A dynamic prognosis scheme for flexible operation of gas turbines

TSOUTSANIS, Elias <http://orcid.org/0000-0001-8476-4726>, MESKIN, Nader, BENAMMAR, Mohieddine and KHORASANI, Khashayar

Published version

TSOUTSANIS, Elias, MESKIN, Nader, BENAMMAR, Mohieddine and KHORASANI, Khashayar (2016). A dynamic prognosis scheme for flexible operation of gas turbines. Applied Energy, 164, 686-701.

A dynamic prognosis scheme for flexible operation of gas turbines

Elias Tsoutsanis[a,b], Nader Meskin[a,*], Mohieddine Benammar[a], Khashayar Khorasani[c]

[a]*Department of Electrical Engineering, College of Engineering, Qatar University, Doha, Qatar*
[b]*School of Engineering, Emirates Aviation University, Dubai, United Arab Emirates*
[c]*Department of Electrical and Computer Engineering, Concordia University, Montreal, Canada*

Abstract

The increase in energy demand has led to expansion of renewable energy sources and their integration into a more diverse energy mix. Consequently the operation of thermal power plants, which are spearheaded by the gas turbine technology, has been affected. Gas turbines are now required to operate more flexibly in grid supporting modes that include part load and transient operations. Therefore, condition based maintenance should encapsulate this recent shift in the gas turbine's role by taking into account dynamic operating conditions for diagnostic and prognostic purposes. In this paper, a novel scheme for performance-based prognostics of industrial gas turbines operating under dynamic conditions is proposed and developed. The concept of performance adaptation is introduced and implemented through a dynamic engine model that is developed in Matlab/Simulink environment for diagnosing and prognosing the health of gas turbine components. Our proposed scheme is tested under variable ambient conditions corresponding to dynamic operational modes of the gas turbine for estimating and predicting multiple component degradations. The diagnosis task developed is based on an adaptive method and is performed in a sliding window-based manner. A regression-based method is then implemented to locally represent the diagnostic information for subsequently forecasting the performance behavior of the engine. The accuracy of the proposed prognosis scheme is evaluated through the Probability Density Function (PDF) and the Remaining Useful Life (RUL) metrics. The results demonstrate a promising prospect of our proposed methodology for detecting and predicting accurately and efficiently the performance of gas turbine components as they degrade over time.

Keywords: Gas turbine, Prognostics, Diagnostics, Operational flexibility, Adaptive methods

---

Highlights

- A prognosis scheme for predicting the performance of gas turbine components is presented.
- The proposed prognosis scheme takes into consideration flexible and dynamic operating conditions of gas turbines.

*Corresponding author
Email address: nader.meskin@qu.edu.qa (Nader Meskin)

- The performance of the scheme is tested under transient conditions of gas turbines.
- The proposed scheme is utilized to detect and forecast compressor fouling and turbine erosion.

Nomenclature

Acronyms

AB	Accuracy Bounds
DI	Diagnostic Index
EoL	End of Life
ERUL	Equivalent Remaining Useful Life
GPA	Gas Path Analysis
ISA	International Standard Atmosphere
NN	Neural Networks
OF	Objective Function
PDF	Probability Density Function
RUL	Remaining Useful Life

Symbols

a	coefficient of linear regression model
l	time length of diagnostic window overlap (h)
L	time length of diagnostic window (h)
$\dot{m}$	mass flow rate (kg/s)
n	total number of operating points
N	corrected shaft rotational speed
p	probability
P	pressure (Pa)
q	total number of diagnostic windows
t	time instant (h)
T	temperature (K)
$\mathbf{u}$	ambient and operating conditions vector
W	component work (W)
x	variable
$\mathbf{X}$	component characteristics vector
$\mathbf{Y}$	measurement vector

Greek

α	accuracy bound
Γ	mass flow capacity
Δ	deviation
ϵ	average prediction error
η	isentropic efficiency
μ	mean
π	pressure ratio
σ	spread

Subscript

amb	ambient
c	compressor
cl	clean
d	diagnosis
deg	degraded
des	design point
e	effective
f	fuel
inj	injected
$lreg$	linear regression
p	prognosis
$pred$	predicted
pt	power turbine
r	reference engine
ref	reference
t	turbine
th	thermal
thr	threshold
$1-6$	engine gas path station

1. Introduction

The ever-growing demand for environmental friendlier and more efficient power generation sources has triggered a diverse family of challenges that have to be met by gas turbines which are the prime movers of thermal power plants. One of these challenges involves the development of high fidelity, accurate and computationally efficient health monitoring, diagnostic and prognostic schemes for ensuring a reliable and effective gas turbine asset management [1].

Efficiency still remains as one of the top priorities of gas turbine manufacturers and users. However, there has been a significant shift towards products that can operate with increased reliability and flexibility in load following and grid supporting roles. A significant part of this shift is due to the fact that gas turbine power plants have to compensate for intermittent renewable energy sources in a more diverse energy mix. This new type and mode of gas turbine operation has been recently implemented in the Siemens Flex-Power$^{\mathrm{TM}}$ [2] and GE's FlexEfficiency$^{\mathrm{TM}}$ [3] technologies. A typical gas turbine operating profile is shown in Fig. 1.

The recent trend for increased flexibility in gas turbine operation implies that the engines are required to start up and shut down faster, and at the same time produce power at high thermal efficiency. Since the power output available from renewable energy sources is prioritized in the grid, the gas turbines will have a supporting role for fulfilling the energy demands depending on the wind capacity and the solar radiation. Consequently, majority of the gas turbine's new operating profile will be dominated by part-load operation, followed by fast start ups and shut downs as depicted in Fig. 1. This increased demand on the gas turbine flexibility has motivated the gas turbine community to evaluate the effects of this transition in terms of accuracy of diagnostic and prognostic schemes.

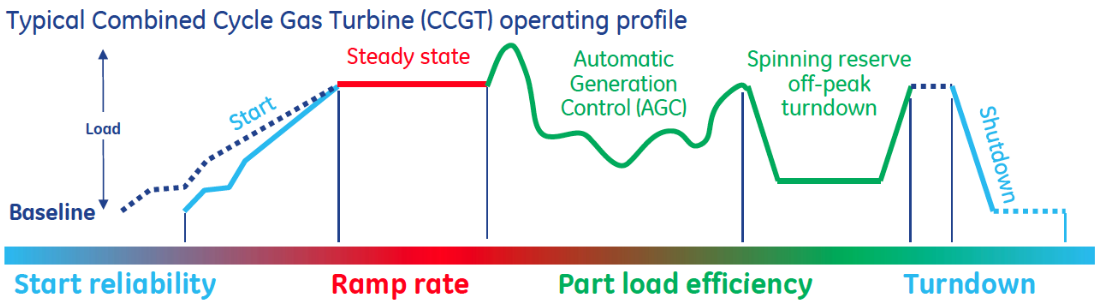


Figure 1: Flexible gas turbine operating profile [3], Courtesy of General Electric ©.

Apart from a limited number of works in the literature [4, 5, 6, 7] most diagnostic and subsequently prognostic schemes have been developed based on the steady state performance operation. Moreover, in dynamic operating conditions the useful life of gas turbine components is consumed faster than the steady state and the maintenance intervals suggested by manufacturers [8] are brought out forward, as shown from Fig. 2. The peaking unit given in Fig. 2 refers to a unit where its operational profile is characterized by an increased number of start ups and shut downs which characterize the transient conditions. The midrange unit refers to a unit that is dominated by part-load operations with a smaller number of start ups and shut downs, and the continuous unit refers to a unit that operates most of its lifetime at base load mode.

The problem of prognosis deals with prediction of the future condition of a system. The most common

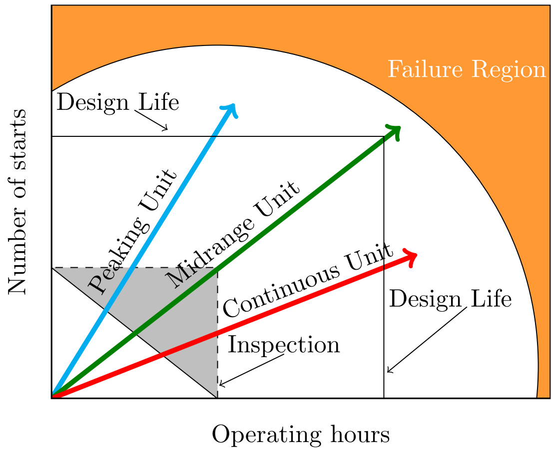


Figure 2: Gas turbine maintenance intervals for various operational modes with respect to the number of starts and operating hours as reproduced from [8], Courtesy of General Electric ©.

issue in prognostics deals with calculation of the Remaining Useful Life (RUL) [9, 10] of a life limited component of the system. In particular, for gas turbine prognostics there are several available methods, such as model-based [11], data-based [12, 13] and statistical [9, 14] approaches, although these schemes are only tested and developed when diagnosis is performed at steady state conditions. The capabilities of a prognosis scheme for implementing the engine's dynamic transient performance information has to be further investigated. Among a wide selection of methods, such as exponential models [15] and particle filtering [11, 16] that are applied for prognostics of various energy systems the most common method for gas turbine prognosis is trending through regression fitting of gas turbine component degradations as developed in [9].

In comparison to our earlier works on transient diagnostics [17, 18], in this study the proposed adaptation method is further developed and implemented for gas turbine prognostics. Specifically, the proposed prognosis scheme is not continuous as suggested in [9], where all the past diagnostic results under steady state operation were used to fit a multiple regression model based on a data skewness criterion. In contrast to [9], in this study a linear regression method is implemented that is based on a local window-based segment. Furthermore, the proposed scheme takes into consideration the transient operations, variable ambient conditions as well as multiple component degradations.

Our proposed prognosis scheme within a local window-based segment is fundamentally different from the conventional forecast of engine health and RUL based on pattern recognition methods that utilize the entire historical operating data of the engine. The main reason for this change in the prognosis approach lies in the fact that most existing gas turbine prognosis schemes [1, 12, 13] rely on diagnostic methods that have been tested only for steady state operating conditions. In addition, for model-based diagnostic algorithms, such as the Gas Path Analysis (GPA), it is a common practice to take into account engine historical data that are close to the International Standard Atmosphere (ISA) conditions to minimize the uncertainty involved with measurement corrections when these are corrected back to ISA conditions [9]. This type of correction enables the gas turbine users to compare the health of their gas turbine assets, expressed in terms of the component efficiency and mass flow rate, with the ones that are provided by the manufacturer at the ISA conditions.

Given that the gas turbine's role is becoming more flexible, the rate of engine component degradations at such dynamical operational modes will significantly change their degradation patterns and their corresponding RUL will be shorter. Performing prognostics that take into account the entire set of operational data which encapsulate the increased number of the firing start ups, shut downs and extended periods of inactivity for the new type and mode of flexible operational gas turbines will produce results that will be difficult to interpret for condition based maintenance. It is more practical and realistic for such types of flexible gas turbine units to forecast the engine components health for a shorter time frame that will be based upon the previous diagnostic results window that cover only the recent history of the engine operation. Therefore, the proposed prognosis scheme may provide the gas turbine users with an improved insight on the engine's health at such dynamical operating conditions.

Generally speaking, the accuracy of a prognosis is dependent on the diagnosis accuracy. From a series of available gas turbine diagnostic methods [19] such as model-based GPA [9] and data-based [20, 21, 22] approaches only a few [7, 23, 6, 24, 4, 5] have been tested for transient conditions. This study will develop and implement an adaptive diagnostic method that has been successfully applied and tested for engine dynamical conditions in our earlier work [17]. The advantage of this approach is that it can satisfy at a high level of accuracy and low computational complexity and time a set of objectives ranging from the component map reconstruction and the engine model tuning up to an effective diagnosis of degradations that are experienced by multiple engine components [25].

An additional challenging aspect of the prognosis task is the fact that model-based gas turbine diagnostic methods are heavily relying on the engine model [1]. On principle the accuracy of a gas turbine model depends on detailed understanding of its components behavior as captured by component performance maps. The former challenges have been effectively addressed in our earlier works [26, 18], where a number of component map modeling approaches have been proposed and implemented in a dynamic engine model that was developed in Matlab/Simulink, and successfully tested for the gas turbine performance adaptation. It is well-known that model-based gas turbine prognostics is a challenging task since it integrates a series of processes and suggested technologies [27].

Our proposed method is applied to a model of a two-shaft gas turbine that is injected with soft multiple component degradations over time to illustrate and demonstrate the effectiveness of our approach. The capabilities of our proposed method are evaluated for predicting multiple component degradations when the engine operates under variable operating and dynamical performance conditions for a period of up to 25,000

h. A series of prognosis performance metrics, as suggested by Saxena et al. [28], have also been developed and implemented to assess the accuracy of the proposed prognosis scheme. The proposed prognostic method has the capability to enhance and refine the current gas turbine performance prediction approaches, and to improve and extend performance-based prognostic techniques.

To summarize, the main contributions of this paper are as follows. First, the prognosis of an engine component performance degradation for an industrial gas turbine operating under dynamical conditions is investigated by using an adaptive diagnostic and prognostic scheme. In contrast to our earlier works [17, 18], where the concept of performance adaptation was developed and implemented only for diagnostics, this study extends the corresponding scheme for prognostic purposes. Specifically we propose a sliding-window based performance adaptation concept that can effectively deal with prediction of multiple engine component degradations. Therefore, detecting and predicting the health of multiple engine components that degrade with respect to time time under dynamical conditions through the use of a new sliding window based performance adaptation method is developed and examined for the first time in the literature, to the best of the authors knowledge. In contrast to other available prognostic approaches in the literature, such as those in [9, 11, 12, 13, 14], our proposed scheme is capable of predicting effectively the component degradations under dynamical operation and variable ambient conditions. By using a regression method for fitting the diagnostic results of each diagnostic window, the health of each engine component can be accurately and efficiently predicted. Finally, we assess the accuracy of our proposed prognosis scheme by evaluating the equivalent RUL of each component and the probability of the distributed prognostic results to lie within the acceptable levels of accuracy.

The remainder of this paper is organized as follows. In Section 2, the assumptions and the methodology for the proposed scheme that integrates performance adaptation, diagnostic and prognostic capabilities is described. The description of the case studies is presented in Section 3. Simulation results of the proposed approach are presented in Section 4, followed by the conclusions in Section 5.

2. Methodology

2.1. Assumptions

Generally speaking, the gas turbine degradation is heavily influenced by various factors such as ambient and operating conditions, manufacturing tolerances and imperfections that make the task of prognosis quite challenging one. In this context, several prognostic schemes have been developed and applied for gas turbines and this emphasizes the fact that there does not exist a unique approach to cover effectively such a wide range of degradation scenarios. However, in order to make the proposed scheme more generic and applicable to real engine applications the following assumptions are made in this study:

- Only soft engine performance degradations due to the compressor fouling and turbine erosion that are developed over time are examined.

- The ambient conditions and engine operational mode are variable and dynamic, respectively and represent the ever growing demand for flexibility in a gas turbine operation.

- The degradation patterns examined for the compressor fouling and turbine erosion are monotonically increasing or decreasing depending on the examined type of component degradation.

- The degradation patterns that are examined are independent of maintenance actions and are mainly attributed to the aging of the component. For instance, when the compressor is experiencing fouling the lost efficiency and mass flow capacity cannot be fully recovered by offline washing and such an unrecoverable degradation accumulates over time.

- The component degradations are described by deviations of isentropic efficiency and mass flow capacity from their clean/healthy values.

2.2. Performance Adaptation

The concept of performance adaptation is the process of tuning the nonmeasurable component parameters, such as the mass flow capacity and isentropic efficiency, of an engine model in order to match the measurable engine performance parameters, such as the temperature and pressure along the gas path, of a reference engine. The process involves, invokes and implements an optimization algorithm for minimizing the residuals between the performance parameters of the model and the reference engine, as depicted in Fig. 3. Such a method forms the foundation of refining an engine model and matching it to the engine under investigation.

The advanced performance adaptation approach that is empowered by a novel component map generation scheme is the one that was developed by the authors in [17, 18] and has been also used in this study. A brief description of this method follows. Generally the engine behavior, assuming there is no presence of measurement noise and bias, can be expressed as follows:

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

where $\mathbf{Y}$ denotes the engine performance vector consisting of the measurable parameters, $\mathbf{X}$ denotes the component characteristic vector that consists of nonmeasurable parameters and $\mathbf{u}$ denotes the ambient and operating conditions vector consisting of ambient conditions and a control input parameter called handle that can be either fuel flow rate, rotational speed or any other quantity.

The engine performance vector can be either the field data of a service engine or simulations from a different engine model. To conduct testing of our proposed method two engine models are used. The

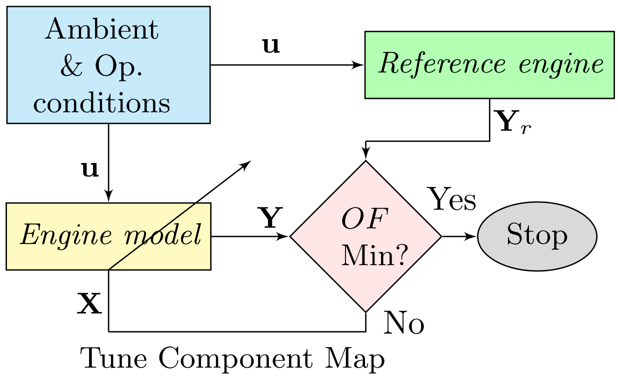


Figure 3: The flow chart of the performance adaptation process.

engine model that uses the performance maps of PROOSIS [29] gas turbine simulation software is going to be referred to as the *reference engine*. The second engine model implements the advanced map modeling method that was developed by the authors in [18] and is going to be referred to as the *engine model*.

For this study, the difference between the predicted $\mathbf{Y}$ by the *engine model* and the observed $\mathbf{Y}_r$ measurements from the *reference engine* is evaluated by means of an Objective Function (OF) that is defined as follows:

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

where n denotes the total number of operating points and $\mathbf{Y}_i$ and $\mathbf{Y}_{r_i}$ denote the $i-th$ predicted and measurable performance vector, respectively. Further details regarding the performance adaptation can be found in [17, 18].

2.3. Adaptive Diagnostics

Performance degradation of an engine component is represented by deviation of its parameters from their nominal/clean/healthy values. The deviation of a component parameter such as the mass flow capacity $\Delta\Gamma$ can be expressed as the absolute difference between the degraded Γ_{deg} and the clean Γ_{cl} divided by the clean Γ_{cl} as follows, i.e. $\Delta\Gamma = \left|\Gamma_{deg} - \Gamma_{cl}\right| / \Gamma_{cl}$.

In order to emulate such a component degradation deviations in the mass flow capacity and efficiency of each component of the reference engine are injected. Therefore, the nominal/clean/healthy vector $\mathbf{X}_{r_{cl}}$ which is the output of the component map is multiplied by a time dependent injected deviation signal $\Delta\mathbf{X}_{r_{inj}}$ that results in a deviated component vector $\mathbf{X}_{r_{deg}}$. Consequently, the *reference engine* operates at degraded conditions and produces a new set of degraded measurable parameters $\mathbf{Y}_{r_{deg}}$, as schematically depicted in Fig. 4.

The injected deviations of the component vector $\Delta\mathbf{X}_{r_{inj}}$ can be expressed as a function of time t, i.e. $\Delta\mathbf{X}_{r_{inj}} = g(t)$. The type of the function g depends on the degradation pattern that each component

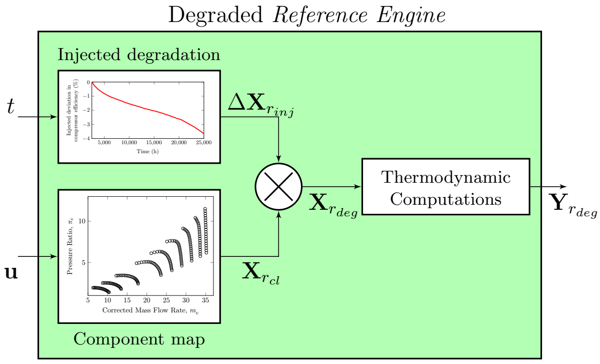


Figure 4: Representation of time dependent injected degradations into the engine component.

experiences. In this study component degradation patterns such as the ones shown in Fig. 5 will be examined. When the engine operates under dynamical conditions the degradation of the engine components evolves faster than that at steady state conditions, as shown in Fig. 5, where it is assumed that the rate of component degradation due to aging is represented as a drop of -1% per year in the health component parameter. The health component parameter simply refers to the mass flow capacity and the efficiency. Typical values of degradation rates with respect to the above health indicators depend on the engine type and its operating conditions [30]. The former observation highlights the importance and the challenging aspect of predicting the performance of engine degraded components when the gas turbine is operating at dynamical transient conditions.

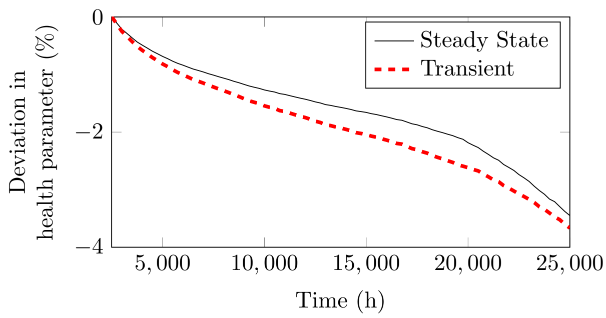


Figure 5: Typical engine health parameter deviation with respect to time for 25,000 h of steady state and transient engine operations.

The objective of the diagnosis problem is to determine the level of degradations that are injected in the components of the *reference engine*. This is achieved by minimizing the observed residuals between the component parameters of the *reference engine* and the *engine model* through implementation of the performance adaptation methodology [17].

It should be emphasized that the performance adaptation scheme has the capability of generating and tuning a set component maps to match the engine measurements for a wide range of operating conditions.

Once each component map is fed with its corrected rotational speed and pressure ratio inputs, its corresponding outputs that are the mass flow rate and the efficiency are determined and subsequently used for thermodynamic computations. For simulating the time evolving component degradation the outputs of the maps are injected with time dependent signals as shown in Fig. 4, before their utilization for the thermodynamic computations. Therefore, the degraded *reference engine* might operate under the same operating conditions (inputs) as the clean *reference engine* but their outputs will be different since the time dependent injected faults alter the initial clean/healthy output of the component map. The complexity of decomposing the time parameter in the estimated degraded component parameters can be resolved by partitioning the diagnostic results into smaller time increments so that the adaptation approach can handle. Therefore, in this work a sliding window-based method is proposed that has the advantage of filtering out the effects that time-dependent injected degradations have on the adaptation procedure.

From the bank of available degraded data, the diagnostics tasks are performed through a set consisting of q sliding windows that cover the entire range of the available data. On a local level, each window that is initiated at the time instant t_d has a width of L that includes n operating points as shown in Fig. 6. The n operating points corresponding to each window refer to the samples of data that one may utilize to perform the diagnostic analysis and is different from the total number of measurement data that are available within the time frame of width L. The n operating points corresponding to each window refer to the samples of data that one may utilize to perform the diagnostic analysis and is different from the total number of measurement data that are available within the time frame of width L. The number of operating points n selected for an analysis depends on how sensitive it would be to the data resolution. If the total data captured in a time width L is of high resolution having repeated values and at the same time present a uniform distribution, then one may reduce the data samples that are utilized for a diagnostic analysis to a number n to reduce the computational time without sacrificing the diagnostic accuracy. Several data reduction and smoothing techniques could be implemented for accomplishing the above. The above method is more practical and suited for real applications given that the gas turbine users may not have access to high quality engine data for covering a wide range of operational history of the engine.

For each diagnostic sliding window, the *engine model* matches the degraded measurements of the *reference engine* by generating a new set of component maps that form the degraded vector $\mathbf{X}_{deg}$. The initial adaptation of the *engine model* is in fact a training phase for the fault diagnosis task given that it acts as the reference frame for the engine healthy/clean condition.

Another key aspect of the above process is that the time t_d when the adaptive diagnosis is initiated and the time t_e when the proposed scheme starts detecting the component degradation effectively are different. This occurs due to the fact that the proposed diagnostic algorithm requires time to tune itself with the degradation progression data before it can reach an accurate diagnosis. Therefore, the sliding windows for diagnostic analysis overlap with one another at a data length of l as shown in Fig. 7. It follows that at

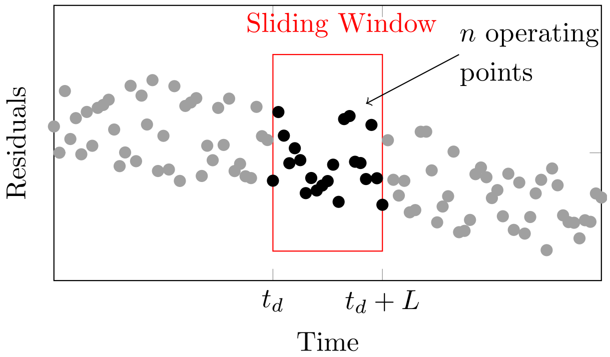


Figure 6: Representation of the sliding window-based diagnostic parameters.

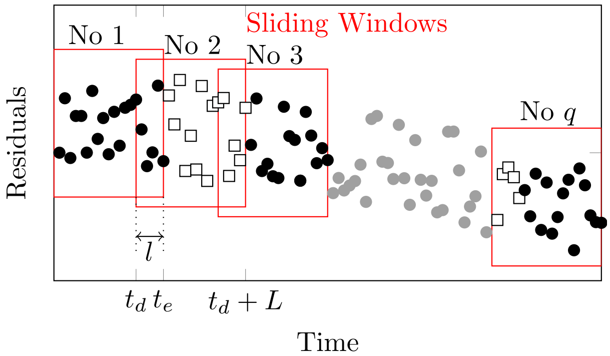


Figure 7: Representation of the overlap between the sliding windows that are used for the diagnostic problem.

the diagnostic window No. 2, the process is initiated at t_d and only the diagnostic information after t_e that is depicted as squares is considered. For the region between t_d and t_e, the diagnostic information refers to the previous window No. 1. This process is repeated until the final set of data is used in the final window No. q. A Diagnostic Index (DI) as described in [18] is now utilized to assess the accuracy of the diagnosis information and is defined as follows:

$$DI = 100\left(\frac{1}{1+\epsilon}\right) \tag{3}$$

where ϵ denotes the mean error in the component vector $\mathbf{X}$. Consequently, the accuracy level that component maps are optimized to match the degraded measurements is evaluated according to:

$$\epsilon = \frac{\sum_{i=1}^{n}\left|\frac{\Delta\mathbf{X}_{pred_i} - \Delta\mathbf{X}_{r_{inj_i}}}{\Delta\mathbf{X}_{r_{inj_i}}}\right|}{n} \tag{4}$$

2.4. Prognostics

Prognosis is concerned with the prediction of the engine future health that is analyzed with the adaptive performance diagnostic method for all the past operating points. The main objective of the adaptive prognosis scheme is to forecast the performance of each engine component that degrades over time for a specific prognostic window.

Taking into consideration the fact that the sliding window-based diagnostic approach partitions the degradation pattern into smaller time increments, it is reasonable to assume that at such a local scale the engine components performance degrades linearly with time. In order to ensure that the degradation pattern will be linear at such a local scale, data analysis methods such as the Probability Density Functions (PDF), the skewness and kurtosis criteria [10] could be utilized to investigate the data distribution and estimate whether the rate of degradation satisfies the above assumption. Once this is performed then the data can be effectively handled by the sliding window diagnostic method. A wide spread PDF or sign changes in the skewness of data distribution [9] can indicate an increase or decrease in the degradation rate and can serve as guide for tuning the width L of the diagnostic windows. For this study, the diagnostic windows had fixed width L but one could easily modify this as stated above.

This observation allows one to perform the prognosis on a local window level instead of using the complete set of the past diagnostic windows. Therefore, a regression model can be used to determine the function h by which the degraded component parameter $\Delta\mathbf{X}_{lreg}$ varies with respect to time t as follows:

$$\Delta\mathbf{X}_{lreg} = h(t), t \in [t_d, t_d + L] \tag{5}$$

The linear regression method [9, 31] was implemented for this case. Therefore, the function h is obtained by:

$$h(t) = a_1 t + a_2, t \in [t_d, t_d + L] \tag{6}$$

where the coefficients a_1 and a_2 are determined based on a least square minimization scheme. Once the degradation pattern is fitted accurately through the linear regression model, the health of the engine component is predicted for a prognostic window of time with width M. The accuracy of the prognosis is determined by comparing the obtained results with the actual *reference engine* degradation data $\Delta\mathbf{X}_{r_{inj}}$ and by determining the probability of this distribution to lie within specified accuracy bounds.

The next step of this process involves the utilization of the PDF in order to estimate the likelihood of the fitted regression model to take any given value. Among several probability distributions available, the most common for statistics and forecasting is the normal (Gaussian) distribution. The advantage of the normal distribution that has the characteristic bell-shape curve is that it is simple to manipulate mathematically and derive results that can be easily interpreted. Therefore, the normal distribution is going to be implemented in this study. The PDF of the normal distribution for a variable x is as follows:

$$f(x) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right) e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \tag{7}$$

where x in this study refers to the degraded component parameter $\Delta\mathbf{X}_{lreg}$ and μ denotes its mean with a standard deviation of σ.

In order to compute the total probability of the distribution that lies within the specified Accuracy Bounds (AB) $[\alpha^-, \alpha^+]$ of the actual degradation, the PDF is integrated as follows:

$$p = \int_{\alpha^-}^{\alpha^+} f(x)dx \tag{8}$$

The integral has a maximum of 1 and a minimum of 0 when the entire PDF lies inside or outside the AB of the actual degradation, respectively. The actual degradation accuracy bounds at time t_p when prognosis is initiated are given by the following equations:

$$\alpha^-_{(t_p)} = x^\alpha_{(t_p)} - \alpha x^\alpha_{(t_p)} \tag{9}$$

and

$$\alpha^+_{(t_p)} = x^\alpha_{(t_p)} + \alpha x^\alpha_{(t_p)} \tag{10}$$

where α denotes the level of accuracy and $x^\alpha_{(t_p)}$ refers to the actual deviation in the component parameter $\Delta\mathbf{X}_{r_{inj}}$ at the time instant t_p. The AB of 90% implies that the value of α is 0.10. It should be emphasized that in real gas turbine applications the component degradation $\Delta\mathbf{X}_{pred}$ can only be estimated and the actual degradation such as $\Delta\mathbf{X}_{r_{inj}}$ remains an unknown.

The AB of the actual degradation which is based on the injected degradation $\Delta\mathbf{X}_{r_{inj}}$ is not used here as a direct prognosis accuracy metric, but it is only an indication of how the prognostic results are distributed with respect to the actual degradation. Therefore, the PDF of the distributed prognostic results $\Delta\mathbf{X}_{lreg}$ that are implemented here can serve as a guide for evaluating the width L of the diagnostic window that is used for the prognosis. A PDF that has a wide spread indicates that the past diagnostic window could be further partitioned into smaller time width L in order to achieve a PDF that has a narrower spread, and therefore the prognosis will be more reliable. A schematic representation of the PDF for the normal distribution of linearly regressed component parameter $\Delta\mathbf{X}_{lreg}$ with respect to the diagnostic predictions $\Delta\mathbf{X}_{pred}$ within the AB $[-\alpha, \alpha]$ corresponding to the actual degradation $\Delta\mathbf{X}_{r_{inj}}$ is shown in Fig. 8.

The final step in the prognostic process is to estimate the RUL of the engine components. Generally the gas turbine users have *a priori* information that is specified by the manufacturer for the End of Life (EoL) of the engine. This EoL criterion is associated with a performance threshold associated with the degraded component parameters $\Delta\mathbf{X}_{thr}$, beyond which maintenance actions should be performed. Majority of the gas turbine prognostic approaches [16, 32, 9] compute the RUL based on the estimate of the components degradation and by projecting the fitted degradation results to future. The latter is used in order to

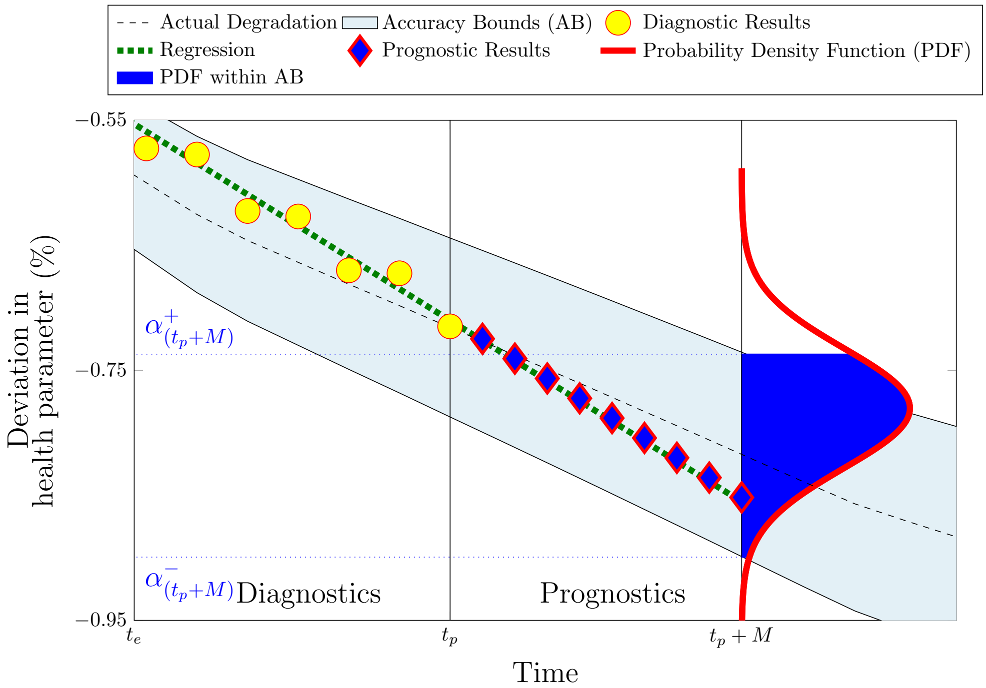


Figure 8: The PDF for the normal distribution of the degradation as predicted by the regression method at time t_p. The blue filled section of the curve represents the amount of this PDF that lies within the accuracy bounds $[\alpha^{-}, \alpha^{+}]$ of the actual degradation. The diagnostic results are depicted in yellow filled points.

evaluate how pessimistic or optimistic their prediction is with respect to the EoL which is normally based on steady state operation as presented by Li and Nilkitsaranont [9].

For a gas turbine operation that is dynamic the corresponding degradation pattern will change and consequently the RUL cannot be mapped to typical component degradation estimations that occur at steady state. Moreover, the main principle of our proposed prognostic scheme is to move away from conventional approaches [33] of projecting the fitted degradation pattern into future time until a specified value of the component degradation is reached and a probability is assigned to this final prediction. The proposed scheme is performed under a discrete window-based level that focuses on the pattern by which the engine components degrade over time and a PDF is assigned to the predicted degradation pattern itself at the end of each prognostic window.

Therefore, in this study we utilize an alternative methodology to the RUL metric that is designated as the Equivalent RUL (ERUL). This will be mapped only to the level of component degradation that is detected and not based on the projected line of the prognostic results that meets a specific level of degradation. Let us now make a reasonable assumption that if the diagnostic process is initiated at time t_d with a degraded health component parameter $x_{(t_d)}$, the threshold corresponding to the degraded health parameter $x_{(t_{EoL})}$ would be reached at the maximum number of operating hours as suggested by the manufacturer EoL. This is shown in Fig. 9.

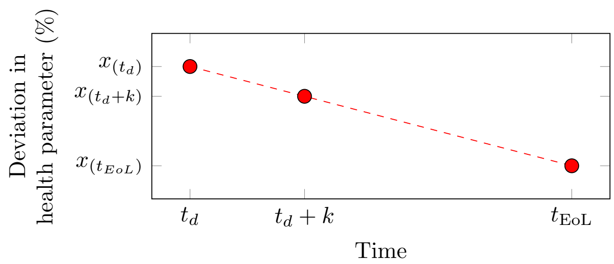


Figure 9: Representation of the component degradation parameters with respect to time as used for estimation of the ERUL.

The above assumption allows one to compute the ERUL at a time instant $t_d + k$ by associating it with the degradations that are detected as follows:

$$\mathrm{ERUL}_{(t_d+k)} = -(t_{\mathrm{EoL}} - t_d)\left(\frac{x_{(t_{\mathrm{EoL}})} - x_{(t_d+k)}}{x_{(t_{\mathrm{EoL}})} - x_{(t_d)}}\right) + (t_{\mathrm{EoL}} - t_d) \tag{11}$$

where the variable $x_{(.)}$ refers to the degradations in the component parameters $\Delta\mathbf{X}_{lreg}$ as predicted by the regression method. The major difference between the conventional RUL and our proposed ERUL is the fact that the latter is mapped directly to the degradation pattern at each time instant. Moreover, by taking into account that this pattern is partitioned into several linear segments one may compute the ERUL without having the entire operational history of the engine.

Finally, accuracy bounds similar to the ones described earlier are utilized to represent the true ERUL that is based on the actual degradation of the component parameters $\Delta\mathbf{X}_{r_{inj}}$. Therefore, the ERUL for each component can be approximated by and compared with the true ERUL. The ERUL also reflects the rate that an engine component 'consumes' its life depending on the engine operating conditions.

To summarize, the prognosis procedure that is depicted in Fig. 10, is described as follows:

- Adapt the *engine model* to *reference engine* corresponding to a wide range of operating conditions. This will be used as the reference for future diagnostic analysis.

- The *engine model* is readapted to the new degraded conditions and match the component parameters of the degraded *reference engine* by implementing the sliding-window method.

- Once diagnosis is performed, the diagnostic results that are available in the diagnostic window are fitted by the regression method and the future health of each component is estimated. The prognostic window associated with the linear regression is determined by the user.

- The probability of the distributed prognostic results to lie within certain accuracy bounds of the actual degradation is assessed by implementing the PDF of the normal distribution.

- The capability of our proposed method to predict the engine health accurately is evaluated through the use of the RUL metric and the time before main maintenance actions can be estimated.

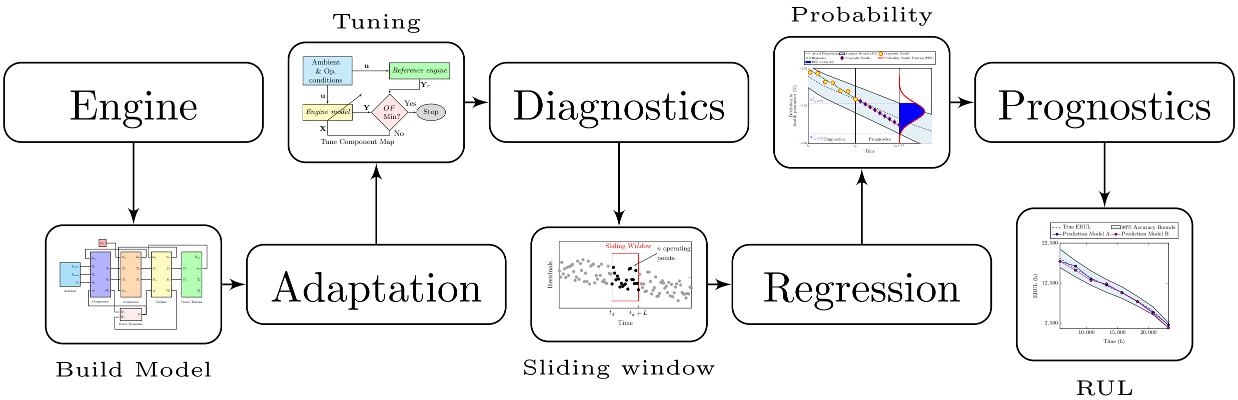


Figure 10: The flow chart of our proposed adaptive prognosis scheme.

2.5. Gas Turbine Model

The proposed diagnostic and prognostic approaches introduced and developed in previous subsections are now integrated with a dynamic model of a two shaft industrial gas turbine developed in Matlab/Simulink environment and validated with PROOSIS [29]. The average error that is observed between the PROOSIS measured output and the simulated output of the initial developed engine model was of the magnitude of 1% in [34] which was further reduced to 0.1% through the implementation of the performance adaptation in [26, 18]. The engine model consists of a compressor, a combustor, a compressor turbine and a power turbine as shown in Fig. 11. A detailed description of the model used for this application can be found in our earlier works in [34, 18].

3. Case Study Description

Our proposed prognosis scheme is implemented in a dynamic engine model [18, 34] and is evaluated and analyzed under transient conditions. Analysis of the diagnostic and prognostic results and discussions are provided in the subsequent results section 4.

One of the prerequisites for a successful adaptive diagnosis and prognosis scheme is that the engine measurable parameters are directly influenced by the component characteristic parameters to be adapted. Our primary objective for presenting the case studies is to evaluate and illustrate the achievable accuracy improvements of our proposed schemes that incorporate the performance adaptation, adaptive diagnostics and prognostics and take into consideration the above prerequisite. Therefore, the selection of the inlet and outlet measurements of the degraded components are well justified. The list of the selected input and

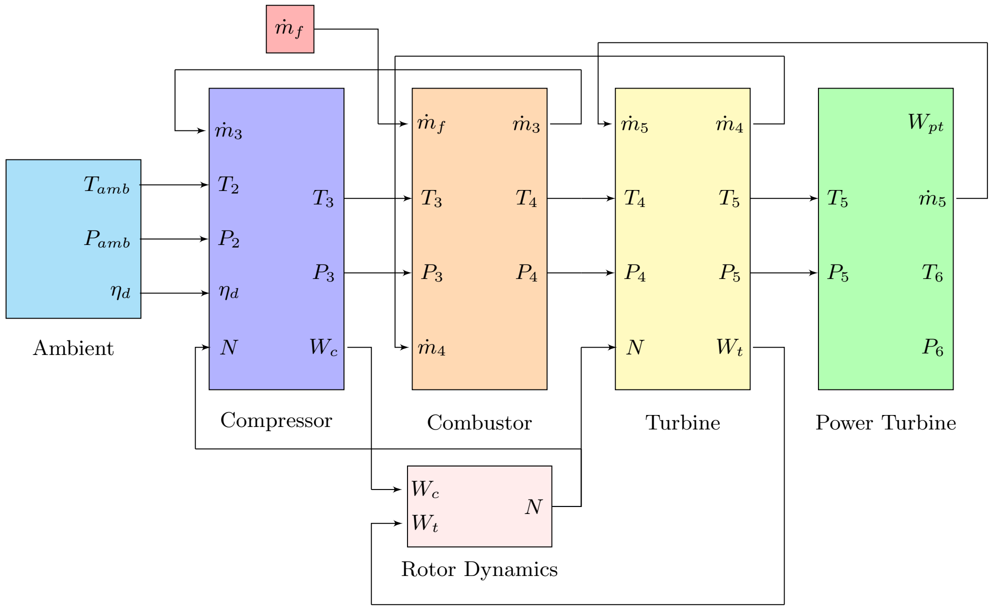


Figure 11: The two shaft industrial gas turbine engine model layout that is developed in Matlab/Simulink. For definitions of variables, refer to the Nomenclature section.

measurable parameters for the adaptive performance diagnosis and prognosis are provided in Tables 1 and 2, respectively.

Table 1: The engine input parameters.

Symbol	Parameter	Units
P_{amb}	ambient pressure	Pa
T_{amb}	ambient temperature	K
$\dot{m}_f$	fuel flow	kg/s

Performance specifications of the *reference engine* are shown in Table 3. The nominal operating point that is chosen as the model design for this configuration is at 3.4 MW with the fuel flow rate $\dot{m}_f$ set as the control input of the engine. At this point it should be noted that both diagnosis and prognosis are concerned with the difference Δ between the estimated and observed measured output of the engine and not the actual output itself. Consequently, the main objective of this scheme for assessing and evaluating the accuracy and performance of diagnosis and prognosis at dynamic operating conditions is independent of the actual measured parameters and design specifications of a gas turbine. The design specifications of a gas turbine play an important role in the model adaptation phase where component maps have to be generated and tuned to match the performance of such an engine. This is a topic that is extensively covered in our

Table 2: The 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
P_5	turbine exit pressure	Pa
T_5	turbine exit temperature	K
P_6	exhaust gas pressure	Pa
T_6	exhaust gas temperature	K
W_{pt}	power output	Watts
N	shaft rotational speed	rpm

Table 3: Performance specifications of the *reference engine*.

Symbol	Parameter	Value	Units
W_{pt}	Power	3.4	MW
π_c	Pressure Ratio	10.8	
η_{th}	Thermal efficiency	38	%
$\dot{m}_4$	Exh. flow rate	34	kg/s

earlier works. [18, 35].

It is important at this point to describe how the data corresponding to the *reference engine* are produced. The simulation step size that is used in Simulink for the case studies examined is set to 1 ms. The total simulation run time is 100 s and this results in 100,000 data samples. Since the objective of this study is to examine the maximum amount of degradation that each component is experiencing for a total of 25,000 h of operation, the available results should be correlated to represent this time interval. It is therefore assumed that 4 operating points correspond to one hour of operation. This implies that we capture the behavior of the engine every 15 minutes. The large size of the data samples ensures that the dynamic effects of the engine behavior are present during this analysis. For instance, a transient operating point at the time instant t_1=1 h will follow by another transient operating point at the time instant t_2=1 h and 15 min. On a global scale the collection of the operating points as the engine degrades over time are representative of the engine's dynamic behavior. This follows due to the fact that the selected fuel flow, which is the control parameter in the simulation model, is random and highly nonlinear for this time interval. Therefore, the dynamic effects of the engine are not sacrificed during this correlation analysis and mapping of the available data.

It follows that in order, to make the case studies more realistic and representative of the dynamic engine behavior, both the ambient and operating conditions acting as inputs to the models are not considered constant and instead change with respect to time. The fuel flow schedule for this study is depicted in Fig. 12. The ambient conditions are simulated so as to be periodic both on a daily basis as well as a yearly basis and the resulting ambient temperatures are shown in Fig. 13.

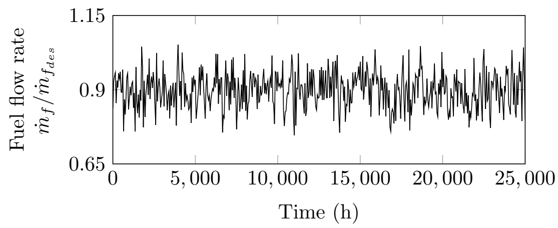
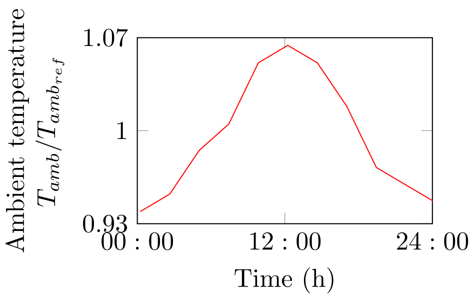
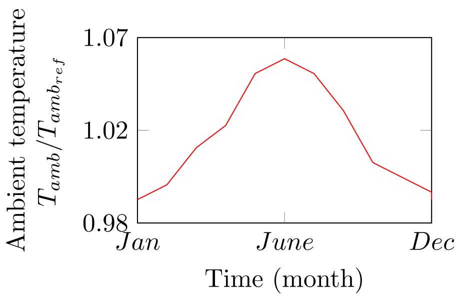


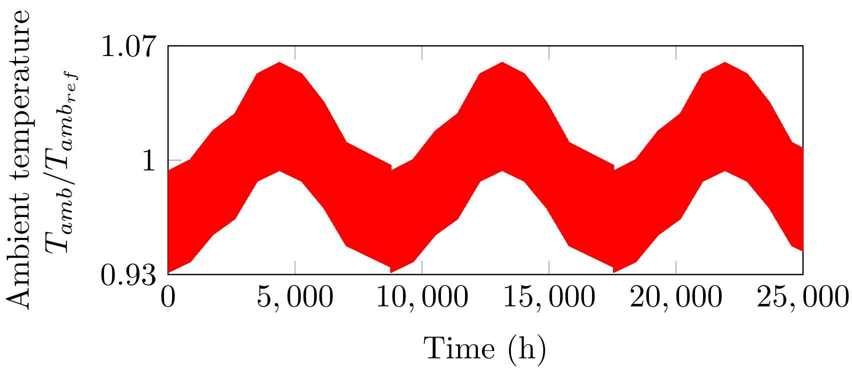
Figure 12: The variation of the fuel flow rate with respect to time.



(a) Temperature variation for 1 day.



(b) Temperature variation for 1 year.



(c) Temperature variations for 25,000 h.

Figure 13: The variation of ambient temperature with respect to time.

The required data for case studies are generated by performance simulations of the *reference engine* at degraded conditions, where prognosis is performed at different instants of the data time series. The degraded conditions are represented by injecting deviations $\Delta\Gamma$ and $\Delta\eta$ in the mass flow capacity and efficiency into the *reference engine*, respectively. The range of injected deviations is summarized in Table 4.

Table 4: Injected deviations of the component parameters.

Component	Degradation	Parameter	Deviation Range (%)
Compressor	Fouling	$\Delta\Gamma_c$	0-(-1.8)
		$\Delta\eta_c$	0-(-2.7)
Turbine	Erosion	$\Delta\Gamma_t$	0-(2.5)
		$\Delta\eta_t$	0-(-1.8)
Power Turbine	Erosion	$\Delta\Gamma_{pt}$	0-(2.5)
		$\Delta\eta_{pt}$	0-(-2.7)

Two case studies are conducted. The objective of the first case study is evaluate the capability of the adaptive sliding window diagnostic method to detect accurately the injected degradations. The required measurements for the first case study are generated by performance simulations of the *reference engine* at degraded conditions.

The objective of the second case study is to prognose the performance behavior of each component based on the diagnostic results of the first case study. This is accomplished by the linear regression model on a local and discrete window-based method that takes into consideration only data from the previous diagnostic window. This specific proposed prognosis method will be designated as the Model A. In addition, the prognostic method that was suggested in [9], and that takes into account all the past diagnostic results on a global scale, is adopted and will be designated as the Model B, for facilitating its comparison with Model A.

In terms of the diagnostics, the Model B employs the adaptive diagnostic method that was developed by the authors and not the GPA method [9]. The GPA method that is used in [9] implements steady state data, however our adaptive diagnostic method can deal effectively with transient operations. This is conducted intentionally since uncertainty or improved accuracy that is provided by different diagnosis schemes should be filtered out in order to focus solely on the capability of each method to predict the engine performance, and therefore ensure that the comparisons among them are more realistic. The accuracy of the prognosis scheme is evaluated by means of the PDF and the RUL in order to compare these results with the actual degradation and actual RUL.

4. Results and Discussion

Our proposed prognosis scheme now is tested under dynamic transient conditions. The results for each case study are presented and discussed in the following subsections.

4.1. Diagnostics - Case Study 1

The objective of the first case study is to evaluate the accuracy of our proposed adaptive diagnostic methodology. This forms the foundation by which the prognosis will be developed and evaluated. Before commencing the diagnostic process, one needs first to adapt the *engine model* to the healthy *reference engine* for a wide range of operating conditions. This initial adaptation is the benchmark by which deviations in the component parameters will be determined subsequently. Therefore, degradation is injected to the engine component at t_d=2,500 h. The first set of data up to t_d is used for the initial adaptation of the *engine model* and represents the nominal/clean/healthy condition of the engine.

The diagnosis process is initiated at t_d on a sliding window manner, where the width L of the diagnostic window that is used here is L=3,000 h, and the length of their overlap is l=500 h. The total number of q diagnostic windows that are used is 9 and the number of operating points n that are utilized for detecting the degradation in each diagnostic window is 100.

The diagnostic results of this case study for the compressor isentropic efficiency are shown in Fig. 14. The capability of our developed adaptive diagnostic method that implements the sliding window method is clearly shown to be able to deal effectively with time dependent degradation process.

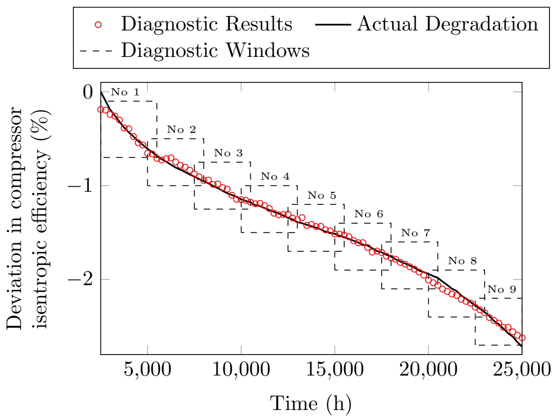


Figure 14: The compressor isentropic efficiency as predicted by our proposed diagnostic method for the specified windows.

The mean error for each diagnostic window is shown in Fig. 15, where it follows that the average error is below 0.1% for all diagnostic windows. As expected, the error is more evident in the first and the last group of diagnostic windows. The reason for this behavior is that for certain diagnostic windows the gradient of

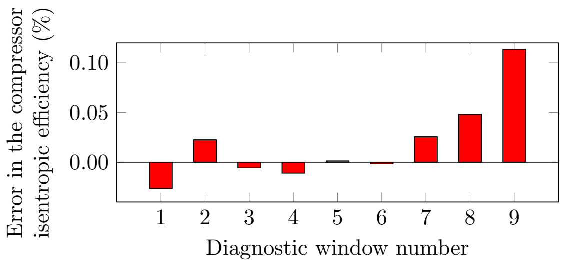


Figure 15: The average diagnostic error for the compressor isentropic efficiency for each diagnostic window.

the deviated component parameter is relatively greater than the other windows, and therefore this leads to a more challenging situation for the adaptive diagnostic method.

The diagnostic index associated with our proposed methodology for the compressor isentropic efficiency is obtained as 0.99. This implies that our diagnosis is 99% effective. The same level of diagnostic accuracy is achieved for all the degraded components of the engine. This case study results demonstrate the promising prospect of our adaptive diagnostic method for diagnosing accurately degradations of gas turbine engine components. This high accuracy performance of the diagnosis scheme is now shown to be transferable to the prognostics case study that follows in the next subsection.

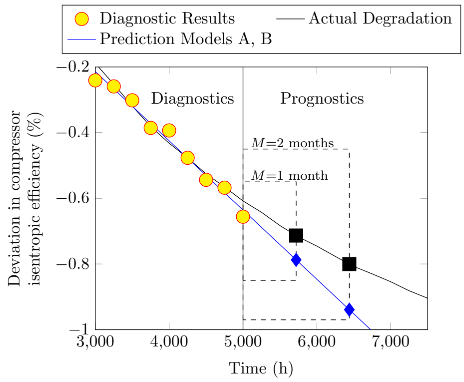
4.2. Prognostics - Case Study 2

The objective of the second case study is to evaluate and demonstrate the accuracy of our proposed prognosis scheme under transient conditions. Prognosis is initiated at different data points instants based on the local or global past diagnostic results for Model A and Model B, respectively. The capability of our method is assessed by determining the accuracy of the prognosis subject to forecasting the performance of each component and then comparing it with the actual degradation as injected to the *reference engine*.

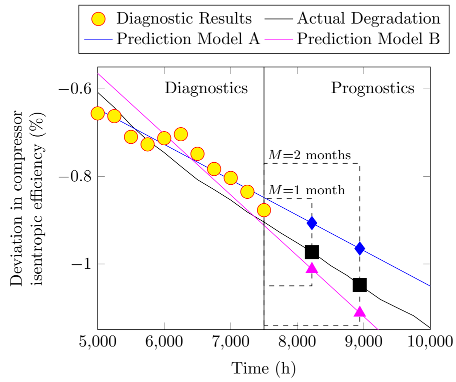
The prognosis process starts at t_p=5,000 h and is conducted every 2,500 h until one reaches the 22,500 h of operation. Two prognostic windows of M=1 month and M=2 months width are used. In terms of the operation and maintenance strategy of industrial gas turbines the specific width M of the prognostic window corresponds to a practical time frame that facilitates gas turbine users to plan in advance for forthcoming maintenance activities depending on the engine condition.

The number of diagnostic results in each window that is utilized for forecasting the engine component performance is denoted by n and is set to 100. This number is always fixed for the Model A that implements only the diagnostic results of the previous diagnostic window. In case of Model B that builds upon the entire set of past data, the number n increases with respect to time. The compressor isentropic efficiency deviations that are predicted by Models A and B are shown in Figs. 16 and 17, corresponding to different initiations times.

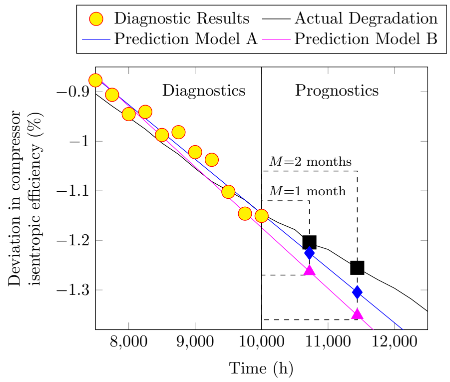
As can be observed from Figs. 16 and 17, the Model A provides more accurate component performance



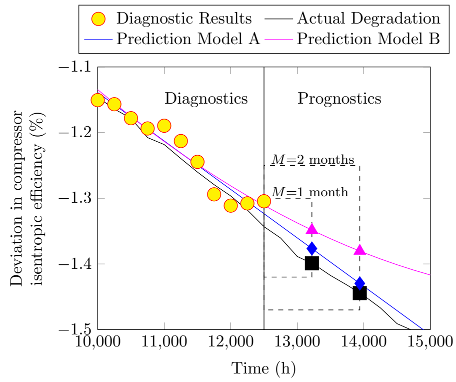
(a) Prognosis at t_p=5,000 h.



(b) Prognosis at t_p=7,500 h.



(c) Prognosis at t_p=10,000 h.



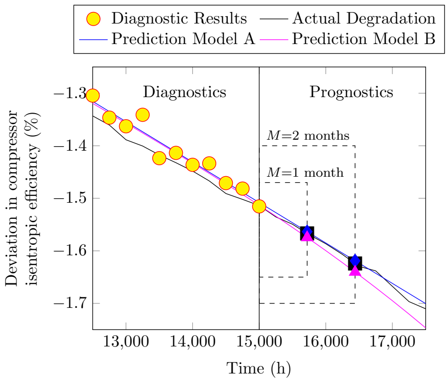
(d) Prognosis at t_p=12,500 h.

Figure 16: The predicted compressor isentropic efficiency for prognostic windows of width M when the process is initated at t_p=5,000, 7,500, 10,000 and 12,500 h of operation.

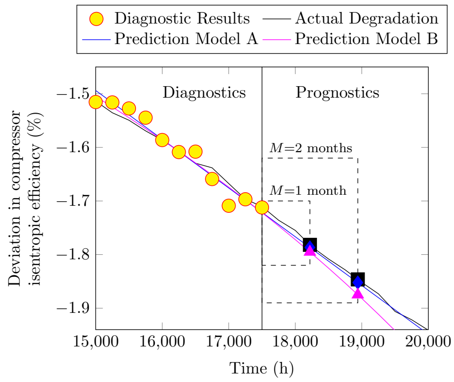
parameter predictions than Model B. This is actually expected since partitioning the degradation pattern into small increments of time ensures that the diagnostic results present a linear trend that can be captured expeditiously and more accurately as compared to having the entire performance data of the engine component.

In contrast to the linear regression method of Model A, the regression fit of Model B ranges from linear corresponding to the first diagnostic window up to quadratic corresponding to the last diagnostic window. The mean errors in predicting the compressor isentropic efficiency for one month and two months prognostic windows, when both Models A and B are implemented, are shown in Figs. 18 and 19, respectively. It is clearly evident that Model A is more accurate as compared to Model B.

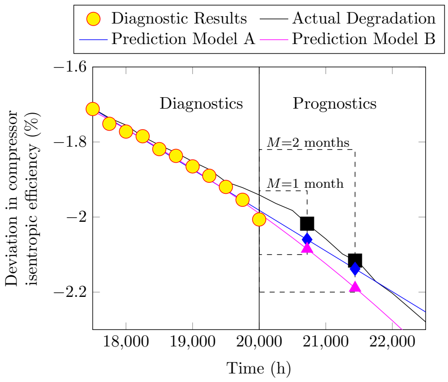
At this point it should be emphasized that both prognosis models are using the regression approach that fits the trends in the diagnostic results. Both Model A and B benefit significantly from the improved accuracy of the adaptive diagnostic method that was encapsulated in Figs. 14 and 15. However, if the diagnosis scheme is not this accurate then Model B will be influenced significantly more than Model A as



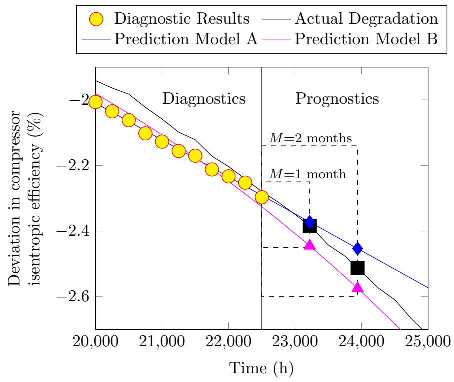
(a) Prognosis at t_p=15,000 h.



(b) Prognosis at t_p=17,500 h.



(c) Prognosis at t_p=20,000 h.



(d) Prognosis at t_p=22,500 h.

Figure 17: The predicted compressor isentropic efficiency for prognostic windows of width M when the process is initated at t_p=15,000, 17,500, 20,000 and 22,500 h of operation.

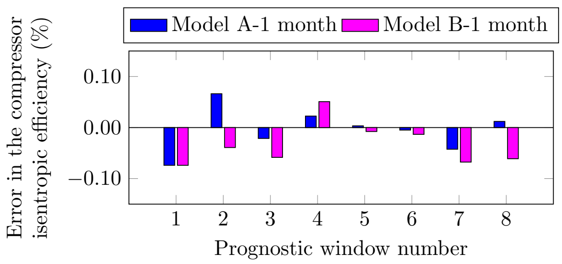


Figure 18: The prediction error for the compressor isentropic efficiency for M=1 month prognostic window.

it relies on a larger set of diagnostic data. In such a case, the error in the diagnosis scheme will accumulate significantly for all past diagnostic points where the prognosis of Model B is based upon.

It is therefore important to evaluate the probability of the prognostic results that lie within certain accuracy bounds corresponding to the actual degradation. For this case study where the accuracy bounds have been set at 90% of the actual degradation, the PDF for all the predicted component parameters lie

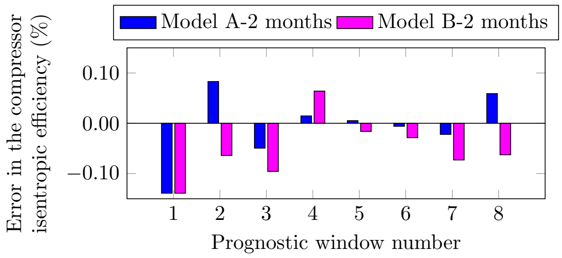
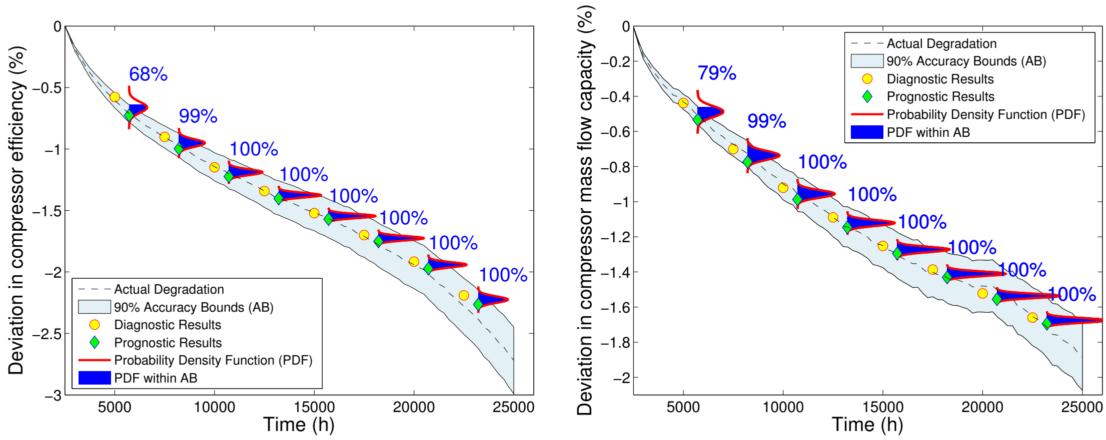


Figure 19: The prediction error for the compressor isentropic efficiency for M=2 months prognostic window.



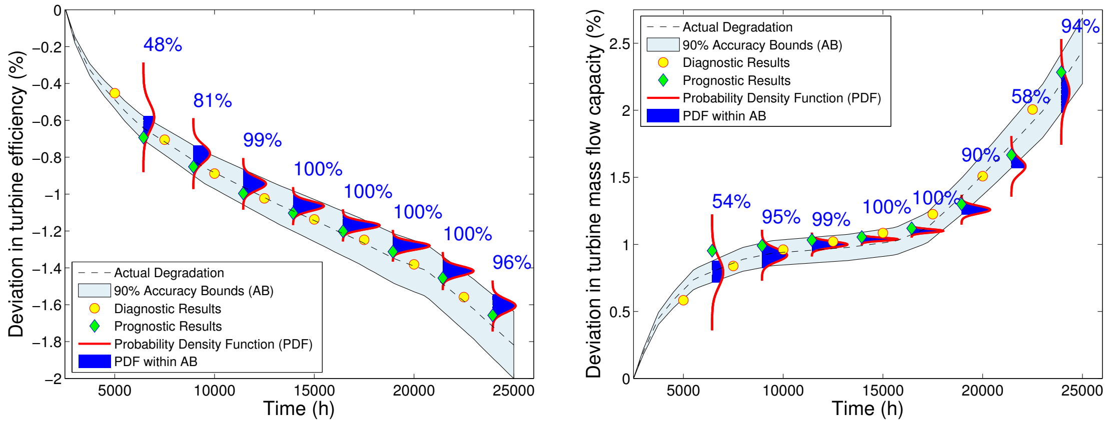
(a) Compressor isentropic efficiency.

(b) Compressor mass flow capacity.

Figure 20: Probability distribution of the predicted compressor degradation with respect to the actual degradation for prognostic windows of width M=1 month. The red line represents the PDF of the predicted component parameter and the blue filled vertical slice represents its probability to lie within the accuracy bounds. The depicted diagnostic results correspond to the last detected degradation of the diagnostic window at $t_d + L$. Similarly, the prognostic results correspond to the last prediction of the prognostic window at $t_p + M$.

within these bounds as observed in Figs. 20, 21 and 22. As shown in Fig. 20, with the prognostic window of width M=1 month the probability starts from a moderate value at the first prognostic window and starts to reach 100% from the second prognostic window until the last set of data that are used for prognosis. Apart from the first prognostic window, the spread of the PDF for the compressor efficiency and mass flow capacity is quite small for a time frame of one month and representative of a reliable prognosis.

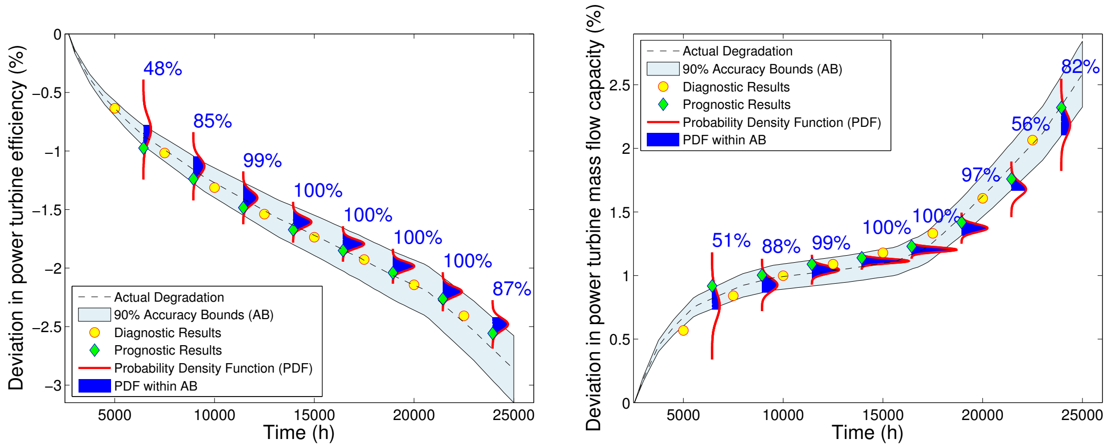
In case of the turbine and power turbine degradation where a 2 months prognostic window is depicted in Figs. 21 and 22, respectively, it is evident that initially the prognosis results lying within the accuracy bounds are moderate and they keep increasing with time. A closer look at the turbine and power turbine component degradations reveals the effects that specific diagnostic patterns have on the accuracy of the prognosis. For instance, there are regions along the path of each diagnostic pattern where the gradient of the deviated component parameter is significantly higher than the other regions. This implies that the rate



(a) Turbine isentropic efficiency.

(b) Turbine mass flow capacity.

Figure 21: Probability distribution of the predicted turbine degradation with respect to the actual degradation for prognostic windows of width M=2 months. The red line represents the PDF of the predicted component parameter and the blue filled vertical slice represents its probability to lie within the accuracy bounds. The depicted diagnostic results correspond to the last detected degradation of the diagnostic window at $t_d + L$. Similarly, the prognostic results correspond to the last prediction of the prognostic window at $t_p + M$.



(a) Power turbine isentropic efficiency.

(b) Power turbine mass flow capacity.

Figure 22: Probability distribution of the predicted power turbine degradation with respect to the actual degradation for prognostic windows of width M=2 months. The red line represents the PDF of the predicted component parameter and the blue filled vertical slice represents its probability to lie within the accuracy bounds. The depicted diagnostic results correspond to the last detected degradation of the diagnostic window at $t_d + L$. Similarly, the prognostic results correspond to the last prediction of the prognostic window at $t_p + M$.

of degradation in these regions progresses faster than others. The latter affects the accuracy of the prognosis scheme given that it yields a wider spread of the PDF and the probability to lie within the accuracy bounds is smaller.

One way to address this issue would be to add an additional criterion that will partition the diagnostic pattern into even smaller time increments for regions in which the degradation propagates faster. Therefore, the spread of the PDF can serve as a guide for modifying the width L of the diagnostic windows based on the optimal level of gradient that is acceptable for achieving accurate diagnosis and prognosis results. An additional metric that evaluates the accuracy of prognosis is the ERUL of the component. In case of the compressor mass flow capacity the ERUL that is predicted by both Model A and Model B is shown in Fig. 23 for a one month prognostic window.

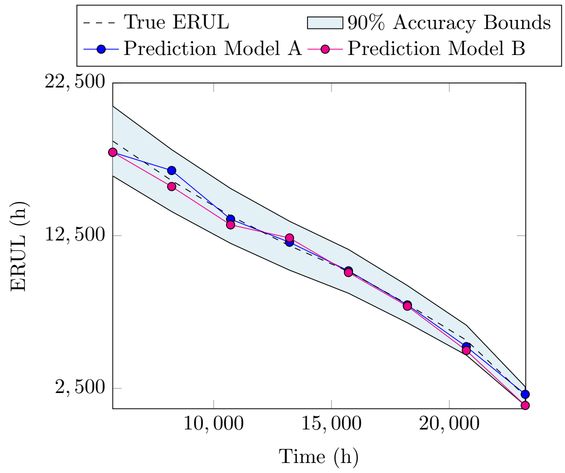


Figure 23: The ERUL of the compressor based on the compressor mass flow capacity as predicted by Model A and Model B for a 1 month prognostic window.

It follows from Fig. 23 that the Model A results lie within the true ERUL, whereas Model B is very close to the true ERUL although it deviates slightly at the end of the prediction. The former observation is further highlighted when one considers the relative error in the ERUL estimation as shown in Fig. 24. As the prognosis process is initiated at different times instances t_p the relative error drops significantly for Model A and lies within the 90% accuracy bounds. However, the ERUL prediction error for Model B, although initially converges within the acceptable limits, does at later stages of the time series becomes significantly higher than that of Model A.

Since the prognosis integrates a series of processes, the observed error is accumulated from the processes of component map generation, engine model adaptation, and the diagnosis. This prediction error can be traced back to the reconstruction and tuning of the model's component maps, and more specifically that of the compressor which is more complex. Once the output of the compressor map is injected with time evolving faults, the adaptive diagnostic process attempts, through the sliding window method, to decompose the time variable from the estimated output of the map. During the above process it is important to analyze

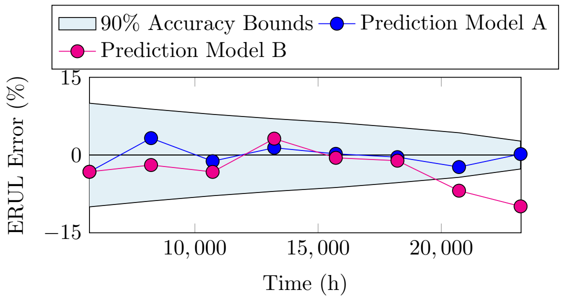


Figure 24: The relative error (%) in the ERUL of the compressor based on the compressor mass flow capacity as predicted by Model A and Model B for a 1 month prognostic window.

the pattern of the data available in each diagnostic window. If the available data correspond to accelerated or decelerated rate of degradation, this implies that the diagnostic pattern could be further partitioned into smaller time increments in order to facilitate the adaptive diagnostic process and reduce further the error.

It can be concluded that the performance of our proposed prognostic scheme is dependent upon the accuracy of the adaptive diagnostic method, that in turn relies heavily on the engine model. Therefore, it is crucial to continuously adapt the *initial engine model* to match the performance of the engine under investigation in order to establish a good benchmark for future diagnostic and prognostic analysis. Variable operating conditions make the adaptation of the *engine model* to the *reference engine* a challenging task. However, it gives a greater insight into the dynamics of the engine health and how this evolves with time.

As far as the practical aspects and limitations of our proposed scheme are concerned when used in real engines and real fault cases several considerations must be taken into account. Two key areas that need special attention for successfully implementing the proposed scheme are the data preprocessing and the engine model adaptation. Data preprocessing ensures that the data available from a service engine are properly corrected, smoothed, averaged and filtered out from noise and bias. One of the limitations of the proposed scheme is that it does not include a method for handling measurement noise and bias. This is something that can be successfully handled by Kalman filters, Neural Networks (NN), or other data-based methods at the preprocessing phase or in conjunction with the engine adaptation process and before the adaptive sliding window diagnostics. The width L of each diagnostic window can be adjusted based on the distribution of the available data for diagnosis so that the linear regression assumption made for prognosis will be adequately justified. A good quality set of engine data that is utilized by our proposed scheme is of crucial importance for the accuracy of diagnosis, and therefore for prognosis.

Another practical consideration deals with the maintenance activity of an engine from the time of the most recent model adaptation up to the time that the diagnosis and prognosis are pursued. For a unit that is on grid supporting operational modes with many transients this implies that the engine model should be adapted to the widest possible operational envelope. Another limitation of our proposed scheme is that it is not readily applicable for detecting and predicting gas turbine performance that is below 50% of the engine's rotational speed. This low operational speed regime is governed by a group of component maps that are different than the ones implemented for the engine model adaptation and diagnosis. However, one could utilize low speed component map generation methods for adapting and implementing the current scheme to diagnose and prognose engine behavior at very low speeds. Finally, the engine model should be continuously refined to its most recent health condition so that the prognosis could be performed with an increased reliability and accuracy.

Therefore, implementation of our proposed scheme to any gas turbine performance simulation or as a health monitoring, diagnosis and prognosis tool could provide a more reliable and accurate information for gas turbine engines and supports the users in making more accurate decisions on efficiently managing their assets.

5. Conclusions

In this paper, a novel prognostic scheme is introduced and developed that aims to improve the accuracy of gas turbine engine performance prediction under dynamic operating conditions. The concept of an advanced performance adaptation method is integrated with a dynamic gas turbine engine model that is developed in Matlab/Simulink environment. An optimization methodology was utilized to match the dynamic engine model to a reference model, that utilizes component characteristic maps that are available from the PROOSIS and implemented as look up tables.

Testing of our proposed methods to a two shaft industrial gas turbine engine model operating for 25,000 h subject to multiple component degradations demonstrate the following observations. The component degradation pattern is accurately captured by locally fitting linear regression functions at specific sliding diagnostic windows. This is achieved by implementing a nonlinear unconstrained optimization method for reconstructing the component map curves until the resulting simulated measurements match those of the reference engine for each diagnostic window. The engine health is predicted accurately with a prognostic window ranging from one month up to two months of operation.

The capability of our proposed schemes to adapt, diagnose and prognose the gas turbine performance when this is represented by dynamic operating conditions gives a great insight into the dynamics of the degradation pattern mechanisms. The implementation of our proposed method to any condition monitoring and heath estimation strategy could enhance the understanding of the gas turbine dynamic behavior, and therefore could significantly improve the operational and maintenance strategy of gas turbine assets.

Acknowledgements

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

References

[1] A. Volponi, Gas turbine engine health management: Past, present, and future trends, Journal of Engineering for Gas Turbines and Power 136 (5) (2014) 051201.

[2] Siemens, Flex Power Services for Siemens Fossil Power Plants, see also `http://www.energy.siemens.com/` (2013).

[3] GE, FlexEfficiency 60 A new standard of high efficiency and operational flexibility Portfolio, see also `http://www.ge.com/` (2012).

[4] J. Simmons, K. Danai, In-flight isolation of degraded engine components by shape comparison of transient outputs, Journal of Engineering for Gas Turbines and Power 134 (6) (2012) 061602.

[5] S. Borguet, M. Henriksson, T. McKelvey, O. Léonard, A study on engine health monitoring in the frequency domain, Journal of Engineering for Gas Turbines and Power 133 (8) (2011) 081604.

[6] Y. G. Li, A gas turbine diagnostic approach with transient measurements, Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy 217 (2) (2003) 169–177.

[7] G. Merrington, Fault diagnosis of gas turbine engines from transient data, Journal of engineering for gas turbines and power 111 (2) (1989) 237–243.

[8] J. Janawitz, J. Masso, C. Childs, Heavy duty gas turbine operating and maintenance, Tech. rep., GE Power and Water (2015).

[9] Y. G. Li, P. Nilkitsaranont, Gas turbine performance prognostic for condition-based maintenance, J. Appl. Energy 86 (10) (2009) 2152–2161.

[10] A. Saxena, Prognostics the science of prediction, in: Proc. PHM Conference, Portland, OR, 2010.

[11] N. Daroogheh, N. Meskin, K. Khorasani, A novel particle filter parameter prediction scheme for failure prognosis, in: American Control Conference (ACC), 2014, IEEE, 2014, pp. 1735–1742.

[12] M. A. Zaidan, R. F. Harrison, A. R. Mills, P. J. Fleming, Bayesian hierarchical models for aerospace gas turbine engine prognostics, Expert Systems with Applications 42 (1) (2015) 539 – 553.

[13] A. Vatani, K. Khorasani, N. Meskin, Health monitoring and degradation prognostics in gas turbine engines using dynamic neural networks, in: ASME Turbo Expo, GT2015-4401, ASME, 2015.

[14] D. Zhou, H. Zhang, S. Weng, A novel prognostic model of performance degradation trend for power machinery maintenance, Energy 78 (2014) 740–746.

[15] J. Dai, D. Das, M. Ohadi, M. Pecht, Reliability risk mitigation of free air cooling through prognostics and health management, Applied Energy 121 (2013) 104–112.

[16] C. Hu, G. Jain, P. Tamirisa, T. Gorka, Method for estimating capacity and predicting remaining useful life of lithium-ion battery, Applied Energy 126 (2014) 182–189.

[17] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, Transient gas turbine performance diagnostics through nonlinear adaptation of compressor and turbine maps, Journal of Engineering for Gas Turbines and Power, GTP-14-1630 137 (9) (2015) 091201.

[18] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, A component map tuning method for performance prediction and diagnostics of gas turbine compressors, Applied Energy 135 (2014) 572–585.

[19] L. Marinai, D. Probert, R. Singh, Prospects for aero gas-turbine diagnostics: a review, Applied Energy 79 (1) (2004) 109 – 126.

[20] Z. S. Vanini, N. Meskin, K. Khorasani, Multiple-model sensor and components fault diagnosis in gas turbine engines using autoassociative neural networks, Journal of Engineering for Gas Turbines and Power 136 (9) (2014) 091603.

[21] S. Ogaji, L. Marinai, S. Sampath, R. Singh, S. Probert, Gas-turbine fault diagnostics: a fuzzy-logic approach, Applied Energy 82 (1) (2005) 81 – 89.

[22] S. Ogaji, S. Sampath, R. Singh, D. Probert, Novel approach for improving power-plant availability using advanced engine diagnostics, Applied Energy 72 (1) (2002) 389 – 407.

[23] G. Merrington, O. K. Kwon, G. Goodwin, B. Carlsson, Fault detection and diagnosis in gas turbines, Journal of Engineering for Gas Turbines and Power 113 (2) (1991) 276–282.

[24] S. Sampath, Y. G. Li, S. Ogaji, R. Singh, Fault diagnosis of a two spool turbo-fan engine using transient data: A genetic algorithm approach, in: ASME Turbo Expo 2003, collocated with the 2003 International Joint Power Generation Conference, American Society of Mechanical Engineers, 2003, pp. 351–359.

[25] D. L. Simon, S. Borguet, O. Léonard, X. F. Zhang, Aircraft engine gas path diagnostic methods: Public benchmarking results, Journal of Engineering for Gas Turbines and Power 136 (4) (2014) 041201.

[26] E. Tsoutsanis, N. Meskin, M. Benammar, K. Khorasani, An efficient component map generation method for prediction of gas turbine performance, in: ASME Turbo Expo 2014, GT2014-25753, ASME, 2014, p. V006T06A006.

[27] J. Finn, F. Wagner, W. Basilly, Monitoring strategies for a combined cycle electric power generator, Applied Energy 87 (2010) 2621–2627.

[28] A. Saxena, J. Celaya, E. Balaban, K. Goebel, B. Saha, S. Saha, M. Schwabacher, Metrics for evaluating performance of prognostic techniques, in: Prognostics and health management, 2008. PHM 2008. International conference on, IEEE, 2008, pp. 1–17.

[29] PROOSIS, Propulsion Object-Oriented Simulation Software, see also `http://www.proosis.com/` (2015).

[30] N. Aretakis, G. Doumouras, I. Roumeliotis, K. Mathioudakis, Compressor washing economic analysis and optimization for power generation, J. Appl. Energy 95 (2012) 77–86.

[31] D. C. Montgomery, G. C. Runger, Applied statistics and probability for engineers, John Wiley & Sons, 2010.

[32] R. Joly, S. Ogaji, R. Singh, S. Probert, Gas-turbine diagnostics using artificial neural-networks for a high bypass ratio military turbofan engine, Applied Energy 78 (4) (2004) 397 – 418.

[33] A. K. Jardine, D. Lin, D. Banjevic, A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mechanical systems and signal processing 20 (7) (2006) 1483–1510.

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

[35] E. Tsoutsanis, Y. G. Li, P. Pilidis, M. Newby, Part-load performance of gas turbines: part 2 multi-point adaptation with compressor map generation and ga optimization, in: Proc. ASME Gas Turbine India, Vol. 1, Mumbai, India, 2012, pp. 743–751.