \quad (15)$$

327 For multiple operating points, n denotes the total number of points corresponding to q number of different
 328 corrected rotational speed lines. The simulation case studies that have been carried out are now described
 329 in the following section.

330 3. Case Study Description

331 Our proposed adaptation approach is implemented in a dynamic engine model that is developed in
 332 the Matlab/Simulink environment and is evaluated and analyzed for the steady state and the transient

333 conditions. As described earlier, the *reference engine* is a similar model with simple lookup tables whereas
 334 the *engine model* utilizes our proposed map generation process. The performance specifications of the
 335 *reference engine* are provided in Table 2.

Table 2: Performance specification of the *reference engine*.

Parameter	Value	Units
Power	3.4	MW
Pressure ratio	10.8	
Thermal efficiency	38	%
Exhaust flow rate	34	kg/s

336 One of the prerequisites for successful model adaptation is that the engine measurable parameters are
 337 directly influenced by the component characteristic parameters to be adapted, otherwise non-physical devi-
 338 ations may appear on the component parameters which are not the cause of the initial difference between
 339 the predicted model and the measured values. Our primary objective of presenting the case studies is to
 340 evaluate the achievable accuracy improvement of our proposed method that incorporates the compressor
 341 map tuning and takes into consideration the above pre-requisite. Therefore, the selection of the inlet and the
 342 outlet measurements of the compressor are well justified. The list of the selected measurable parameters for
 343 conducting the adaptive performance simulations is given in Table 3. The nominal operating point that is
 344 chosen as the model design point for this configuration is set at 3.4 MW with the shaft corrected rotational
 345 speed N set as the *handle* of the engine.

Table 3: Engine performance measurable parameters.

Symbol	Parameter	Units
p_2	Compressor Inlet Pressure	Pa
T_2	Compressor Inlet Temperature	K
p_3	Compressor Discharge Pressure	Pa
T_3	Compressor Discharge Temperature	K
N_{act}	Shaft Rotational Speed	rpm

346 Four case studies are conducted. The target measurements in the first case study are the *deck data* that
 347 represent the off-design steady state performance of the *reference engine*, when the corrected rotational speed
 348 N is reduced from 100% to 55% of its nominal value, and with the selected compressor map implemented

349 as a lookup table.

350 The second case study focuses on the performance of the proposed adaptation method when the *deck*
351 data are the outcome of the transient performance of the *reference engine*. The effect that the initial map
352 shape has on the accuracy of the proposed method is also assessed. This is accomplished by using a different
353 initial compressor map shape than the one in Fig. 1, and is available from the PROOSIS gas turbine simu-
354 lation software [14]. Once again, the initial map seen in Figs. 9 and 10, is used for fitting elliptical curves
355 and determining the values of the sub-coefficients. Based on this map the proposed method is integrated
356 into an additional engine model which is tested in transient conditions.

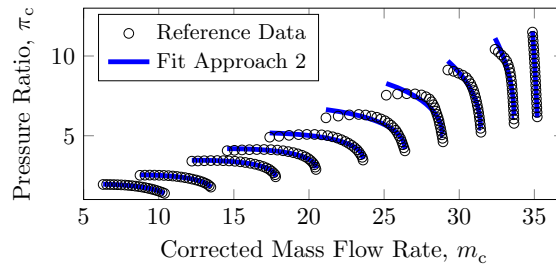


Figure 9: π_c vs. m_c map from PROOSIS [14]

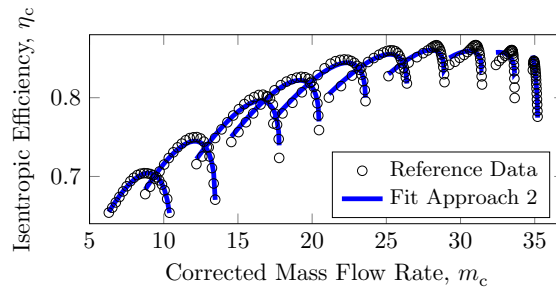


Figure 10: η_c vs. m_c map from PROOSIS [14]

357 In the third case study the goal of the *engine model* is to match a set of *reference engine* measurements
358 when degradation is injected in the compressor of the latter. Therefore, the method's prediction capability
359 is not only evaluated for improving the performance simulation of the model but also for estimating the
360 severity of the degradation that is injected in the *reference engine*.

361 In addition, a typical Linear Scaling (LS) method as suggested by Kong *et al.* [3] and the Non Linear
362 Scaling (NLS) method recently developed by Li *et al.* [4] have both been adopted and tested for facilitating
363 their comparison with the proposed method. Both existing methods are integrated in a similar engine
364 model based on the compressor map shape of Fig. 1. In terms of the optimization, both existing methods
365 employed the Matlab [fminsearch] [21] algorithm and not the GA optimization scheme that the authors of
366 [3], [4] have implemented in their work. This is done intentionally since uncertainty or improved accuracy

367 that is provided by different optimization schemes should be filtered out in order to focus purely on the
 368 capability of each method to modify the compressor map shape, and therefore ensure that the comparisons
 369 between them are more realistic.

370 For the transient mode cases, the fuel flow rate varies according to the fuel flow command schedule and
 the engine is decelerated and accelerated as described in Sections 4.2 and 4.3. The adaptation case study

Table 4: Simulation parameters of the adaptation case studies.

Case	Mode	Points	Iterations	Fun. Eval.	Error Tol.
1	Steady	9	10^3	2×10^3	10^{-8}
2	Transient	100	10^4	2×10^4	10^{-14}
3	Transient	60	10^4	2×10^4	10^{-14}

371
 372 parameters are provided in Table 4, where the number of maximum iterations range from 10^3 to 10^4 with
 373 the function evaluations being twice these values and the error tolerance ranges from 10^{-8} to 10^{-14} . The
 374 function evaluations refer to the number of times that the optimization algorithm is allowed to evaluate the
 375 objective function, whereas the iterations refer to how many times this algorithm is allowed to be performed.

376 The fourth case study is a techno economic assessment of each adaptation method and their associated
 377 cost in terms of the maintenance if adopted in a thermal power plant for performance estimation of the
 378 compressor degradation.

379 4. Results and Discussion

380 Our proposed adaptation approach is tested for both the steady state and the transient modes of the
 381 healthy and degraded conditions. The results for each case study are presented and discussed in the following
 382 subsections.

383 4.1. Steady State Case Study

384 4.1.1. Case 1

385
 386 The objective of the first case study is to evaluate the accuracy of our proposed adaptation method and
 387 compare it with the LS and NLS methods for a wide range of off-design steady state operations. Having the
 388 corrected rotational speed as the *handle*, the *engine model* is able to match the *deck data* of the *reference*
 389 *engine* at a variable level of accuracy for each method as seen in Fig. 11. It is concluded from Fig. 11 that

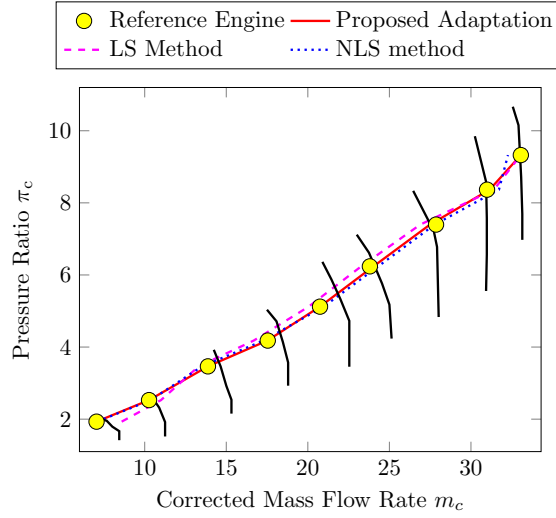


Figure 11: Steady state operating line as predicted by various adaptation methods.

390 the proposed method is very accurate. The NLS method has a similar accuracy with that of the proposed
 391 method, but this is not the case for the LS method. The former observation is more evident from Fig. 12.

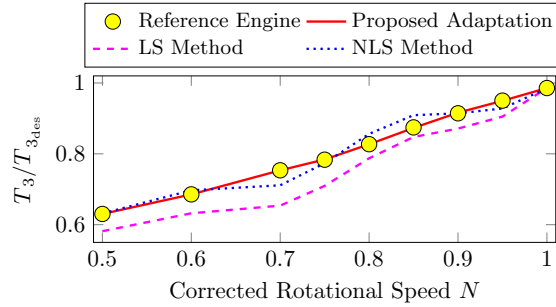


Figure 12: Normalized to design conditions compressor discharge temperature as predicted by various adaptation methods for the steady state.

392 The *engine model* prediction error for each method is shown in Fig. 13. The engine model prediction
 393 error for the LS method is increasing when the operating point is far away from the design conditions. This
 394 is due to the fact that a major assumption for a successful adaptation in this method is that the compressor
 395 map to be tuned should be of very similar shape to that of the one used by the *reference engine*. On the
 396 other hand, the accuracy of the NLS method is distributed in a balanced way, and any deviations are due to
 397 the specific shape of the *reference engine* map as seen in Fig. 1 and the wide range for which that adaptation
 398 is pursued.

399 The compressor discharge pressure p_3 and the temperature T_3 for the engine model show a maximum error
 400 in the range of -2% to 2% for the proposed method. On the other hand, the maximum engine model errors
 401 for the LS and the NLS methods are in the ranges of -10% to 10% and -5% to 4%, respectively. Moreover, the

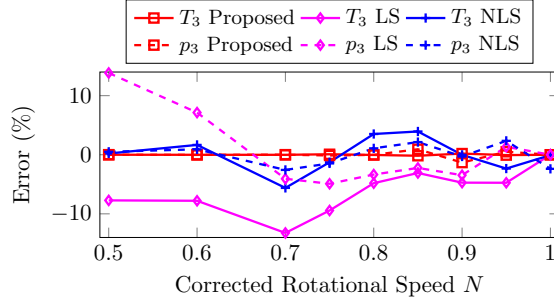


Figure 13: Measurable parameters error of various adaptation methods for the steady state.

402 engine model that utilizes the proposed adaptation method has an average error in T_3 which is equivalent to
 403 0.05K, whereas for the linear and the nonlinear scaling methods this is 15K and 2K, respectively. Figure 14
 404 shows the margin by which each one of the 23 sub-coefficients that control the compressor map generation
 405 process proposed are modified in order to match the target measurable parameters. The normalized values
 406 as shown in Fig. 14 simply refer to the ratio between the tuned and the initial sub-coefficients.

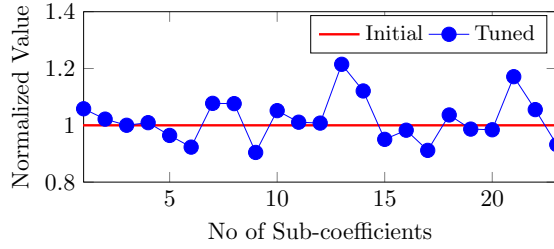


Figure 14: Initial and tuned map sub-coefficients for the proposed adaptation method.

407 Another key aspect of the entire optimization process, which involves the tuning of the sub-coefficients,
 408 is its rapid convergence. For this case study where 800 iterations and a total 2000 function evaluations
 409 were required the computation time when performed in a modern PC equipped with Intel's i5 quad-core
 410 processors and 4GB of RAM memory was only 0.23 sec. The computation time for the LS and the NLS
 411 methods was 0.1 sec and 0.4 sec, respectively.

412 4.2. Transient Mode Case Studies

413 4.2.1. Case 2

414

415 **The objective of the second case study is to evaluate the accuracy of our proposed adaptation method**
 416 **in transient conditions and evaluate how this may be affected by the initial map shape selected. Therefore,**
 417 **in this case study an additional model (Model II) is employed in which the compressor map sub-coefficients**
 418 **have been determined by fitting the data of another compressor map from PROOSIS, as described earlier**

419 in Section 3. The initial engine model where the compressor map generation was based on the map shown
 420 in Fig. 1 is going to be referred to as Model I for this case study.

421 In contrast to the previous steady state case where the operating range was wide, in this transient case
 422 we are focusing on a much narrower range, i.e. from 100% to 90% of the nominal value of the rotational
 423 speed N . The reason for this selection is firstly due to the fact that the majority of industrial gas turbines
 424 used for power generation spend most of their lifetime within this operating range, and secondly because
 425 we want to compare different adaptation methods in a operating region where their accuracy seem to be of
 426 similar magnitude as shown in Fig. 13.

427 It should be emphasized that the transient case sheds more light on the accuracy by which each adaptation
 428 method reconstructs a compressor map shape. Note that by default the acceleration and deceleration
 429 trajectories of the engine access a larger proportion of the map shape itself in comparison with the steady
 430 state operating points which are within a single running line of the map. The fuel flow rate for this case is
 scheduled accordingly and the fuel flow command is shown in Fig. 15. Simulation results for the specified fuel

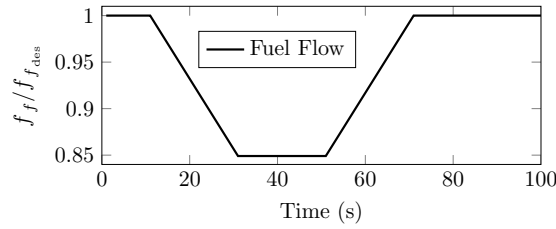


Figure 15: Fuel flow schedule for the transient response.

431 flow schedule of the reference engine and the engine models after employing different adaptation methods
 432 are shown in Figs. 16 and 17.

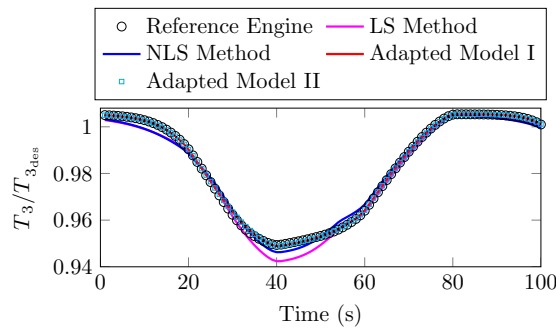


Figure 16: Normalized to design conditions compressor discharge temperature as predicted by various adaptation methods during transient response.

434 As observed from Fig. 16, both Model I and Model II employing the proposed adaptation are in excellent
 435 agreement with the reference engine. It should be noted that although Model I and Model II are based on

436 a different compressor map their prediction is identical. This is something expected for a couple of reasons
 437 that is going to be described below. The difference between the two scaling methods [3], [4] is not significant
 438 since the operating range is small and both have matched the targeted measurements with an appropriate
 439 level of accurately.

440 The proposed adaptation is capable of following the transient response as seen from the acceleration and
 441 deceleration trajectories that are shown in Fig. 17 more accurately than the other scaling methods. A closer
 442 look at Fig. 17 reveals the effects that the different compressor map shapes employed in each Model I and
 443 Model II have on the accuracy of the prediction before the adaptation is employed. It becomes clear that
 444 Model II underperforms significantly in comparison with Model I before adaptation. This has to do solely
 445 with the difference in the initial compressor map shape selected, as the one of Model I is similar to the one
 446 used by the *reference engine*. This difference has been minimized by employing the adaptation procedure.

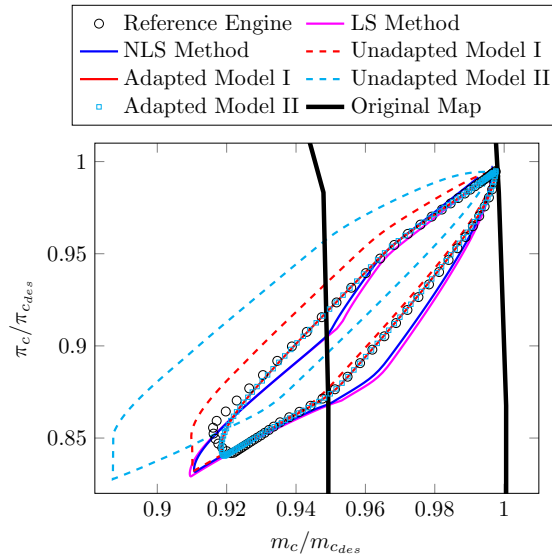


Figure 17: Transient trajectories on the compressor characteristic map for various adaptation methods.

447 The unconstrained nature of the optimization algorithm employed and the method by which the compres-
 448 sor map curves are fitted are the most important factors in matching any compressor map shape, independent
 449 of the initial map selected. The margin by which the 23 sub-coefficients of Model II have to be tuned to
 450 match the *reference engine* data is larger than the one of Model I, as seen from Fig. 18. Furthermore, the
 451 values of the sub-coefficients after adaptation are the same for both Models I & II. This confirms the fact
 452 that the [fminsearch] algorithm [21] was capable of converging to the same solution even if the initial values
 453 of the 23 sub-coefficients employed in Models I & II were different. It can be concluded that the proposed
 454 method, independent of the initial map shape, can successfully control the position, distribution, spacing
 455 and curvature of the elliptical curves passing through multiple data points. Hence compressor map shapes

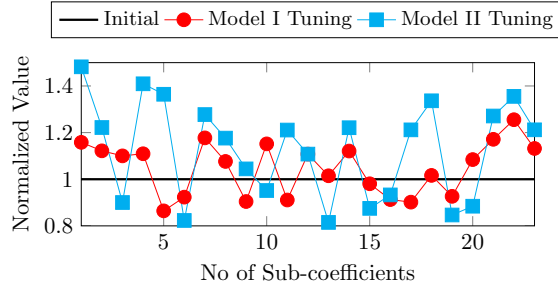


Figure 18: Initial and tuned map sub-coefficients for the adapted engine Models I & II.

456 can be effectively generated.

457 In terms of the optimization process where a total of 100 discrete operating points were used for this case
 458 the process converged after 5000 iterations, 20000 function evaluations with the elapsed CPU time of 0.8 sec
 459 for the Model I. The difference in computation performance between Model I and Model II was negligible, as
 460 Model II performed 6400 iterations to reach the same tolerance criteria at an elapsed CPU time of 1.1 sec.
 461 On the other hand, the elapsed CPU time for the LS and NLS methods was 0.2 sec and 2.1 sec, respectively.

462 The prediction error of each method for the transient case study is shown in Fig. 19. The prediction
 463 error in the compressor discharge pressure p_3 and the temperature T_3 for the proposed adaptation are in
 464 the range of -0.3% to 0.1%, as opposed to the LS and NLS methods that are both within the range of -1.2%
 465 to 1.1%.

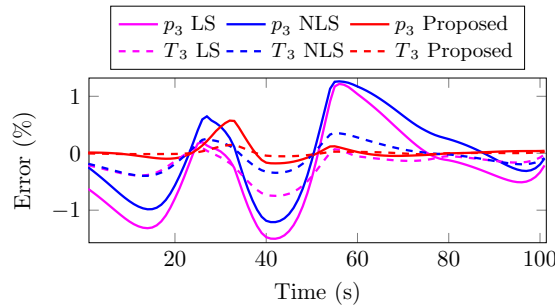


Figure 19: Measurable parameters error of various adaptation methods during transient response.

466 For instance, the adapted Models I & II have an average error in T_3 which is equivalent to 0.2K, whereas
 467 for the scaling method the average error is about 1K. A prediction error of 1% for scaling methods is
 468 acceptable in terms of engine performance prediction, but it should be once more noted that the operating
 469 range that the adaptation is performed is close to the design point of the engine where both methods perform
 470 accurately in principle. In the following subsection the degradations are injected in the *reference engine* so
 471 that the capabilities of each adaptation method are tested to their limits.

472 4.2.2. Case 3

473

474 The objective of this case study is to evaluate the capability of our proposed method to predict a
 475 component degradation. As described earlier in Section 2.3, the mass flow capacity and efficiency of the
 476 *reference engine* compressor are reduced by -5% and -2.5%, respectively. This percentage decrease represents
 477 a typical maximum rate of the compressor fouling for a gas turbine that can be partly recovered with off-line
 478 washing. Generally, given that steady state data of high quality are difficult to obtain, diagnosing the health
 479 of a gas turbine might be based on transient data. Although the former is computationally challenging it
 480 should be noted that transient behavior is much more sensitive to the degradation than the steady state.
 481 Consequently, transient data can provide a better insight when one is required to perform fault diagnosis
 482 and health monitoring during this operational mode.

483 The fuel flow for the transient maneuver is identical to the one shown in Fig. 15. A total of 60 discrete
 484 operating points were used for the adaptation case. The *engine model* after adaptation matches the degraded
 485 *reference engine* measurable parameters at a different level of accuracy depending on the method employed.
 486 The engine model predictions are in good agreement with the *reference engine* for the degraded conditions
 487 as well. The deviations $\Delta\Gamma_c$, $\Delta\eta_c$ used in Figs. 20 and 21 refer to the difference between the predicted and
 488 injected component degradation as defined in eq. (13), i.e. $\Delta\Gamma_c = \Delta\Gamma_{c_{pred}} - \Delta\Gamma_{c_{inj}}$. As can be observed,
 489 the errors are in the range of -0.2% to 0.2% for the proposed adaptation method. For the LS and NLS
 490 methods the errors are in the range of -6.0% to 2.3% and -2.2% to 1.0%, respectively.

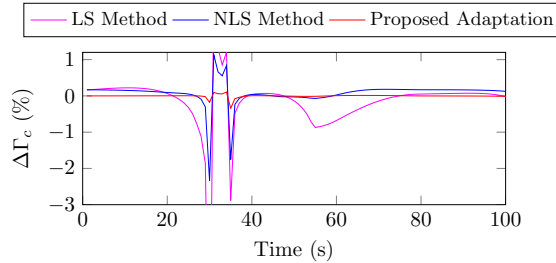


Figure 20: Deviation in mass flow capacity as predicted by various adaptation methods during transient response.

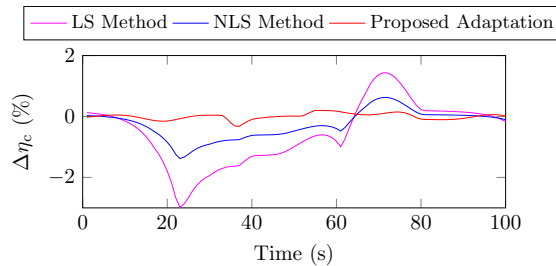


Figure 21: Deviation in compressor isentropic efficiency as predicted by various adaptation methods during transient response.

Table 5: Adaptation results for various case studies (CS).

Approach	Performance			Computation		
	Mean Error (%)	Mean Error (%)	DI (%)	Time (sec)		
	CS 1	CS 2	CS 3	CS 1	CS 2	CS 3
LS	3.0	0.9	67	0.1	0.2	0.18
NLS	1.2	0.8	88	0.4	2.1	1.6
Proposed	0.15	0.1	98	0.23	0.8	0.7

As expected, the error becomes more evident in the transient phase of the operation. Our employed adaptation method predicts the injected degradation with an average error of 0.08% for the mass flow capacity and 0.027% for the isentropic efficiency. On the other hand, the average error for the LS and the NLS methods is 0.6% and 0.2% for the mass flow capacity and 1.3% and 0.7% for the isentropic efficiency, respectively. The diagnostic index for our proposed method is 0.9894, which implies that the diagnosis is 98.94% effective and in comparison with the LS and the NLS methods it is more accurate by 31% and 10%, respectively. The case study results demonstrate the promising prospect of our method when applied for a gas turbine performance diagnosis. The proposed adaptation process converged after 6000 iterations, 20000 function evaluations with an elapsed CPU time of 0.9 sec.

The maximum deviations of -5% in the compressor flow capacity and -2.5% in the isentropic efficiency are selected specifically in order to demonstrate the capability of our proposed approach to a more challenging diagnostic task than considering deviations of -1% and lower. However, it should be noted that the accuracy of our method remains unchanged even for smaller deviations of the component parameters. The results from all case studies (CS) are summarized as shown in Table 5.

4.3. Techno Economic Case Study

4.3.1. Case 4

The primary objective of this case study is to assess the effects that each adaptation method have on the quality of engine performance information that are usually implemented by the gas turbine users for maintenance of a power plant. Generally gas turbine users implement various tools for estimating the health of gas turbine compressor in terms of the mass flow capacity and the efficiency. Depending on the severity of degradation that is predicted by the selected approaches, the plant has to be shut down and an off-line washing is carried out to recover the lost performance of the compressor and the engine.

Although both on-line and off-line washing are performed on gas turbine compressors, the former is not accounted here. The reason is that the off-line washing has a higher impact on both recovering the

516 compressor fouling and increasing the maintenance cost of the plant. The assumptions that are made for
 517 this case study are as follows:

- 518 • The time frame for which a gas turbine operation is investigated is 12 months.
- 519 • Only the compressor degradation due to the fouling is examined.
- 520 • A typical constant rate of -1% drop in the compressor efficiency per month is assumed.
- 521 • Off-line washing is performed once the estimated drop in the compressor efficiency is 1%.
- 522 • After each off-line washing 95% of the lost compressor efficiency is recovered.
- 523 • The gas turbine operates most of the time from 100% down to 90% of the nominal rotational speed
 524 N .
- 525 • Within the above operating range a small proportion (20%) is considered as transient and the remaining
 526 (80%) as steady state.
- 527 • A weighted average error is determined to account for the earlier assumption, i.e. $\epsilon_w = 0.8\epsilon_s + 0.2\epsilon_{tr}$,
 528 where ϵ_s and ϵ_{tr} denote the average errors for the steady state and transient conditions, respectively.
- 529 • The proposed adaptation method in conjunction with the scaling methods are employed.

530 The number of off-line compressor washings that are suggested by each method is shown in Fig. 22 and
 531 is compared with the optimum number of washings that are required by the reference engine when adopting
 532 the maintenance strategy as encapsulated by the above assumptions.

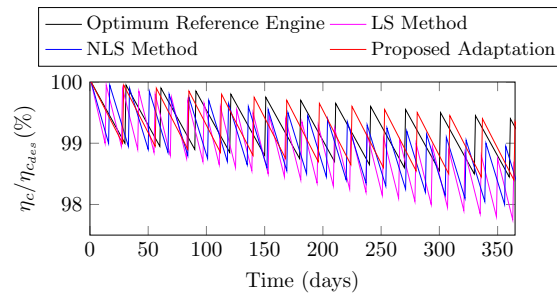


Figure 22: Normalized to design conditions percentage of the compressor efficiency before and after off-line washings as suggested by various adaptation methods. Local troughs represent the estimated drop of the compressor efficiency before performing off-line washing. Peaks represent the recovered compressor efficiency after off-line washing.

533 It can be observed that the accuracy of the proposed adaptation method suggests 13 off-line washings
 534 for a one year period in comparison with the actual compressor degradation of the reference engine that can
 535 be optimally recovered with 12 washings only. The total number of washings suggested by the LS and the

536 NLS methods is 26 and 21, respectively. Although the prediction accuracy of each method that is employed
 537 in this case study as shown in Fig 23 is in reasonable levels, their difference increases exponentially when
 538 it comes to the techno economics and the cost that each method implies in the maintenance of the power
 539 plant.

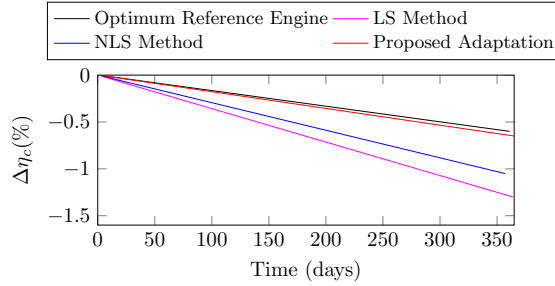


Figure 23: Percentage drop of compressor efficiency as estimated by various adaptation methods when adopting their suggested number of off-line washings.

540 Let us make a reasonable assumption based on the work of Aretakis *et al.* [17] by considering the extra
 541 cost that each method implies in the maintenance of a gas turbine. Let us consider that each off-line washing
 542 costs \$3000, which is reasonable for an aeroderivative gas turbine, and that the shutdown is about 3 hours.
 543 The cost corresponding to each method and its relative cost with respect to the optimum method of the
 544 *reference engine* are summarized in Table 6.

Table 6: Cost of off-line compressor washings suggested by various adaptation method.

Approach	Washings	Cost (\$)	Cost rel. to the Opt. (%)
Optimum	12	36,000	-
LS Method	28	78,000	216%
NLS Method	21	63,000	175%
Proposed Adaptation	13	39,000	108%

545 It is evident from Table 6 that the accuracy of our proposed method has the potential to reduce the
 546 maintenance cost associated only with off-line compressor washing, by 108% and 67% of the optimum cost
 547 in comparison with the existing LS and NLS methods, respectively. In practice, the cost associated with
 548 the compressor washing leads to several other associated costs such as shutdown, personnel, etc. that all
 549 contribute to the overall maintenance cost of a power plant. However, by using a group of assumptions the
 550 effects that the accuracy of various performance adaptation methods have in terms of plant economics are

551 further amplified.

552 As far as the practical aspects and limitations of our proposed method is concerned when used in real
553 engines and real fault cases several considerations must be taken into account. Firstly, our proposed method
554 can predict accurately the performance and health of a gas turbine for the range of operation that the initial
555 model is adapted to. Therefore, one should initially adapt the engine model to a wide operating envelope of
556 the engine. Feeding new operating points that belong to speed lines, not previously employed in the adap-
557 tation, would only test the extrapolation capability of the map generation method and not the accuracy
558 of the optimization for the diagnostic purposes. The proposed method does not consider variable geometry
559 features such as the variable stator vanes (VSV), and how these affect the geometry of the compressor map
560 generated. This is a limiting factor of our approach when one investigates a wide range of engine operations
561 that utilize variable geometry compressor scheduling by the VSVs.

562 Data corrections for measurement noise, humidity etc. should be accounted for before utilizing data
563 smoothing. Data averaging for several engine performance measurements, such as the turbine and the power
564 turbine exits, that rely on a set of instrumentation sensors might be employed. This facilitates the establish-
565 ment of a good quality set of engine operating points to be utilized for the map generation and adaptation.
566 The resulting adapted model forms the benchmark for further diagnostic analysis where deviations of the
567 component parameters will be based upon this. However, one should consider the maintenance activity of
568 an engine from the time of the first adaptation of the engine model up to the time that diagnosis is pur-
569 sued. Meantime updating and refining the engine model should be performed. This process of continuously
570 updating the engine model will improve the accuracy of the diagnosis significantly.

571 The desirable features and performance capabilities of the proposed method motivate the inclusion of
572 variable geometry characteristics to the compressor map generation and also the fitting and modelling of
573 turbine maps; tasks that the authors are currently engaged in.

574 5. Conclusions

575 In this paper, a novel adaptation method is introduced that aims at improving the accuracy of the gas
576 turbine performance prediction and diagnostics at both the steady state and transient operating conditions.
577 The model coefficients that are obtained from the map generation procedure are optimized through a non-
578 linear algorithm in order to match the targeted (healthy or degraded) measurements of a reference model
579 with a compressor map that is available in the literature, working at off-design steady and transient con-
580 ditions. The proposed method deals effectively with the nonlinear behavior of gas turbines away from the
581 nominal operating points by tuning the compressor map shape resulting in accurate compressor degradation
582 diagnostics.

583 Application of the developed approach to a two shaft industrial gas turbine engine model demonstrates

584 the following advantages and benefits. In comparison with earlier adaptation methods, our proposed strategy
585 demonstrates the effectiveness that the compressor map has on the prediction accuracy of the engine model.
586 The accuracy of the proposed method is independent of the similarity between the initial map shape selected
587 and the targeted compressor map. The built-in nonlinear optimizer that is employed for this adaptation is
588 effective in minimizing the prediction errors by adapting the compressor maps. The computational time for
589 a typical multi-point steady state adaptation scenario is approximately 0.2 sec for 2000 function evaluations
590 and 750 iterations with an average prediction error of 0.15%. Similarly, corresponding to the transient
591 conditions and for 100 operating points the elapsed CPU time and the prediction error are 0.8 sec and
592 0.1%, respectively. Our method is applied for predicting a compressor fouling degradation where the results
593 demonstrate a diagnostic accuracy of 99.84% when 60 operating points of the reference engine in the transient
594 mode are considered as the targeted measurements. In addition, the proposed method is capable of reducing
595 the maintenance cost of a plant associated with the compressor washing ranging from 67% up to 108% in
596 comparison with other existing adaptation methods.

597 Our proposed adaptive performance method is a useful tool for progressively refining an engine model
598 based on multiple sets of reference engine test data at both the steady state and the transient off-design
599 operating conditions. The improved accuracy and efficient computational properties of our method have
600 also demonstrated its potential capabilities for gas turbine diagnostics and reducing the maintenance cost.
601 Therefore, implementation of our proposed method to any gas turbine performance simulation or as a
602 condition monitoring and diagnostic tool could provide a more reliable and accurate information for gas
603 turbine engines, and support the users in making informed decisions on managing efficiently their assets,
604 increasing their availability and reducing their maintenance cost.

605 **Acknowledgements**

606 This publication was made possible by NPRP grant No. 4-195-2-065 from the Qatar National Research
607 Fund (a member of Qatar Foundation). The statements made herein are solely the responsibility of the
608 authors. The authors would also like to acknowledge the constructive comments, and suggestions provided
609 by the anonymous reviewers that greatly improved the quality of the article.

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