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Derivative-driven window-based regression method for gas turbine performance prognostics

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Abstract

The domination of gas turbines in the energy arena is facing many challenges from environmental regulations and the plethora of renewable energy sources. The gas turbine has to operate under demand-driven modes and its components consume their useful life faster than the engines of the base-load operation era. As a result the diagnostics and prognostics tools should be further developed to cope with the above operation modes and improve the condition based maintenance (CBM).

In this study, we present a derivative-driven diagnostic pattern analysis method for estimating the performance of gas turbines under dynamic conditions. A real time model-based tuner is implemented through a dynamic engine model built in Matlab/Simulink for diagnostics. The nonlinear diagnostic pattern is then partitioned into data-windows. These are the outcome of a data analysis based on the second order derivative which corresponds to the acceleration of degradation. Linear regression is implemented to locally fit the detected deviations and predict the engine behavior. The accuracy of the proposed method is assessed through comparison between the predicted and actual degradation by the remaining useful life (RUL) metric. The results demonstrate and illustrate an improved accuracy of our proposed methodology for prognostics of gas turbines under dynamic modes.

Keywords: Derivative-Driven Analysis, Window-Based Regression, Gas Turbine Prognostics, Condition Based Maintenance

Highlights

- A data-based method for gas turbine performance prognostics is developed.
- The proposed method takes into account dynamic operating modes and employs a derivative-driven diagnostic pattern analysis.
- Linear regression is performed on a local data window manner to detect degradation.

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- The accuracy of the method is tested under transient operating conditions and compared to an earlier method.
- The proposed method is capable of detecting accurately the evolution of compressor fouling.

Nomenclature

Symbols

A	acceleration of component performance degradation ΔX
g_{1-2}	coefficients of linear regression
k	acceleration threshold
L	width of window
\dot{m}	mass flow rate
n	total number of operating points
N	corrected shaft rotational speed
P	total pressure
q	total number of windows
T	total temperature
\mathbf{u}	ambient and operating conditions vector
W	useful power output
x	component performance parameter
\mathbf{X}	component characteristics vector
\mathbf{Y}	measurement vector

Greek

Γ	mass flow capacity
ϵ	prediction error
Δ	deviation
η	isentropic efficiency
π	pressure ratio
σ	spread

Subscript

c	compressor
d	degraded
exh	exhaust

<i>f</i>	fuel
<i>lreg</i>	linear regression
<i>pt</i>	power turbine
<i>r</i>	reference engine
<i>t</i>	turbine
<i>th</i>	thermal
1 – 6	engine gas path location

1. Introduction

The continuously growing energy demand along with the challenging aspect of reducing greenhouse emissions has transformed the power generation sector. Nowadays, the conventional fossil-fuelled power plants are required to work in partnership with the intermittent renewable energy plants for maintaining the stability and reliability of the electricity grid. This has reformed the gas turbine powered plants. The gas turbines are currently required to start up and shut down faster for satisfying the energy demand that fluctuates according to the intermittent character of the renewables energy sources. An emerging group of works in the literature has addressed the challenging aspect of the part-load performance behavior of gas turbines both at steady state [1, 2] and dynamic/transient conditions [3, 4, 5, 6] for optimizing the energy production and the stability of the electricity grid [7, 8].

Under such dynamic conditions and grid-following modes both the renewable and gas turbine subsystems are expected to degrade at different rates [9, 10] and more importantly to consume their useful life faster than that of a system operating at base-load conditions. Therefore, the CBM of gas turbine systems is going to be affected by this recent shift in the engine operating profile.

By principle, the diagnostic and prognostic tools [11, 12, 13, 14, 15] not only improve our understanding for complex and nonlinear systems such as the gas turbines but their accuracy and reliability are transferable to the effectiveness of the CBM. An example of the impact that these decision making tools have in the CBM can be found in the latest GE Digital Twin and Predix technologies [16]. It follows that the gas turbine community is faced with the challenging aspect of improving the accuracy of diagnostics and especially prognostics solutions for engines operating under dynamic conditions. Apart from a limited number of works available in the literature [17, 18, 19, 20, 21], the majority of the existing diagnostic methods are based on steady state operation. Subsequently, the majority of the existing prognostics methods have been developed and tested by taking into consideration diagnostic information that was primarily based on the steady state conditions .

The ever growing development of prognostic schemes for gas turbine engines has resulted into a large number of prognostic solutions. Generally, these schemes can be divided into two categories, such as data-

27 based and model-based approaches. Amongst the data-based prognostic methods the most popular are
28 neural networks [22, 23] and bayesian networks [24, 25]. A subgroup of the data-based methods are the
29 statistical approaches [26, 27] in which their primary focus is that of forecasting the behavior of a system
30 without necessarily evaluating the remaining useful life of the component.

31 Model-based methods rely heavily on engine model diagnosis which is directly coupled to the prognosis
32 process. For the model-based approaches the most commonly used method is that of trending the available
33 diagnostic information through linear and nonlinear regression models [28, 29]. Another popular model-
34 based prognostic solution is based on the particle filtering [30, 31, 32, 33, 34] methods. Finally, there is a
35 family of hybrid prognostic approaches [35, 10] that combine algorithms coming from the model-based and
36 data-based groups. From the numerous methods employed for gas turbine prognostics only a few examples
37 in the literature [28, 10] have employed dynamic/transient operational modes for diagnosis [18, 32, 36] and
38 prognosis.

39 Therefore, the development of a prognostic system capable of taking into account the dynamic gas
40 turbine operation is fundamental for an effective and successful CBM. Dynamic operating gas turbines have
41 to be monitored at an increased frequency rate which results in a vast amount of data for the gas turbine
42 operators to process, analyze and interpret towards to facilitating the maintenance and operation of the
43 engines. In addition, the fast and highly nonlinear engine dynamics make the interpretation of the gas path
44 information a very complex task since it moves away from the common practice of the industry to forecast
45 the behavior of the engine based on its entire operational history. It would be more practical to focus the
46 prognostic analysis for such dynamic gas turbines in the short-term since the electricity demand dominated
47 by the intermittent character of the renewables affects the operating profile of the gas turbines and alters
48 significantly the degradation pattern of its components. Within this context and taking into consideration
49 the vast amount of engine monitored information contained in data lakes the aim of this study is to develop
50 a method for accurately forecasting the engine component degradation into the future by examining the
51 rate by which the degradation changes with respect to time.

52 Generally, the gas turbine engine performance depends on its components behavior. In our recent
53 study [37], an advanced model-based adaptation method was combined with a dynamic gas turbine model
54 developed in Matlab/Simulink. The outcome of this process was a uniquely tuned set of engine component
55 maps that empowered the engine model to match the performance measurements of a reference engine
56 operating under transient diagnostics.

57 From our recent work [10] on prognostics we utilized an adaptive diagnostic process [18] for a number of
58 sliding windows capturing the entire degraded measurements. Subsequently, the detected degradation was
59 used for a linear regression towards prognostics. In contrast to our earlier study, the proposed method em-
60 ploys a real time data-driven tuner that performs the diagnosis online and each operating point corresponds
61 to a different set of component maps. The information containing the diagnostic data is then divided into

62 smaller time segments referred to as windows. The time range of each window, referred to as width, depends
63 on the time data series distribution. Specifically, the data distribution examined refers to the acceleration
64 of degradation which is represented as the second order derivative of the predicted deviations. It follows,
65 that the bank of data encapsulated in the collection of windows are utilized in a local linear window-based
66 manner for predicting the future behavior of the engine components. The current work is an extension of
67 our recent work [38] which includes a comparison of the proposed method with the one presented in [10].

68 The accuracy improvement of the proposed method is tested for evaluating the level of compressor fouling
69 when the engine experiences concurrently multiple component degradations. At the same time the engine
70 operates under dynamic/transient conditions for a period of time that corresponds to 25,000 h. The metrics
71 of RUL and the PDF [39, 40, 41] have been utilized to assess and evaluate the accuracy improvement of
72 the proposed method over the one developed earlier by the authors [10]. Finally, this prognostic tool can
73 facilitate the gas turbine operators to increase their awareness for the performance of their gas turbine assets
74 when these operate under transient conditions and enable them to optimize the operation of their plants.

75 To summarize the main contributions of this paper can be listed as follows:

- 76 1. The problem of fault prognosis of an industrial gas turbine under transient conditions is investigated by
77 using a regression method which is activated by a derivative-driven criterion of detected degradations.
- 78 2. Compared to the previous related works, the proposed method represents a powerful tool for forecast-
79 ing the evolution of degraded component performance without taking into account the entire diagnostic
80 history of the equipment. This is achieved by splitting the detected component degradation pattern
81 into smaller increments where the evolutions of degradation can be assumed to be linear with respect
82 to time.
- 83 3. Moreover, the distribution of diagnostic data is examined based on a second order derivative crite-
84 rion which corresponds to the acceleration of degradation. Upon this criterion the diagnostic pattern
85 is partitioned into smaller segments that we refer to as windows and the contained information is
86 implemented for performing short-term prognostics. This is the first time in the literature that the
87 acceleration of the diagnostic data is utilized for simplifying the prognostic process.
- 88 4. Furthermore, we compare the proposed method with the one developed earlier by the authors [10] in
89 order to demonstrate and illustrate the prediction accuracy improvement through the use of PDF and
90 RUL metrics.
- 91 5. The main benefit of the proposed prognostic method is its ability to simplify the nonlinear time evolving
92 component degradation into a simple local and linear process for which meaningful prognostic results
93 can be easily interpreted. Using the proposed technique, the prognosis is generalized for gas turbine
94 dynamic operating modes and can be further employed for other demand-driven energy equipment.

95 The remainder of this paper is organized as follows. In Section 2, the proposed prognostic method along
96 with the concept of performance adaptation used for diagnostics and its integration with a dynamic engine
97 model are described. The description of the case studies are presented in Section 3. Simulation results of
98 the proposed approach are presented in Section 4, followed by the conclusions in Section 5.

99 **2. Methodology**

100 *2.1. Assumptions*

101 The component performance degradation of gas turbines is mainly attributed to the ambient conditions,
102 the operating mode and the manufacturing tolerances. These factors increase the complexity of the diagnos-
103 tics and subsequently the prognostics tasks. This is evident by the numerous existing prognostic solutions
104 proposed for gas turbines. In this study several assumptions have been made, for facilitating the application
105 of the proposed method to service engines, as follows:

- 106 • Only incipient component performance faults (no abrupt) are considered for prognostics.
- 107 • All the engine components are experiencing performance degradations simultaneously.
- 108 • The performance degradation of each component corresponds to deviations of the mass flow capacity
109 and isentropic efficiency from their clean/healthy values.
- 110 • The pattern of degradations examined are monotonical.
- 111 • The operating conditions are varying with respect to time.

112 The above assumptions rely on the fact that modern gas turbine that operate under dynamic conditions
113 maintain a monotonically pattern of degradation even if regular maintenance actions such as online and/or
114 offline compressor washings are performed. As far as the gas path information provided by the instrumen-
115 tation set we assume that there is no presence of noise and bias. The reason for this lies in the fact that
116 the main aim of this study is to focus purely on the capability of the developed method to deal effectively
117 with the estimation of the component degradation pattern and not on the validity of the sensor informa-
118 tion. Other approaches for data-smoothing and noise-filtering could be performed prior to diagnostics and
119 prognostics for ensuring a good quality data set for the above purposes.

120 *2.2. Model Tuning*

121 The frequently performed maintenance actions in industrial gas turbines (such as online/offline compres-
122 sor washing, replacement of inlet filtration systems, fuel nozzles and sensors) and the evolving performance
123 degradation of their components alter the performance and health signature of the engine. Therefore, gas
124 turbine users have to progressively refine and update their engine models for improving the accuracy of

125 the performance prediction based on available service engine data. This process is commonly referred to as
 126 model-based performance adaptation and deals with the optimization of component-based parameters such
 127 as mass flow capacities and efficiencies so that the service engine measurable performance parameters such
 128 as gas path temperatures and pressures are properly matched. This is a minimization problem since its goal
 129 is to minimize the observed residuals between the model predictions and the engine test data. This process
 130 establishes the data-set that corresponds to the healthy engine condition. It follows that data from a family
 131 of adapted engine models can be implemented for performance-based diagnostic analysis.

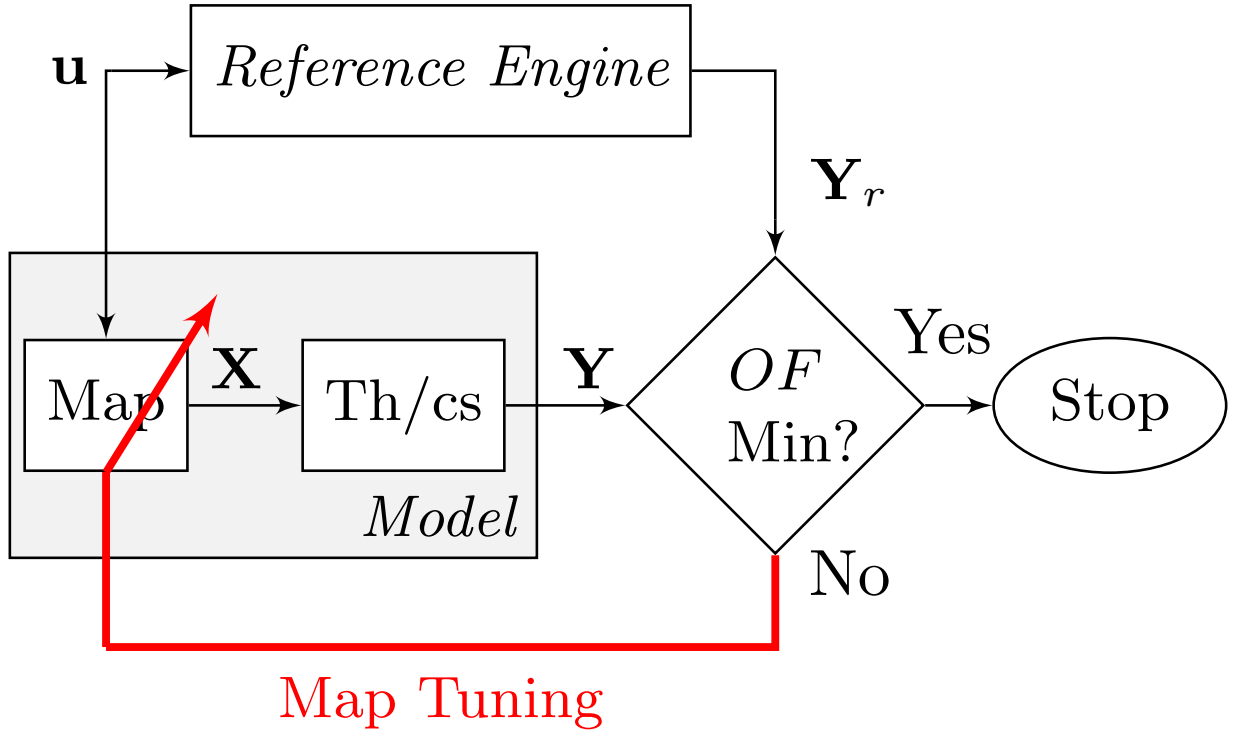


Figure 1: The flow chart of the proposed performance adaptation. Th/cs and OF denote the thermodynamic computations and the objective function eq. 2, respectively.

132 A recently developed adaptation method [18, 37] is implemented for this study. A brief description of
 133 this method follows. The behavior of a gas turbine engine may be represented as follows:

$$\mathbf{Y} = f(\mathbf{X}, \mathbf{u}), \quad (1)$$

134 where \mathbf{Y} , \mathbf{X} and \mathbf{u} denote the measurable performance, the component and the operating conditions pa-
 135 rameters, respectively.

136 The performance of the engine can be captured by the information of the condition monitoring system of
 137 a service engine or via simulated gas turbine measurements available from an engine model. For testing our

138 proposed method two gas turbine models are used. The gas turbine model that implements the component
 139 characteristics of PROOSIS [42] simulation software is referred to as the *reference engine* and acts as the test
 140 engine in this study. The second model, which is going to be referred to as the *engine model*, implements
 141 the recently developed adaptation concept [37].

142 The deviations between the *engine model* predictions \mathbf{Y} and the *reference engine* observations \mathbf{Y}_r are
 143 evaluated by the Objective Function (OF) as follows:

$$OF = \sqrt{\sum_{i=1}^n \left(\frac{\mathbf{Y}_i - \mathbf{Y}_{r_i}}{\mathbf{Y}_{r_i}} \right)^2}, \quad (2)$$

144 where n denotes the number of the operating points and \mathbf{Y}_i and \mathbf{Y}_{r_i} denote the i -th predicted and observable
 145 performance parameter, respectively.

146 For initial engine model adaptation the data generated by the *reference engine* are matched by the *engine*
 147 *model* on a global scale i.e. a single set of component maps is progressively tuned in order minimize the
 148 observed residuals. For a more detailed description and analysis of the adaptation concept the reader is
 149 prompted to our earlier works [18, 37].

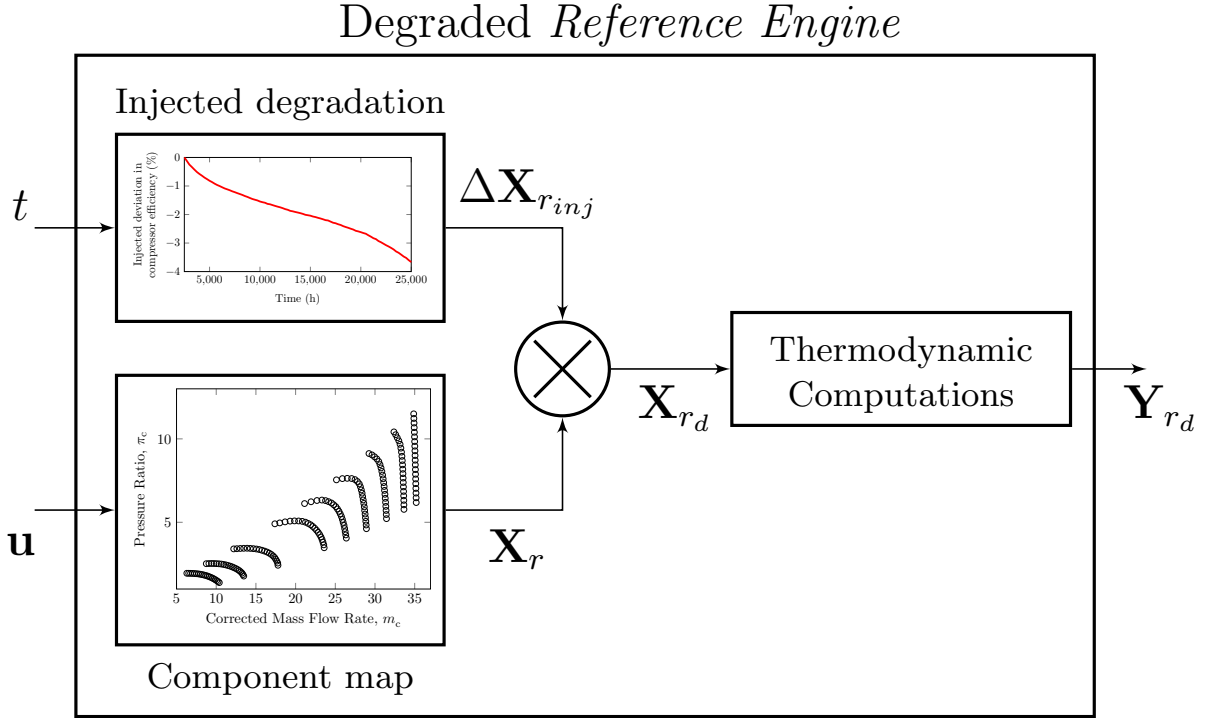


Figure 2: The representation of the time dependent injected degradation into the *reference engine*.

150 *2.3. Diagnostics*

151 Generally the performance deterioration of engine components is oftenly represented by the component
152 parameter deviation ΔX from its nominal/clean value and given by:

$$\Delta X = 100 \times (X_d - X) / X. \quad (3)$$

153 where X and X_d denote the clean and degraded component parameter, respectively.

154 For representing the time evolving performance degradation, the component maps of the *reference engine*
155 are injected with deviation signals which alter the mass flow capacity and efficiency outputs of each com-
156 ponent. Consequently, the initial healthy parameter of the *reference engine* X_r is deviated by the injected
157 signal $\Delta X_{r_{inj}}$ resulting in a fault-contaminated component map output X_{r_d} . This in turn is reflected in the
158 measurable parameter Y_{r_d} of the *reference engine* which corresponds to degraded conditions, as seen from
159 Fig. 2.

160 The component degradation $\Delta X_{r_{inj}}$ with respect to time t may be represented as a function g , i.e.
161 $\Delta X_{r_{inj}}(t) = g(t)$. The mathematical form of the function g depends on the injected deviation signal. In
162 practise, the evolution of component degradation can be captured by a variety of functions however the
163 most common approach is data-trending through linear and polynomial regression models.

164 At this stage the objective of the diagnosis task deals with estimating the level of the component degra-
165 dation of the *reference engine*. The performance adaptation is once again implemented for performing the
166 diagnostic task. However, there is a major difference in the way that the adaptation is implemented here
167 for the diagnostic purpose. The initial adapted component maps remain unaffected and only their output,
168 as shown in Fig. 3, is further tuned. This process can be performed real time by employing the algebraic
169 constraint function of Matlab/Simulink. In contrary to our earlier works, where the adaptation concept
170 was implemented for diagnostics on a global scale, this approach is performed locally for every operating
171 point and the corresponding generated component maps are utilized for matching the evolving degraded
172 measurements.

173 The accuracy of the diagnostic task is evaluated by the Diagnostic Index (*DI*) [37] as follows:

$$DI = 100 \left(\frac{1}{1 + \epsilon} \right), \quad (4)$$

174 where ϵ is the detected residual for the component parameter \mathbf{X} as follows:

$$\epsilon = \frac{\sum_{i=1}^n \left| \frac{\Delta \mathbf{X}_i - \Delta \mathbf{X}_{r_{inj_i}}}{\Delta \mathbf{X}_{r_{inj_i}}} \right|}{n}. \quad (5)$$

175 **At this point it should be pointed out that the accuracy of the diagnostic and subsequently the prog-**
176 **nostic processes is relying heavily on the capability of the engine model to adapt its component parameters**

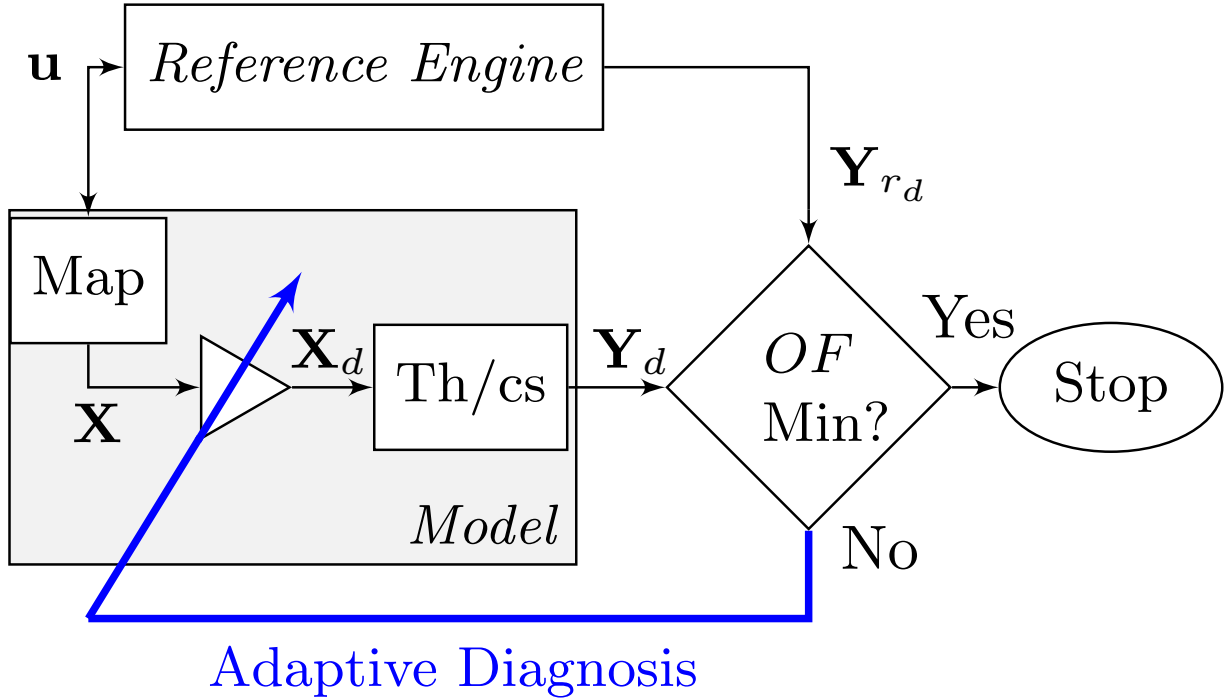


Figure 3: The flow chart of the proposed adaptive diagnostics.

177 in order to match the operating data of the *reference engine*. The engine measurement data are feeding
 178 the tuning process of the gas turbine model towards to minimizing the residuals between the predicted and
 179 actual measurements. For the initial adaptation of the *engine model* to the *reference engine* the entire set
 180 of operating data is used for establishing a benchmark model that represents the clean/healthy condition of
 181 the *reference engine*. For diagnostic purposes the above tuning process is performed discretely for every new
 182 set of engine measurement data as seen from Fig. 4. This results in a group of adapted models for which
 183 the degraded engine performance of the *reference engine* is accurately matched. Collating the estimated
 184 component performance of each uniquely adapted model represents the evolving component degradation of
 185 the *reference engine*.

186 The set of discretely estimated diagnostic information is consequently feeding the window based re-
 187 gression and prognostic process. A reliable, accurate, robust and flexible gas turbine model facilitates the
 188 performance evaluation of progressively degrading engine components.

189 2.4. Window-Based Analysis

190 Upon completion of the diagnosis task the next step involves the interpretation of this information
 191 towards facilitating the task of prognosis. Specifically, we suggest to partition the global nonlinear diagnostic
 192 information into smaller time segments, that we refer to as windows.

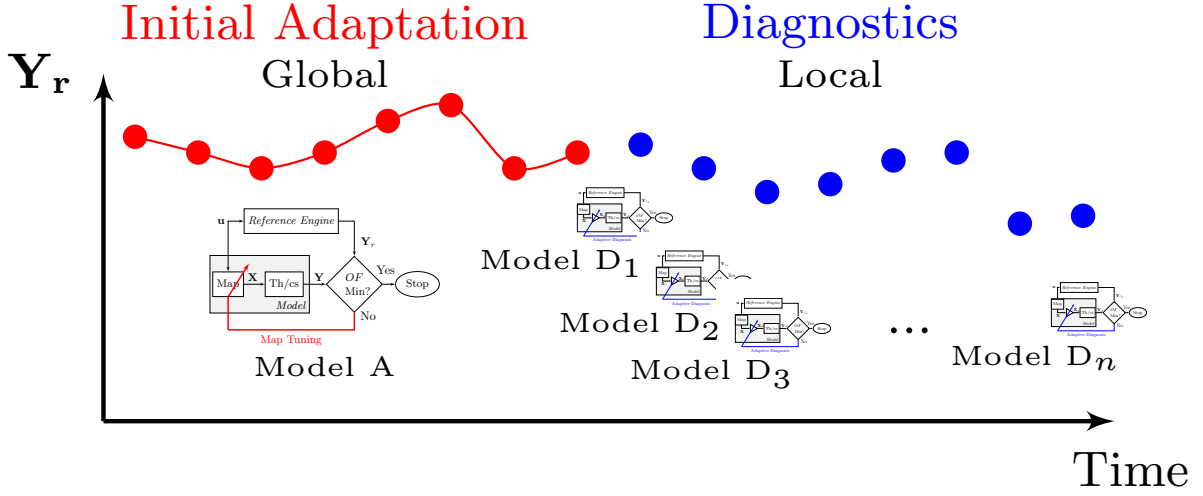


Figure 4: Representation of the engine models implemented for the initial global adaptation and the adaptive local diagnosis processes performed for the *reference engine* measurements.

193 From the diagnostic results, the degradation pattern is then partitioned into a number q of windows that
 194 encapsulate the entire diagnostic information. As shown in Fig. 5 a window activated at t_{w_i} contains n_i
 195 operating points for a time range/width of L_i . In contrary to our recent work [10], where L_i was constant,
 196 the window width in this study varies with respect to the distribution of data. The width L_i is adjusted
 197 based on the degradation acceleration. The second derivative of the component parameter deviation ΔX
 198 represents the performance degradation acceleration, as follows:

$$A_t = \frac{d^2 \Delta X_t}{dt^2} \quad (6)$$

199 The reason for this criterion selection lies in our initial assumption that for every window the engine
 200 component degradation propagates linear with respect to time. Therefore, the second derivative of a linear
 201 function is equal to zero and this enables the activation/deactivation of windows according to the distribution
 202 of the diagnostic results.

203 Now let us assume that for window activated at t_{w_i} the component parameter deviation is $\Delta X_{t_{w_i}}$ and its
 204 acceleration $A_{t_{w_i}}$. If the absolute deviation among the acceleration observed in $t_{w_i} + L_i$ and $t_{w_i} + L_i + 1$ is
 205 exceeding a specific limit/threshold k i.e. $|A_{t_{w_i} + L_i + 1} - A_{t_{w_i} + L_i}| \leq k$ then this window should be terminated
 206 at $t_{w_i} + L_i$ and a new one should be activated at $t_{w_i} + L_i + 1$. A schematic representation of the above
 207 condition is shown in Fig. 5.

208 The specification of k depends on the degradation pattern examined. On a local window-based level the

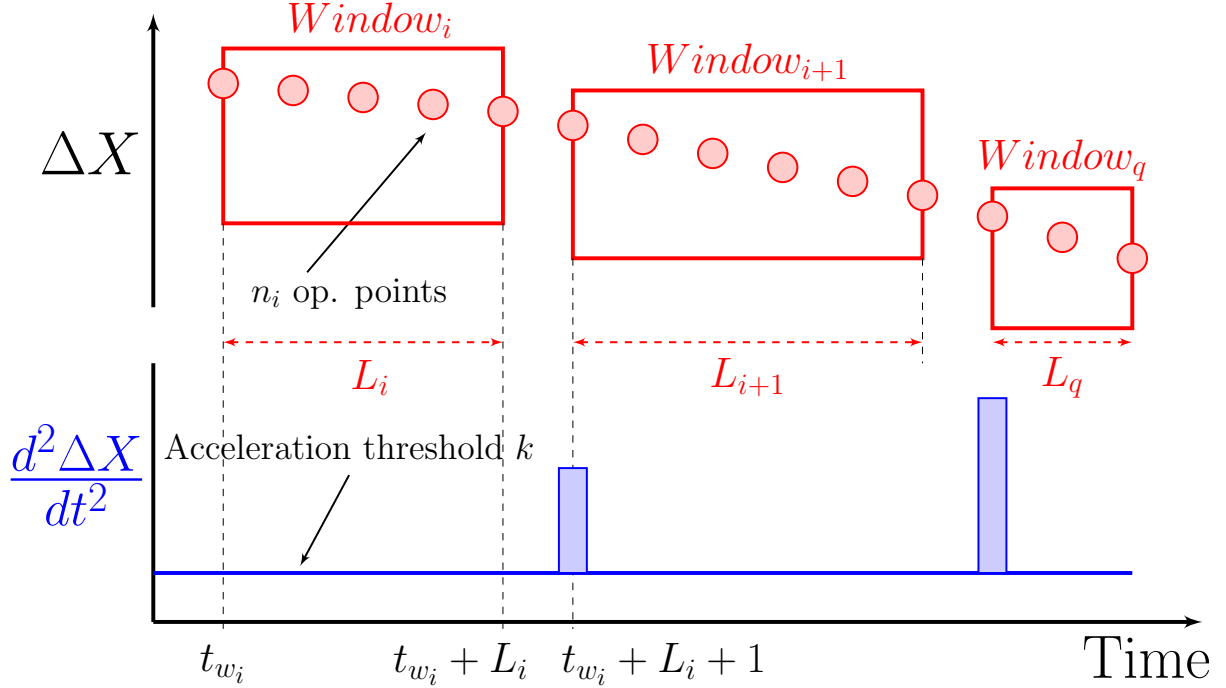


Figure 5: The partition of the diagnostic information into windows of variable width depending on the acceleration of the component degradation.

209 degradation can be expressed as a linear function with respect to time as follows:

$$g(t) = g_1 t + g_2, t \in [t_{w_i}, t_{w_i} + L_i], \quad (7)$$

210 where g_1 and g_2 are the coefficients of the function. Since the second derivative of the initially assumed linear
 211 function in eq. (7) is equal to zero it follows that k is specified to be zero. Therefore, if any acceleration
 212 change is detected a new window will be activated. This data processing approach is performed for the
 213 entire diagnostic information which results in q windows.

214 2.5. Prognostics

215 Generally, the prognosis is the process of estimating the evolution of gas turbine performance degradation
 216 for a specified time period. Given that the proposed window-based process divides the pattern of component
 217 degradation into smaller time increments, this enables prognosis to be carried out locally for every window.
 218 Consequently, a linear regression approach [29, 43] may be implemented to estimate the time evolving
 219 degraded component parameter $\Delta X_{lreg}(t)$ as follows:

$$\Delta X_{lreg} = g(t), t \in [t_{w_i}, t_{w_i} + L_i]. \quad (8)$$

220 Once the localized degradation pattern is approximated by the regression model, the component perfor-
 221 mance is predicted for a time width M , which is referred to as the prognostic window. At this stage the
 222 *reference engine* degradation $\Delta X_{r_{inj}}$ is used to assess the prognosis accuracy.

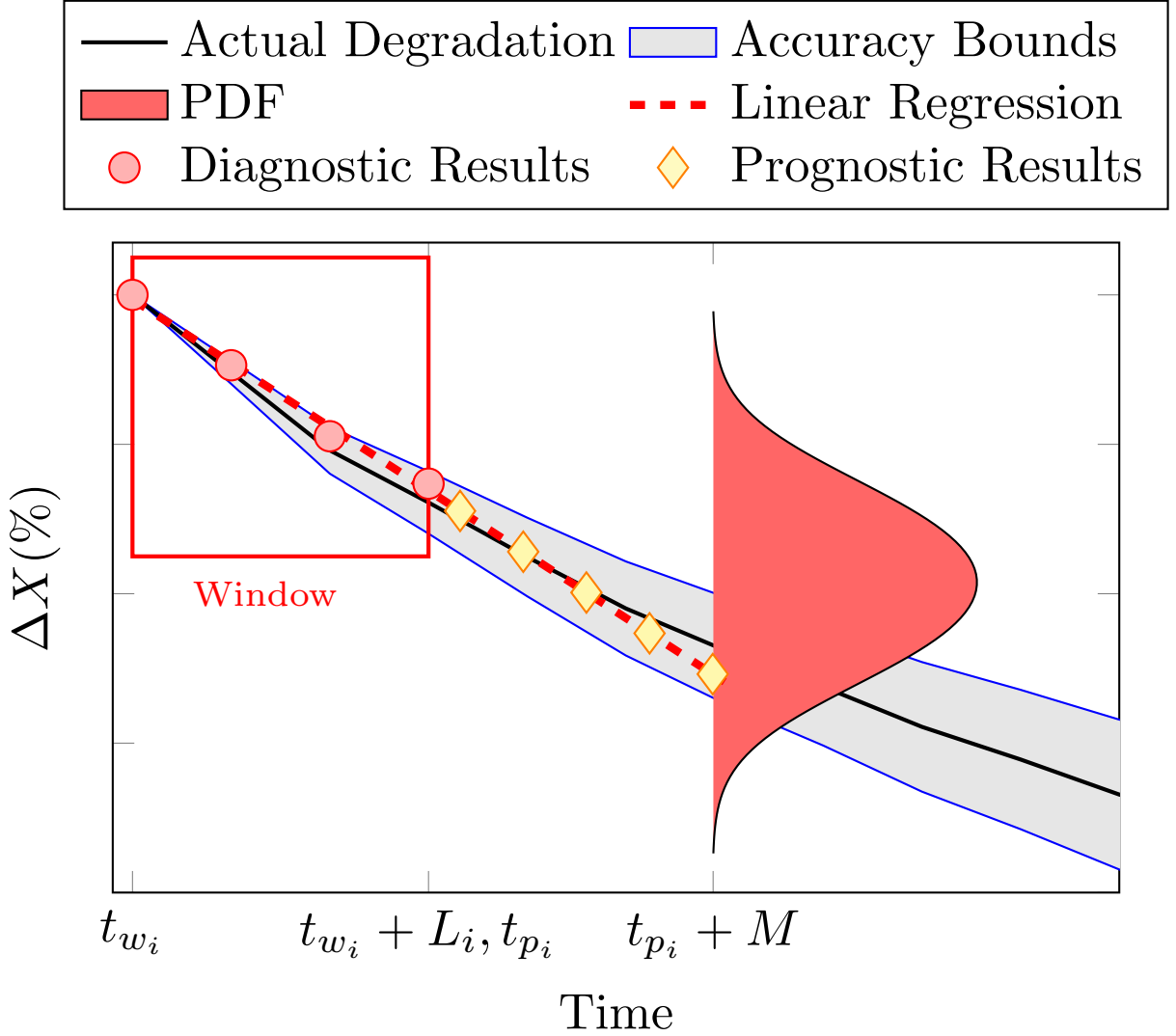


Figure 6: The distribution of the prognostic results, obtained through linear regression of the local diagnostic information, with respect to the actual degradation.

223 Furthermore, the Probability Density Function (PDF) of normal/gaussian distribution is implemented for
 224 determining the probability of the prognosis results to take any given value. The PDF of the normal/gaussian
 225 distribution of x is as follows:

$$f(x) = \left(\frac{1}{\sigma\sqrt{2\pi}} \right) e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2}, \quad (9)$$

226 where x denotes the degraded component parameter ΔX_{lreg} of standard deviation σ .

227 The PDF of the linearly regressed component parameter ΔX_{lreg} information along with the diagnostic
228 predictions ΔX and the actual degradation ΔX_{rinj} with its corresponding accuracy bounds is shown in Fig.
229 6. The final step of the prognosis task is RUL estimation for the component.

230 The majority of the performance-based prognostic algorithms for rotating machinery [29, 28] evaluate
231 RUL by projecting the diagnostic predictions into time and assigning a probability of these predictions to
232 reach a certain threshold. The proposed prognosis is adopting another logic since its main focus is the inves-
233 tigation of the degradation pattern itself and how it evolves over time. The localized linear window-based
234 analysis facilitates the short-term performance prediction of degraded components and the Equivalent RUL
235 (ERUL) metric suggested by the authors is implemented for determining the evolution of the degradation
236 in short-term intervals.

237 Finally, accuracy bounds similar to the diagnostic accuracy bounds are implemented for the true ERUL.
238 The true ERUL is determined by the injected degradation to the engine component parameters ΔX_{rinj} . As
239 a result the comparison between estimated ERUL and true ERUL provides an insight to the performance
240 capability of the proposed method. The ERUL represents the rate at which the component of the engine
241 system ‘consumes’ its useful life according to the mode of operation.

242 3. Case Study Description

243 The proposed adaptive and window-based methods for prognostics approaches are integrated into a an
244 industrial gas turbine model that is developed in MATLAB/Simulink environment. It is worth mentioning
245 that the MATLAB/Simulink environment is becoming very popular for the analysis of energy systems
246 dynamics and the design of controllers [44, 45, 46, 47]. Our developed model has been validated towards
247 PROOSIS [42] simulation software. The engine model is similar to the GE LM2500+ aero derivative gas tur-
248 bine [48] which is a two-shaft industrial gas turbine that consists of a compressor, a combustor, a compressor
249 turbine and a power turbine as schematically represented in Fig 7. The design performance specifications of
250 the engine are tabulated in Table 1.

251 The control input of the gas turbine model configuration is the fuel flow rate \dot{m}_f . A detailed description
252 of the gas turbine model can be found in our recent works in [49, 37]. The objective of the case studies
253 is to evaluate the accuracy improvement of our prognostic method in comparison to the earlier prognostic
254 scheme developed where fixed width windows were implemented. The selected measurable parameters for
255 the diagnostic and prognostic tasks are listed in Table 2.

256 Now let us describe the *reference engine* data generation process. The time step of the simulation
257 procedure is 1 ms. For 100 s simulation time a total of 100,000 data samples are generated. The above data
258 should be mapped to the examined component degradations that are typical for 25,000 h of operation. This

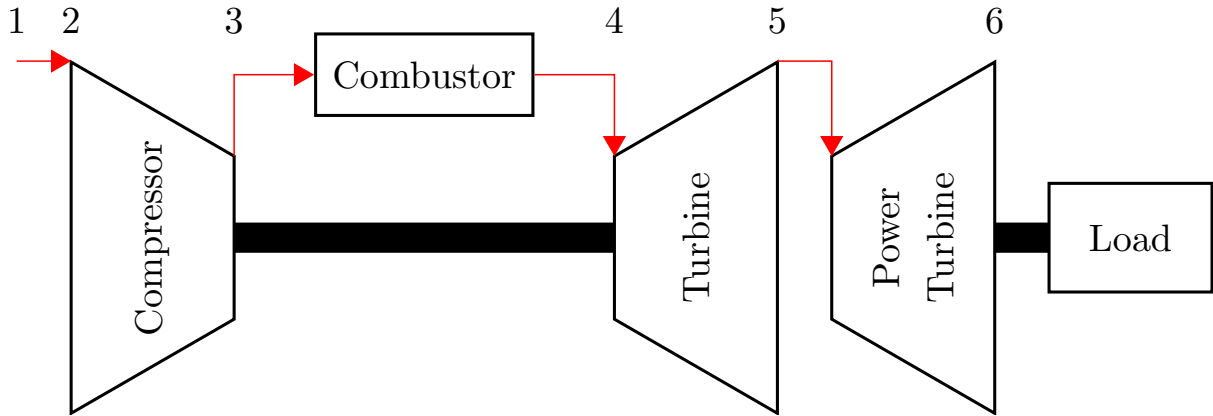


Figure 7: The engine model schematic layout representing a two shaft gas turbine.

Table 1: Design performance specifications of GE LM2500+ [48].

Symbol	Parameter	Value	Units
π_c	pressure ratio	23.1	
\dot{m}_{exh}	exhaust mass flow rate	85.9	kg/s
T_{exh}	exhaust gas temperature	791	K
η_{th}	thermal efficiency	41	%
W_{pt}	power output	31	MW

Table 2: The engine performance measurable parameters.

Symbol	Parameter	Units
P_3	compressor discharge pressure	Pa
T_3	compressor discharge temperature	K
P_5	turbine exit pressure	Pa
T_5	turbine exit temperature	K
P_6	power turbine exit pressure	Pa
T_6	power turbine exit temperature	K
W_{pt}	power output	W
N	shaft rotational speed	rpm

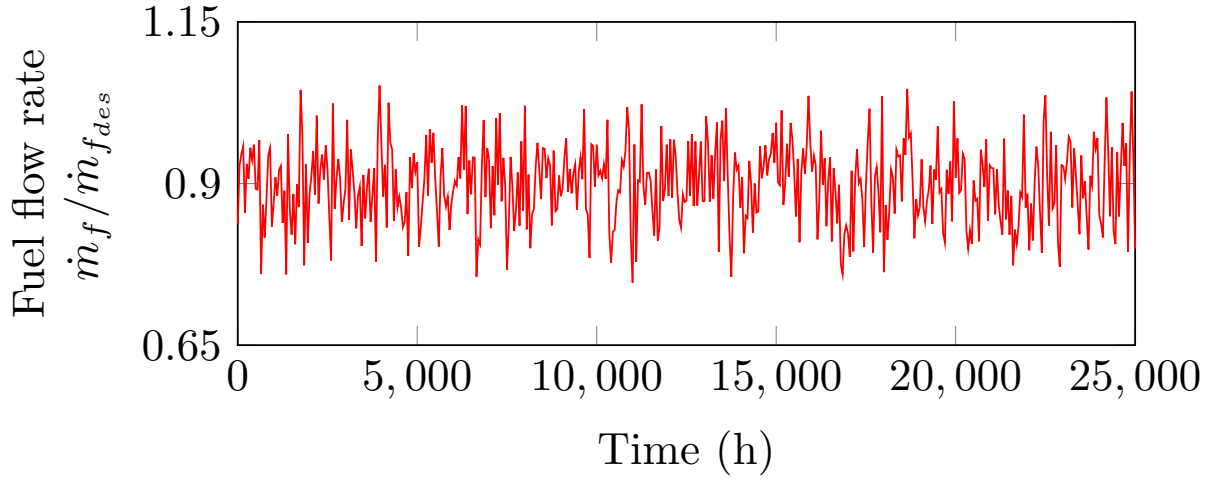


Figure 8: The variation of the fuel flow rate with respect to time.

259 means that 4 data samples are mapped to 1 h of operation. The size of the data samples is adequate for
 260 capturing the nonlinearity of the engine performance. The dynamic aspect of the fuel flow rate which acts
 261 as the control input of the engine model is shown in Fig. 8.

262 Data implemented for the case studies are the *reference engine* degraded simulated measurements and
 263 the prognosis process is performed at various time instants. The degraded measurements are generated
 264 by injecting deviation signals in the component parameters of the *reference engine*. A summary of the
 265 aforementioned deviations is given in Table 3.

Table 3: Injected deviations of the component parameters.

Component	Degradation	Parameter	Deviation Range (%)
Compressor	Fouling	$\Delta\Gamma_c$	0-(-3)
		$\Delta\eta_c$	0-(-3)
Turbine	Erosion	$\Delta\Gamma_t$	0-(2.5)
		$\Delta\eta_t$	0-(-2.5)
Power Turbine	Erosion	$\Delta\Gamma_{pt}$	0-(2.5)
		$\Delta\eta_{pt}$	0-(-2.5)

266 In this study two test cases are carried out. The first case study objective is to assess the prediction
 267 accuracy for the proposed real-time adaptive diagnostic method. It follows that for the second case study
 268 the objective is to predict the evolution of the compressor degradation by implementing both the window-
 269 based analysis and the linear regression methods. Moreover, the comparison of the prognostic method with

270 the one earlier developed by the authors will give an insight of the accuracy improvement by the variable
271 window-width activation introduced. Towards this end the common metrics of PDF and ERUL are utilized
272 for assessing the accuracy of the prognosis.

273 It should be noted that the earlier prognostic method will implement the diagnostic results on a different
274 manner than in [10]. In the earlier study [10] the fixed width method was employed for both the diagnostic
275 and prognostic process. The diagnosis in that case was carried out in a sliding window-based manner and
276 for each diagnostic window the suite of engine model component maps were optimized and degradations
277 were detected on a local window level. Consequently, the diagnostic information was the outcome of collated
278 data from the detected degradations of each window. That approach had the advantage of partly filtering
279 out the time component from the degradation so that the prognosis could be performed on a linear fixed-
280 width window-based method. In contrast to our earlier work, this study waives off the added advantage of
281 performing diagnosis in a window based fashion and only prognosis is performed on local window level.

282 4. Results

283 4.1. Diagnosis

284 The model-based performance adaptation and the adaptive diagnostic method, are implemented for
285 detecting the degradation of each component. The process commenced by initially adapting the *engine*
286 *model* to the clean/nominal condition of *reference engine* for an operational profile that included both
287 steady state and transient operating points. Then degradations were injected to the compressor, turbine
288 and power turbine at $t_d=2,500$ h. The first bank of data up to t_d is utilized for *engine model* adaptation
289 and denote the clean/nominal/healthy condition of the engine.

290 Diagnostic tasks are initiated at t_d and carried out real time by tuning the output of each component
291 map that has been initially optimized by the earlier adaptation process. The detected compressor fouling
292 which is represented by the deviated mass flow component parameter is shown in Fig. 9. The diagnostic
293 results indicated an improved accuracy in the diagnosis and in case of the compressor mass flow capacity
294 the DI is 0.99 which implies that the diagnosis is 99% effective. It should be noted that all the compo-
295 nent degradations have been detected with the same level of accuracy, but only the results concerning the
296 compressor degradation are presented here.

297 Prior to performing prognostics, the diagnostic information encapsulated by the detected deviations is
298 split into a number of windows as seen from Fig. 9. For this case their time width L_i relies solely on the
299 distribution of the component degradation acceleration. The outcome of the above process resulted in a set
300 of $q=13$ windows of variable width L_i spanning from 250 h to 5,000 h.

301 The acceleration of compressor degradation is represented by the second derivative of mass flow capac-
302 ity with respect to time as seen from Fig. 10. At specific time instants, the acceleration of compressor

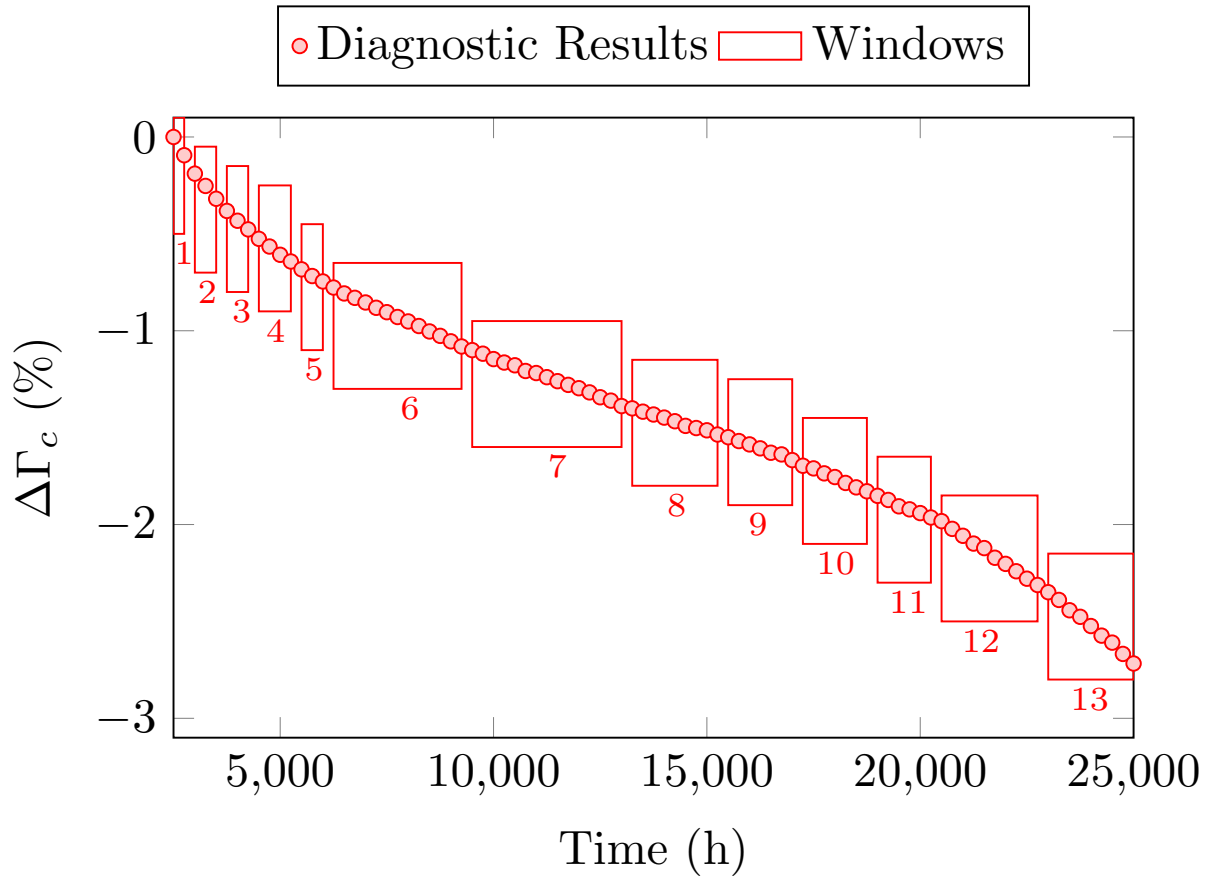


Figure 9: Predicted compressor degradation represented by the deviation of the mass flow capacity. Diagnostic information is splitted into 13 windows where their width is variable and dependent on the acceleration of degradation.

303 degradation exceeds the threshold value $k=0$ which leads to the termination of the existing window and the
 304 activation of a new one so that the initially assumed linear propagation is satisfied. It is also noted from
 305 Fig. 10 that for the initial and final stages of the assumed degradation pattern the diagnostic information
 306 has to be segmented into several windows due to an increased rate of degradation.

307 For demonstrating the advantages of the proposed method in terms of the prediction accuracy, the earlier
 308 fixed width window-based method developed by the authors [10] is also implemented. The results of this
 309 fixed width window-based method are illustrated in Fig. 11 where a number of $q=9$ windows are utilized to
 310 capture the diagnostic data and their width L_i is fixed at 2,500 h.

311 For facilitating the comparison of both window-based linear regression methods in terms of the prognos-
 312 tics accuracy, the proposed variable width and the earlier fixed width window-based methods are going to
 313 be referred to as Method A and Method B, respectively.

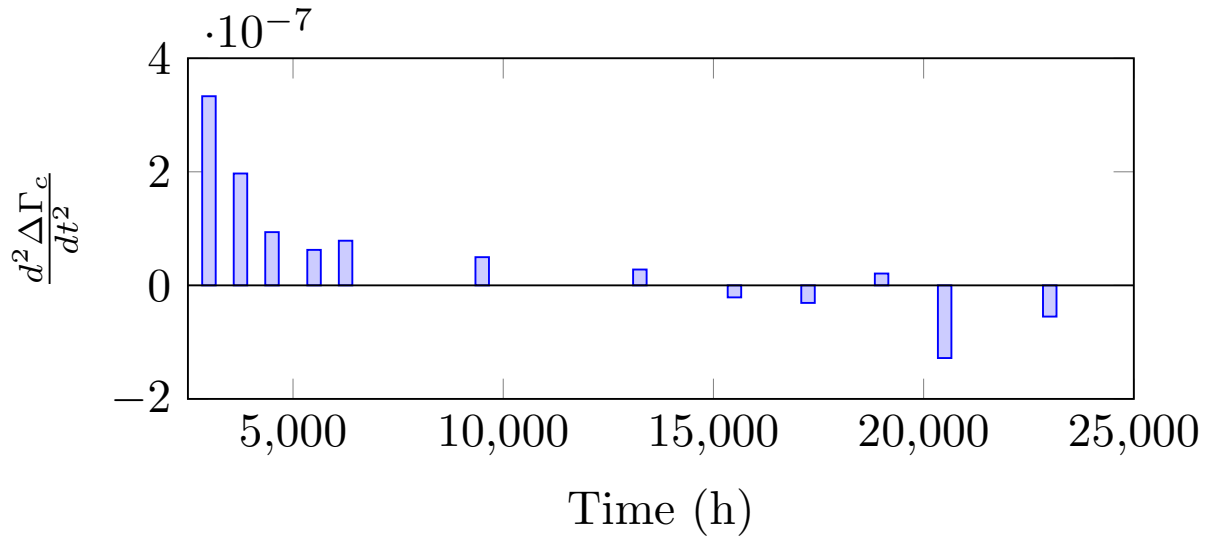


Figure 10: Acceleration of compressor degradation represented by deviation of the mass flow capacity.

314 4.2. Prognosis

315 The objective of this case study is to evaluate the improved accuracy of our proposed method for
 316 prognostics. The time instants when prognosis is initiated are different for Method A and Method B since
 317 each one uses a different approach in partitioning the diagnostic information. A direct comparison between
 318 the predicted and actual compressor degradation forms the means by which the prognostic accuracy is
 319 determined.

320 For Method A the prognosis is initiated at time instant 2,750 h until the 22,500h. The prognostic window
 321 width spans from $M=0.5$ to 1 month of operation, i.e. 360 to 720 h. In case of Method B the prognosis
 322 is initiated at $t_p=4,750$ h and the prognostic window width is constant at $M=1$ month. The number of
 323 operating points corresponding to the diagnostic data of each window is denoted by n_i and depends on the
 324 time width L_i of each window.

325 The deviation in compressor mass flow capacity as predicted by the Methods A and B is shown in
 326 Figs. 12 and 13, respectively. In the proposed method the prognosis task is performed more frequently
 327 than Method B. This is due to the number of windows used for capturing the diagnostic information. It is
 328 clear from Fig. 12, than the normal data distribution of the proposed prognostic method predictions fall
 329 within the accuracy bounds that were set at 90% of the actual degradation. On the other hand Method
 330 B presents similar performance with Method A apart from the first and final stages of the degradation
 331 pattern. One major advantage of the data-driven partitioning of the diagnostic pattern is that of linearizing
 332 the degradation trend and applying a local linear regression model for prognostics.

333 The spread of the predicted mass flow capacity distribution depends on the gradient characterizing the
 334 diagnostic data that are contained in each window. As a result it is observed from Figs. 12 and 13 that

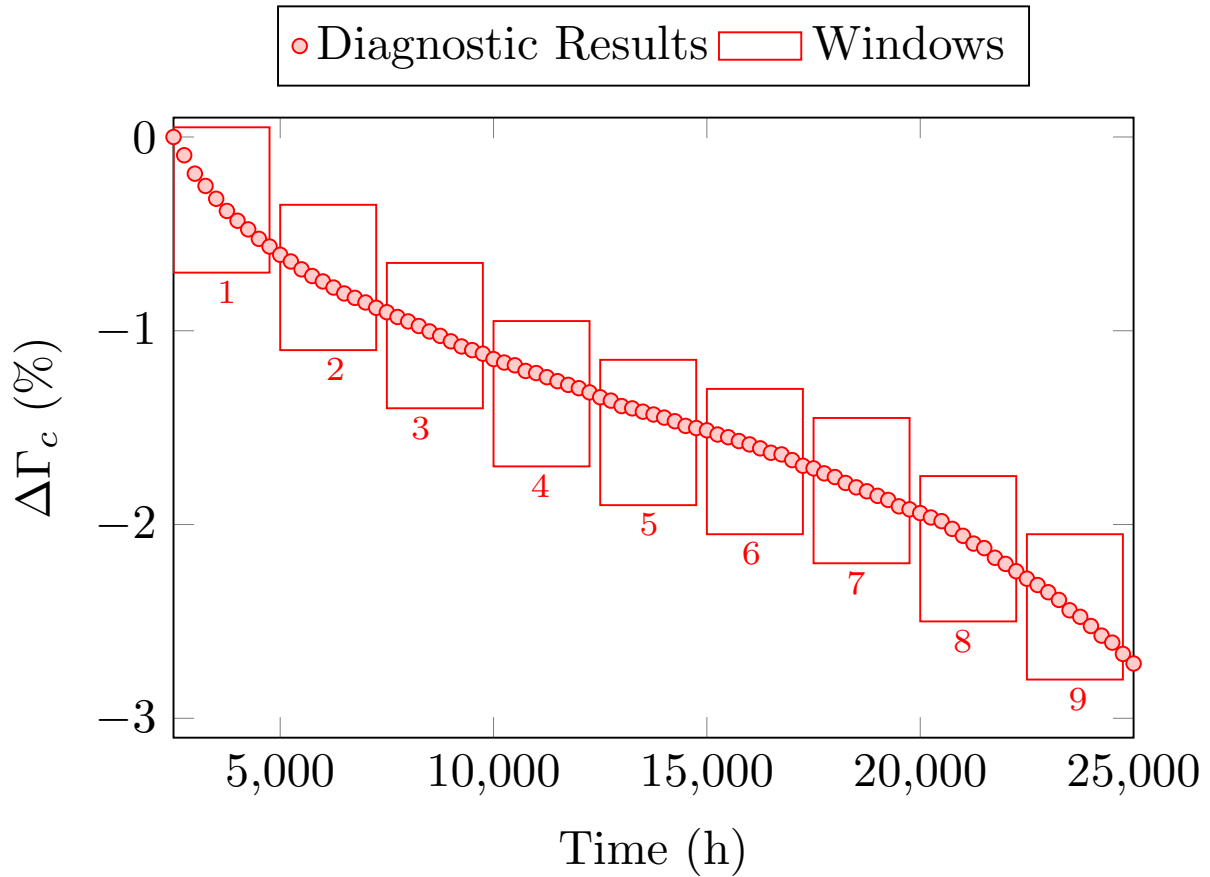


Figure 11: Predicted compressor degradation represented by the deviation of the mass flow capacity. Diagnostic information is splitted into 9 windows where their width is fixed.

335 especially for the first and last stages of the degradation pattern the spread is relatively higher than the
 336 ones for the mid stages.

337 An additional metric that facilitates the evaluation of the prognostic accuracy is that of the ERUL of
 338 the component based on its degradation. The predicted ERUL based on the compressor mass flow capacity
 339 is shown in Fig. 14 where the accuracy bounds refer to the true ERUL of the component. It is evident from
 340 Fig. 14 that the estimated ERUL falls within the accuracy bounds for all the local prognostic tasks for both
 341 Methods A and B. However, it is noticed from Fig. 14 that there is a small deviation in terms of ERUL
 342 between the two methods. The former observation can be amplified by examining the ERUL error of each
 343 method.

344 As expected the ERUL error of the Method A predictions lies consistently within the accuracy levels for
 345 all the time instants and ranges from 0% to 1.6%. On the other hand the error of Method B predictions
 346 might initially lie within the accuracy levels but at the final stages of the degradation pattern, where one
 347 would expect convergence to the true ERUL, the error increases. A closer look to Fig. 15 reveals that for

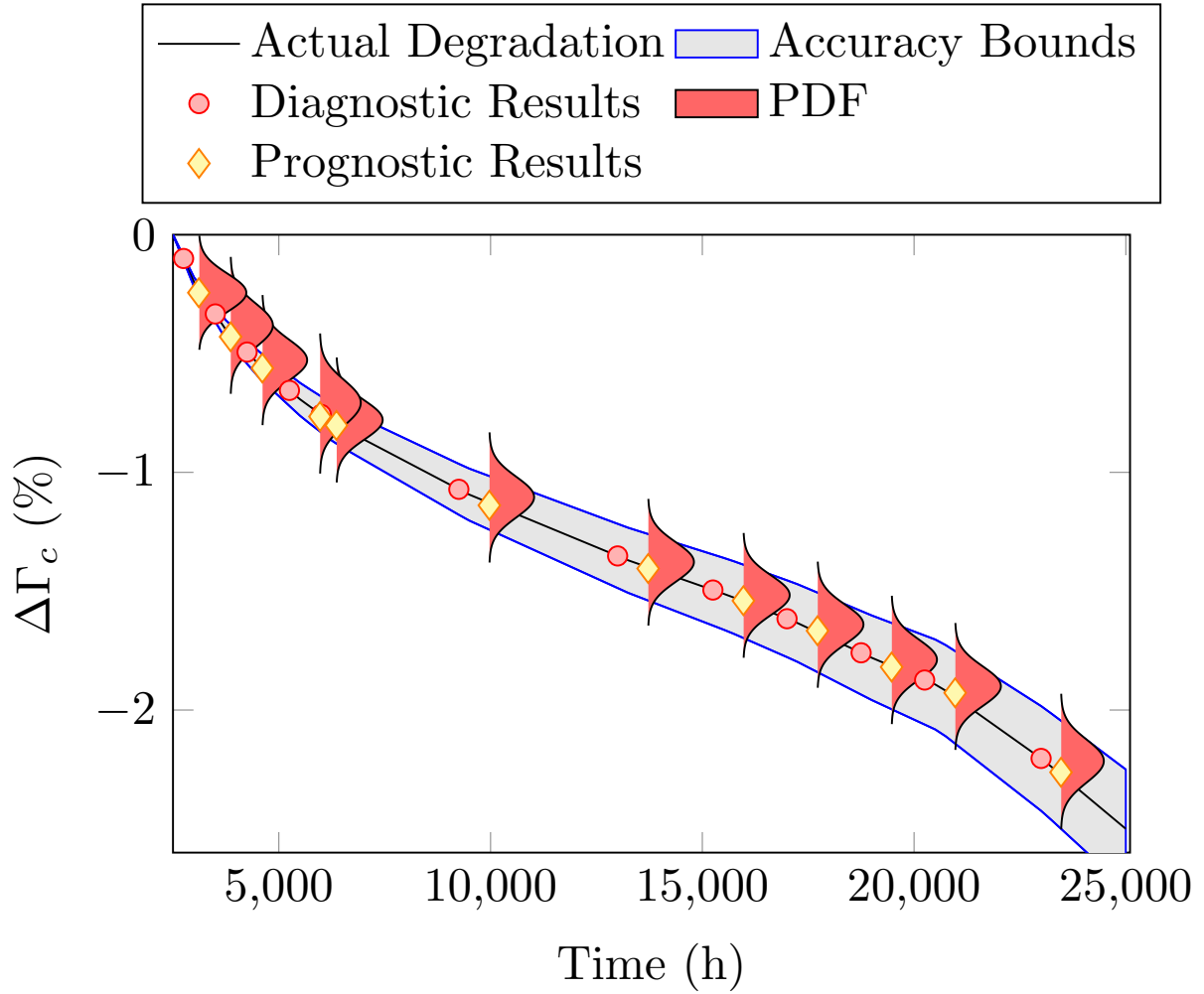


Figure 12: The deviation of compressor mass flow capacity as predicted by variable width window-based Method A.

348 both the initial and final stages of the prognosis task Method B has a prediction error in the range of -5%
 349 to 5%. Although both Methods A and B initially seemed to perform similarly in terms of the prognostic
 350 accuracy it was found that Method B is characterized by under and over-predictions for the initial and
 351 final stages of the examined degradation pattern, respectively. Finally, it should be pointed out that by
 352 principle Method B is a method most suitable for application in which both the diagnosis and the prognosis
 353 are performed with the same local window-based approach. In contrast to Method B, Method A is purely
 354 data-driven and relies solely on the diagnostic information. Selection of one method over the other depends
 355 upon the objective of the investigation and the method selected for the diagnosis process.

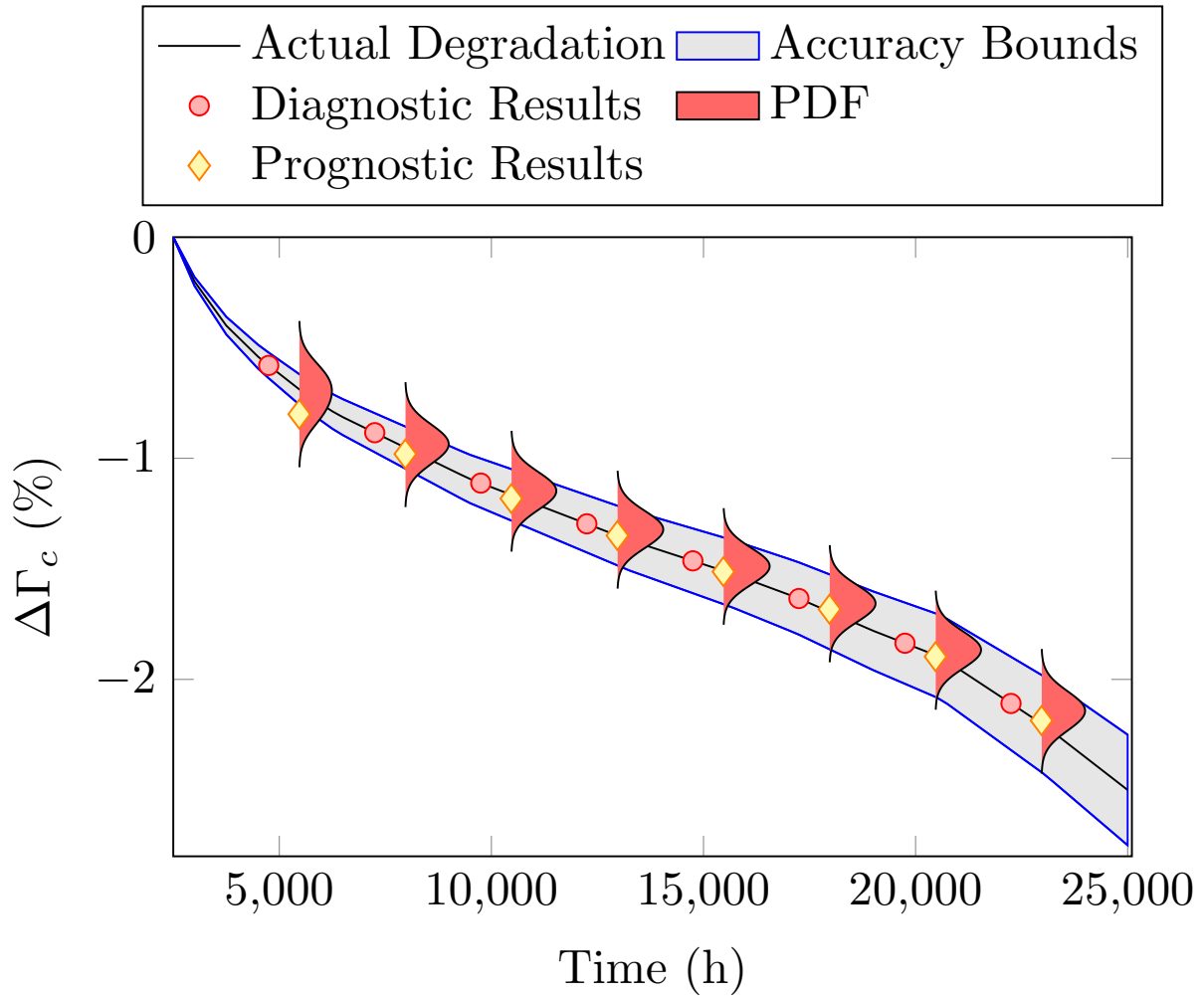


Figure 13: The deviation of compressor mass flow capacity as predicted by fixed width window-based Method B.

356 5. Conclusions

357 In this paper, a data-based prognostics approach is proposed for estimating the performance of gas
 358 turbine engine operating in dynamic conditions. A real time adaptive diagnostic approach and a window-
 359 based prognostic method are coupled with a MATLAB/Simulink gas turbine model.

360 Testing of the proposed methods was based on simulated measurements of an engine model that rep-
 361 resented 25,000 h of gas turbine operation subject to multiple component degradations. The compressor
 362 degradation is accurately predicted by locally fitting a linear regression model which predicts the perfor-
 363 mance behavior of the engine. This is accomplished by utilizing a local linear window-based approach which
 364 splits the diagnostic pattern into several smaller segments in which the progression of degradation can be
 365 approximated by linear functions. The window width is adjusted according to the degraded data accel-
 366 eration. Moreover, the useful life of the compressor is estimated and compared to the its true life within

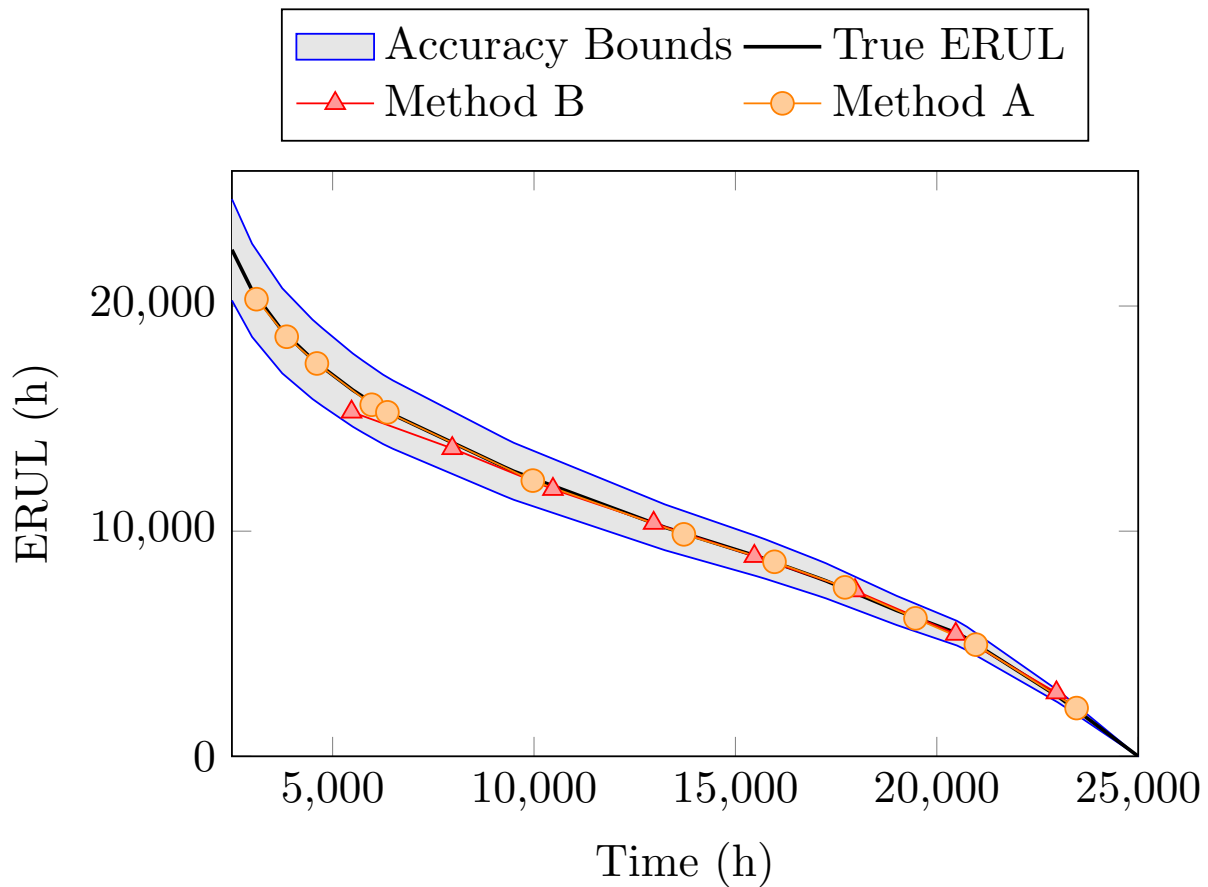


Figure 14: The predicted ERUL based on compressor mass flow capacity.

367 90% accuracy bounds by using the PDF and ERUL metrics. The performance of the engine component is
 368 accurately predicted for prognostic windows that vary from 0.5 to 1 month of operation. The comparison of
 369 the proposed method with an earlier prognostic method, that utilizes a fixed width window-based analysis
 370 of the diagnostic information, highlighted the advantage of the proposed method in dealing with component
 371 degradations that have an increased rate of progression.

372 The proposed method has demonstrated the capability to predict at a computational efficient and accu-
 373 rate manner the gas turbine component degradation for engines operating under dynamic operating modes.
 374 Our proposed method can support the condition based maintenance of gas turbine powered plants since it
 375 provides an improved judgment for the gas turbine short-term performance status.

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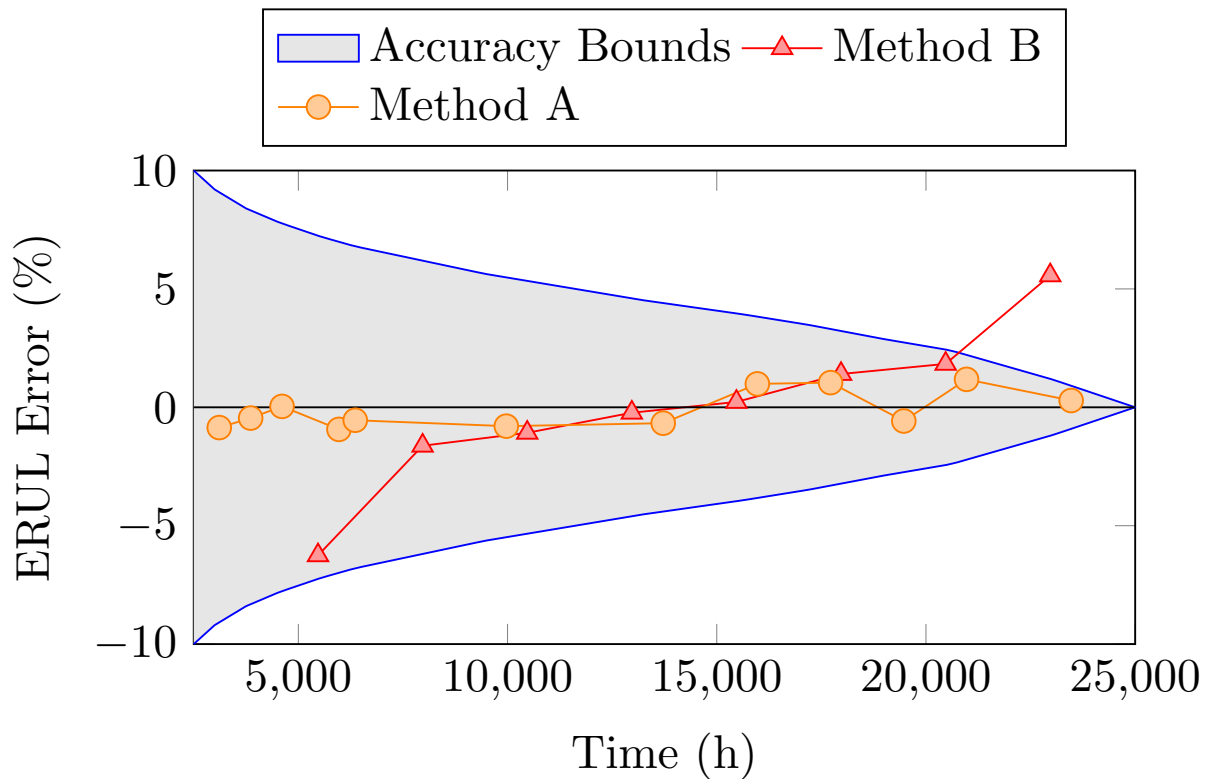


Figure 15: The predicted ERUL error based on compressor mass flow capacity.

379 of the authors.

- 380 [1] G. Zhang, J. Zheng, A. Xie, Y. Yang, W. Liu, Thermodynamic analysis of combined cycle under design/off-design condi-
381 tions for its efficient design and operation, *Energy Conversion and Management* 126 (2016) 76–88.
- 382 [2] F. Haglind, B. Elmegaard, Methodologies for predicting the part-load performance of aero-derivative gas turbines, *Energy*
383 34 (10) (2009) 1484–1492.
- 384 [3] A. Benato, A. Stoppato, S. Bracco, Combined cycle power plants: A comparison between two different dynamic models
385 to evaluate transient behaviour and residual life, *Energy Conversion and Management* 87 (2014) 1269–1280.
- 386 [4] N. Hadroug, A. Hafaifa, A. Kouzou, A. Chaibet, Dynamic model linearization of two shafts gas turbine via their in-
387 put/output data around the equilibrium points, *Energy*.
- 388 [5] X. Xu, K. Li, F. Qi, H. Jia, J. Deng, Identification of microturbine model for long-term dynamic analysis of distribution
389 networks, *Applied Energy*.
- 390 [6] S. Bracco, F. Delfino, A mathematical model for the dynamic simulation of low size cogeneration gas turbines within
391 smart microgrids, *Energy*.
- 392 [7] S. Obara, J. Morel, M. Okada, K. Kobayashi, Study on the load following characteristics of a distributed igcc for inde-
393 pendent microgrid, *Energy* 115 (2016) 13–25.
- 394 [8] C. V. Ponce, D. Sáez, C. Bordons, A. Núñez, Dynamic simulator and model predictive control of an integrated solar
395 combined cycle plant, *Energy* 109 (2016) 974–986.
- 396 [9] V. Zaccaria, D. Tucker, A. Traverso, Operating strategies to minimize degradation in fuel cell gas turbine hybrids, *Applied*
397 *Energy*.

- 398 [10] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, A dynamic prognosis scheme for flexible operation of gas turbines,
399 Applied Energy 164 (2016) 685–701.
- 400 [11] A. Volponi, Gas turbine engine health management: Past, present, and future trends, Journal of Engineering for Gas
401 Turbines and Power 136 (5) (2014) 051201.
- 402 [12] J. Sun, H. Zuo, W. Wang, M. G. Pecht, Application of a state space modeling technique to system prognostics based
403 on a health index for condition-based maintenance, Mechanical Systems and Signal Processing 28 (2012) 585 – 596,
404 interdisciplinary and Integration Aspects in Structural Health Monitoring. doi:[http://dx.doi.org/10.1016/j.ymssp.
405 2011.09.029](http://dx.doi.org/10.1016/j.ymssp.2011.09.029).
406 URL <http://www.sciencedirect.com/science/article/pii/S0888327011003979>
- 407 [13] D. Zhou, H. Zhang, Y.-G. Li, S. Weng, A dynamic reliability-centered maintenance analysis method for natural gas
408 compressor station based on diagnostic and prognostic technology, Journal of Engineering for Gas Turbines and Power
409 138 (6) (2016) 061601.
- 410 [14] M. Y. Asr, M. M. Ettefagh, R. Hassannejad, S. N. Razavi, Diagnosis of combined faults in rotary machinery by non-naive
411 bayesian approach, Mechanical Systems and Signal Processing 85 (2017) 56–70.
- 412 [15] E. Mohammadi, M. Montazeri-Gh, Active fault tolerant control with self-enrichment capability for gas turbine engines,
413 Aerospace Science and Technology 56 (2016) 70–89.
- 414 [16] GE, Transforming GE to Digital Industrial, see also <http://www.ge.com/> (2016).
- 415 [17] Y. G. Li, A gas turbine diagnostic approach with transient measurements, Proceedings of the Institution of Mechanical
416 Engineers, Part A: Journal of Power and Energy 217 (2) (2003) 169–177.
- 417 [18] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, Transient gas turbine performance diagnostics through nonlinear
418 adaptation of compressor and turbine maps, Journal of Engineering for Gas Turbines and Power, GTP-14-1630 137.
- 419 [19] G. Merrington, O. K. Kwon, G. Goodwin, B. Carlsson, Fault detection and diagnosis in gas turbines, Journal of Engineering
420 for Gas Turbines and Power 113 (2) (1991) 276–282.
- 421 [20] M. Amozegar, K. Khorasani, An ensemble of dynamic neural network identifiers for fault detection and isolation of gas
422 turbine engines, Neural Networks 76 (2016) 106–121.
- 423 [21] E. Mohammadi, M. Montazeri-Gh, A fuzzy-based gas turbine fault detection and identification system for full and part-load
424 performance deterioration, Aerospace Science and Technology 46 (2015) 82–93.
- 425 [22] A. Vatani, K. Khorasani, N. Meskin, Health monitoring and degradation prognostics in gas turbine engines using dynamic
426 neural networks, in: ASME Turbo Expo, GT2015-4401, ASME, 2015.
- 427 [23] J. Szoplik, Forecasting of natural gas consumption with artificial neural networks, Energy 85 (2015) 208 – 220. doi:[http:
428 //dx.doi.org/10.1016/j.energy.2015.03.084](http://dx.doi.org/10.1016/j.energy.2015.03.084).
429 URL <http://www.sciencedirect.com/science/article/pii/S036054421500393X>
- 430 [24] M. A. Zaidan, R. F. Harrison, A. R. Mills, P. J. Fleming, Bayesian hierarchical models for aerospace gas turbine engine
431 prognostics, Expert Systems with Applications 42 (1) (2015) 539 – 553.
- 432 [25] M. A. Zaidan, A. R. Mills, R. F. Harrison, P. J. Fleming, Gas turbine engine prognostics using bayesian hierarchical
433 models: A variational approach, Mechanical Systems and Signal Processing 7071 (2016) 120 – 140. doi:[http://dx.doi.
434 org/10.1016/j.ymssp.2015.09.014](http://dx.doi.org/10.1016/j.ymssp.2015.09.014).
435 URL <http://www.sciencedirect.com/science/article/pii/S0888327015004094>
- 436 [26] D. Zhou, H. Zhang, S. Weng, A novel prognostic model of performance degradation trend for power machinery maintenance,
437 Energy 78 (2014) 740 – 746. doi:<http://dx.doi.org/10.1016/j.energy.2014.10.067>.
438 URL <http://www.sciencedirect.com/science/article/pii/S0360544214012171>
- 439 [27] D. Feng, M. Xiao, Y. Liu, H. Song, Z. Yang, L. Zhang, A kernel principal component analysis–based degradation
440 model and remaining useful life estimation for the turbofan engine, Advances in Mechanical Engineering 8 (5) (2016)

- 441 1687814016650169.
- 442 [28] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, Performance-based prognosis scheme for industrial gas turbines,
443 in: Prognostics and Health Management (PHM), 2015 IEEE Conference on, IEEE, 2015, pp. 1–8.
- 444 [29] Y. G. Li, P. Nilkitsaranont, Gas turbine performance prognostic for condition-based maintenance, *Applied Energy* 86 (10)
445 (2009) 2152–2161.
- 446 [30] N. Daroogheh, N. Meskin, K. Khorasani, A novel particle filter parameter prediction scheme for failure prognosis, in:
447 American Control Conference (ACC), 2014, IEEE, 2014, pp. 1735–1742.
- 448 [31] N. Daroogheh, A. Baniamerian, N. Meskin, K. Khorasani, A hybrid prognosis and health monitoring strategy by integrating
449 particle filters and neural networks for gas turbine engines, in: Prognostics and Health Management (PHM), 2015 IEEE
450 Conference on, 2015, pp. 1–8. doi:10.1109/ICPHM.2015.7245020.
- 451 [32] H. Hanachi, J. Liu, A. Banerjee, Y. Chen, Sequential state estimation of nonlinear/non-gaussian systems with stochastic
452 input for turbine degradation estimation, *Mechanical Systems and Signal Processing* 72 (2016) 32–45.
- 453 [33] Q. Wang, J. Huang, F. Lu, An improved particle filtering algorithm for aircraft engine gas-path fault diagnosis, *Advances
454 in Mechanical Engineering* 8 (7) (2016) 1687814016659602.
- 455 [34] D. E. Acuña, M. E. Orchard, Particle-filtering-based failure prognosis via sigma-points: Application to lithium-ion battery
456 state-of-charge monitoring, *Mechanical Systems and Signal Processing* 85 (2017) 827–848.
- 457 [35] D. Zhou, Z. Yu, H. Zhang, S. Weng, A novel grey prognostic model based on markov process and grey incidence analysis
458 for energy conversion equipment degradation, *Energy* 109 (2016) 420 – 429. doi:http://dx.doi.org/10.1016/j.energy.
459 2016.05.008.
460 URL <http://www.sciencedirect.com/science/article/pii/S0360544216305606>
- 461 [36] B. Pourbabaee, N. Meskin, K. Khorasani, Robust sensor fault detection and isolation of gas turbine engines subjected
462 to time-varying parameter uncertainties, *Mechanical Systems and Signal Processing* (2016) –doi:http://dx.doi.org/10.
463 1016/j.ymsp.2016.02.023.
464 URL <http://www.sciencedirect.com/science/article/pii/S0888327016000741>
- 465 [37] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, A component map tuning method for performance prediction
466 and diagnostics of gas turbine compressors, *Applied Energy* 135 (2014) 572–585.
- 467 [38] E. Tsoutsanis, N. Meskin, Forecasting the health of gas turbine components through an integrated performance-based
468 approach, in: Prognostics and Health Management (ICPHM), 2016 IEEE International Conference on, IEEE, 2016, pp.
469 1–8.
- 470 [39] A. Saxena, Prognostics the science of prediction, in: Proc. PHM Conference, Portland, OR, 2010.
- 471 [40] Y. Cheng, C. Lu, T. Li, L. Tao, Residual lifetime prediction for lithium-ion battery based on functional principal component
472 analysis and bayesian approach, *Energy* 90, Part 2 (2015) 1983 – 1993. doi:http://dx.doi.org/10.1016/j.energy.2015.
473 07.022.
474 URL <http://www.sciencedirect.com/science/article/pii/S0360544215009172>
- 475 [41] K.-C. Yung, B. Sun, X. Jiang, Prognostics-based qualification of high-power white leds using lévy process approach,
476 *Mechanical Systems and Signal Processing*.
- 477 [42] PROOSIS, Propulsion Object-Oriented Simulation Software, see also <http://www.proosis.com/> (2016).
- 478 [43] D. C. Montgomery, G. C. Runger, *Applied statistics and probability for engineers*, John Wiley & Sons, 2010.
- 479 [44] L. Barelli, G. Bidini, A. Ottaviano, Integration of sofc/gt hybrid systems in micro-grids, *Energy*.
- 480 [45] R. Chacartegui, D. Sánchez, A. Muñoz, T. Sánchez, Real time simulation of medium size gas turbines, *Energy Conversion
481 and Management* 52 (1) (2011) 713–724.
- 482 [46] M. Sharifzadeh, M. Meghdari, D. Rashtchian, Multi-objective design and operation of solid oxide fuel cell (sofc) triple
483 combined-cycle power generation systems: Integrating energy efficiency and operational safety, *Applied Energy* 185 (2017)

484 345–361.

485 [47] Y. Yu, L. Chen, F. Sun, C. Wu, Matlab/simulink-based simulation for digital-control system of marine three-shaft gas-
486 turbine, *Applied Energy* 80 (1) (2005) 1–10.

487 [48] GE, The LM2500+ Engine, see also <http://www.ge.com/> (2017).

488 [49] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, Dynamic performance simulation of an aeroderivative gas turbine
489 using the matlab simulink environment, in: *Proc. ASME IMECE*, IMECE2013-64102, Vol. 4, San Diego, USA, 2013, p.
490 V04AT04A050.