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

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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

f	fuel
$lreg$	linear regression
pt	power turbine
r	reference engine
t	turbine
th	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-based and model-based approaches. Amongst the data-based prognostic methods the most popular are neural networks [22, 23] and bayesian networks [24, 25]. A subgroup of the data-based methods are the statistical approaches [26, 27] in which their primary focus is that of forecasting the behavior of a system without necessarily evaluating the remaining useful life of the component.

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

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

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

From our recent work [10] on prognostics we utilized an adaptive diagnostic process [18] for a number of sliding windows capturing the entire degraded measurements. Subsequently, the detected degradation was used for a linear regression towards prognostics. In contrast to our earlier study, the proposed method employs a real time data-driven tuner that performs the diagnosis online and each operating point corresponds to a different set of component maps. The information containing the diagnostic data is then divided into smaller time segments referred to as windows. The time range of each window, referred to as width, depends on the time data series distribution. Specifically, the data distribution examined refers to the acceleration of degradation which is represented as the second order derivative of the predicted deviations. It follows, that the bank of data encapsulated in the collection of windows are utilized in a local linear window-based manner for predicting the future behavior of the engine components. The current work is an extension of our recent work [38] which includes a comparison of the proposed method with the one presented in [10].

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

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

1. The problem of fault prognosis of an industrial gas turbine under transient conditions is investigated by using a regression method which is activated by a derivative-driven criterion of detected degradations.

2. Compared to the previous related works, the proposed method represents a powerful tool for forecasting the evolution of degraded component performance without taking into account the entire diagnostic history of the equipment. This is achieved by splitting the detected component degradation pattern into smaller increments where the evolutions of degradation can be assumed to be linear with respect to time.

3. Moreover, the distribution of diagnostic data is examined based on a second order derivative criterion which corresponds to the acceleration of degradation. Upon this criterion the diagnostic pattern is partitioned into smaller segments that we refer to as windows and the contained information is implemented for performing short-term prognostics. This is the first time in the literature that the acceleration of the diagnostic data is utilized for simplifying the prognostic process.

4. Furthermore, we compare the proposed method with the one developed earlier by the authors [10] in order to demonstrate and illustrate the prediction accuracy improvement through the use of PDF and RUL metrics.

5. The main benefit of the proposed prognostic method is its ability to simplify the nonlinear time evolving component degradation into a simple local and linear process for which meaningful prognostic results can be easily interpreted. Using the proposed technique, the prognosis is generalized for gas turbine dynamic operating modes and can be further employed for other demand-driven energy equipment.

The remainder of this paper is organized as follows. In Section 2, the proposed prognostic method along with the concept of performance adaptation used for diagnostics and its integration with a dynamic engine model are described. The description of the case studies are 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

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

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

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

2.2. Model Tuning

The frequently performed maintenance actions in industrial gas turbines (such as online/offline compressor washing, replacement of inlet filtration systems, fuel nozzles and sensors) and the evolving performance degradation of their components alter the performance and health signature of the engine. Therefore, gas turbine users have to progressively refine and update their engine models for improving the accuracy of the performance prediction based on available service engine data. This process is commonly referred to as model-based performance adaptation and deals with the optimization of component-based parameters such as mass flow capacities and efficiencies so that the service engine measurable performance parameters such as gas path temperatures and pressures are properly matched. This is a minimization problem since its goal is to mimimize the observed residuals between the model predictions and the engine test data. This process establishes the data-set that corresponds to the healthy engine condition. It follows that data from a family of adapted engine models can be implemented for performance-based diagnostic analysis.

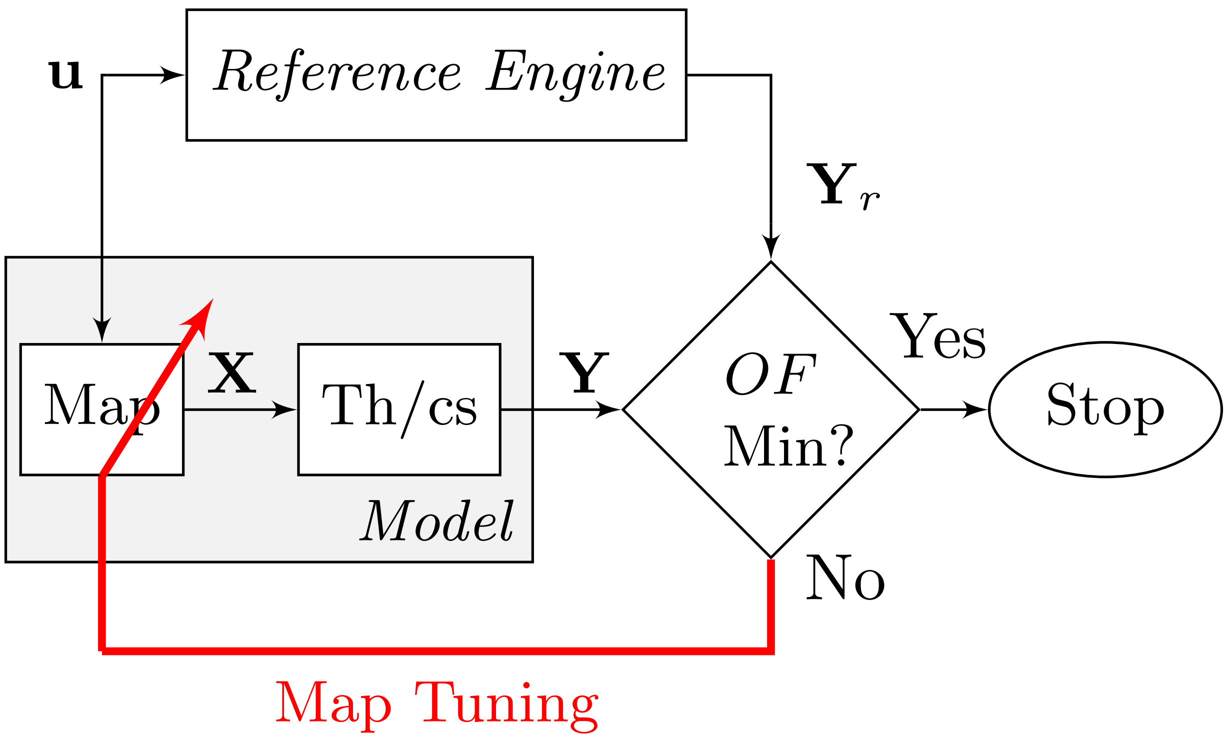

Figure 1: The flow chart of the proposed performance adaptation. Th/cs and OF denote the thermodynamic computations and the objective function eq. 2, respectively.

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

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

where $\mathbf{Y}$, $\mathbf{X}$ and $\mathbf{u}$ denote the measurable performance, the component and the operating conditions parameters, respectively.

The performance of the engine can be captured by the information of the condition monitoring system of a service engine or via simulated gas turbine measurements available from an engine model. For testing our proposed method two gas turbine models are used. The gas turbine model that implements the component characteristics of PROOSIS [42] simulation software is referred to as the *reference engine* and acts as the test engine in this study. The second model, which is going to be referred to as the *engine model*, implements the recently developed adaptation concept [37].

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

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

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 performance parameter, respectively.

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

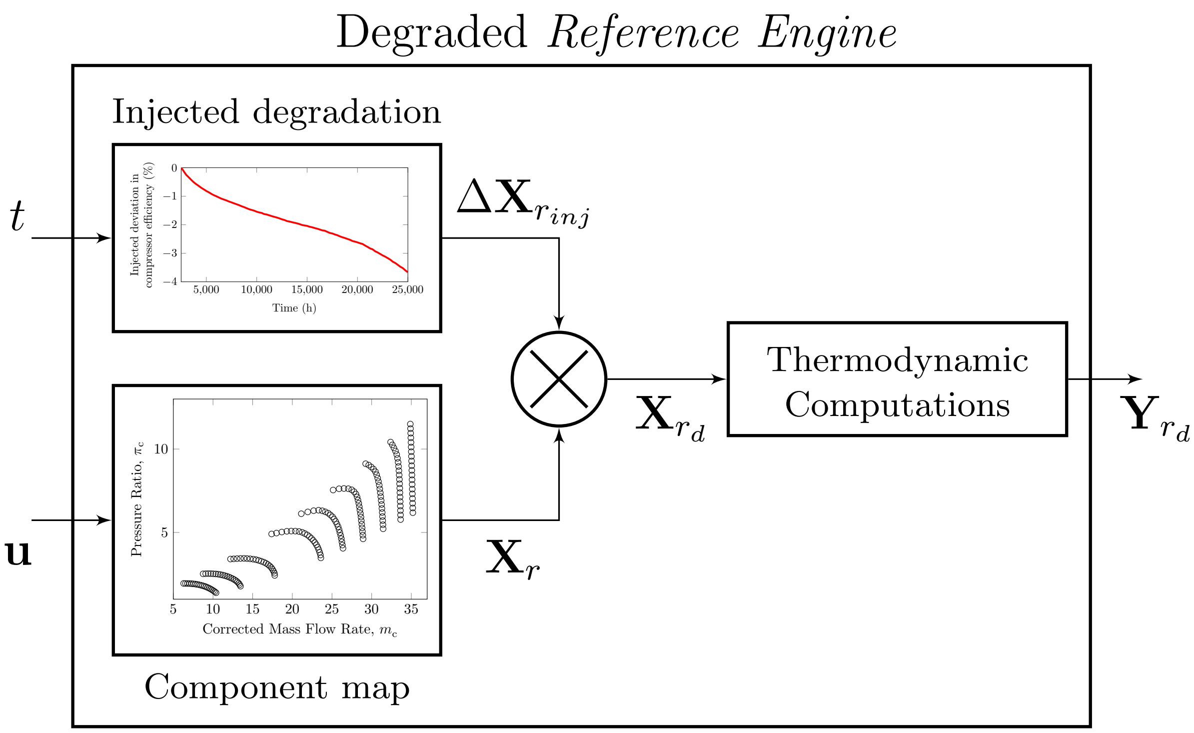

Figure 2: The representation of the time dependent injected degradation into the *reference engine*.

2.3. Diagnostics

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

$$\Delta X = 100 \times (X_d - X)/X. \tag{3}$$

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

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

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

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

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

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

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

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

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

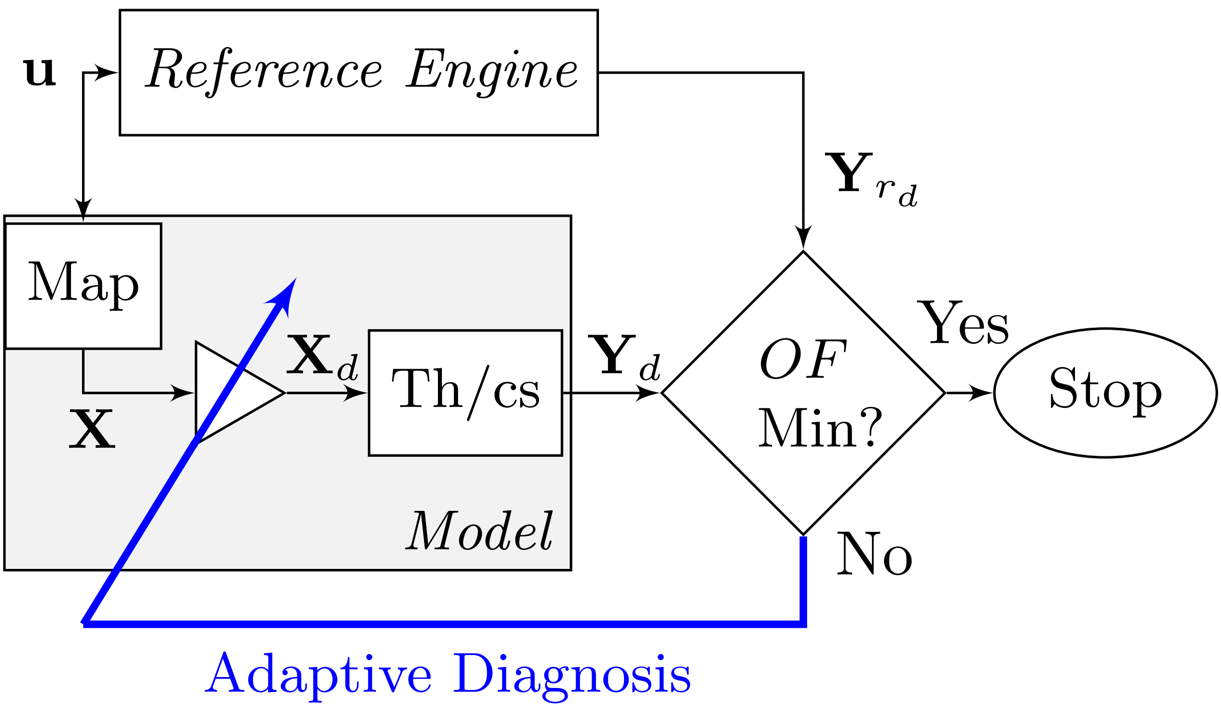

Figure 3: The flow chart of the proposed adaptive diagnostics.

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

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

2.4. Window-Based Analysis

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

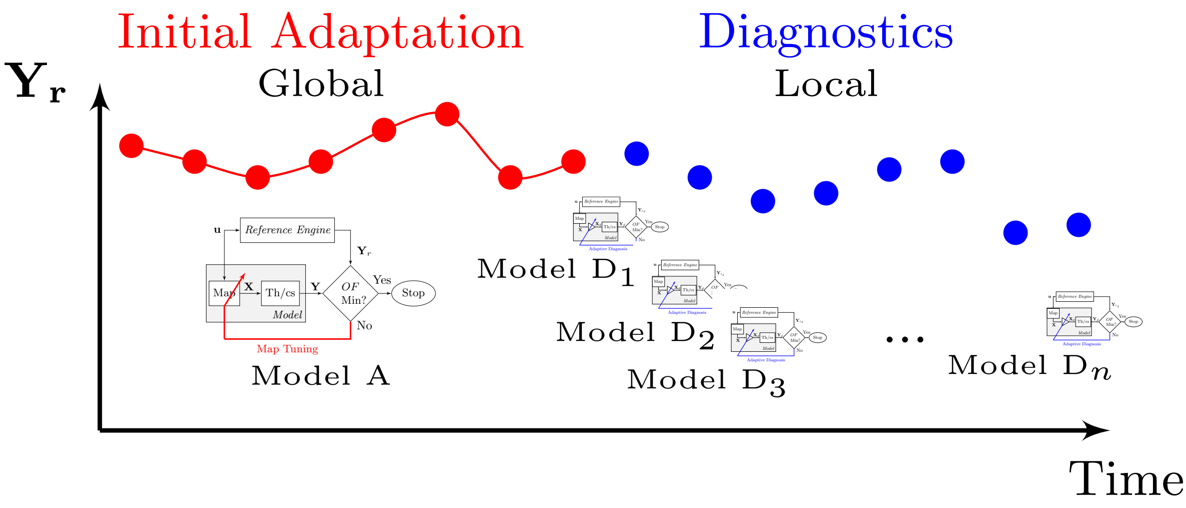

Figure 4: Representation of the engine models implemented for the initial global adaptation and the adaptive local diagnosis processes performed for the *reference engine* measurements.

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

$$A_t = \frac{d^2 \Delta X_t}{dt^2} \tag{6}$$

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

Now let us assume that for window activated at t_{w_i} the component parameter deviation is $\Delta X_{t_{w_i}}$ and its 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 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 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 condition is shown in Fig. 5.

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

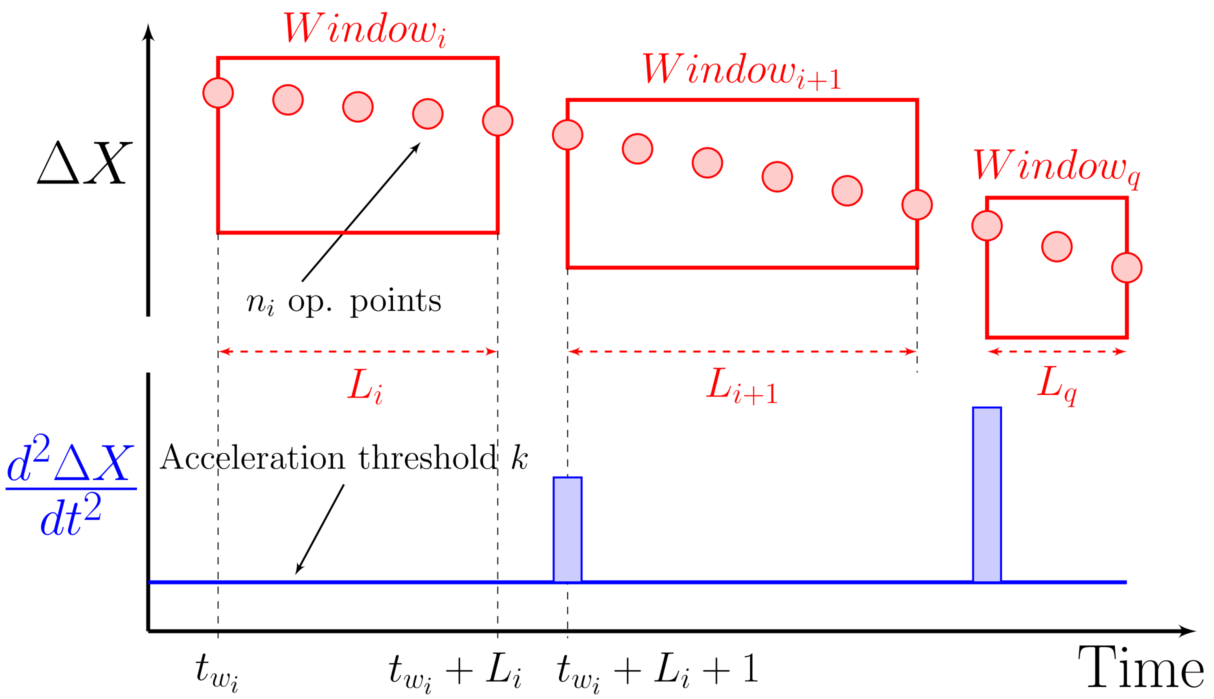

Figure 5: The partition of the diagnostic information into windows of variable width depending on the acceleration of the component degradation.

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

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

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

2.5. Prognostics

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

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

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

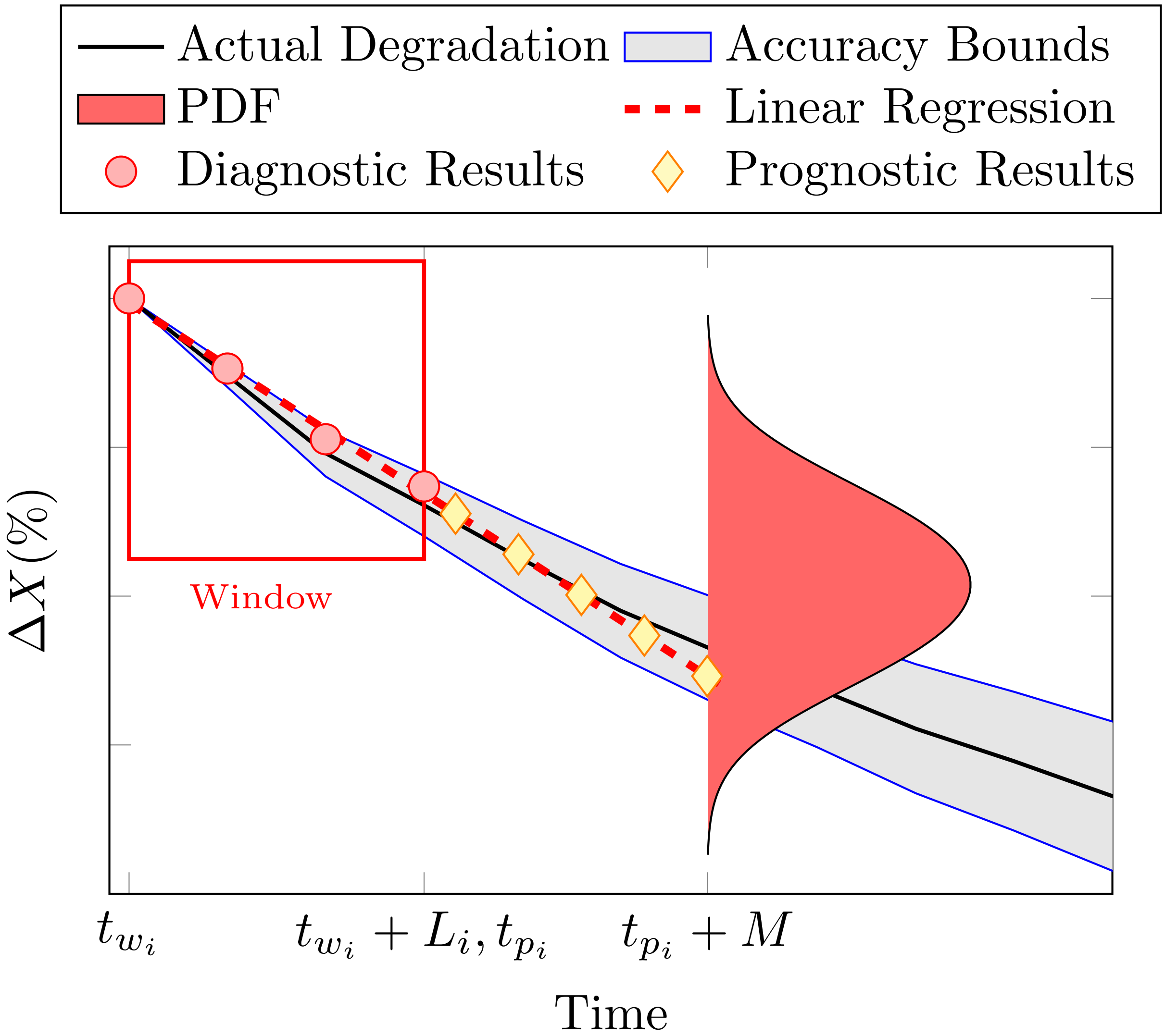

Figure 6: The distribution of the prognostic results, obtained through linear regression of the local diagnostic information, with respect to the actual degradation.

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

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

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

The PDF of the linearly regressed component parameter ΔX_{lreg} information along with the diagnostic predictions ΔX and the actual degradation $\Delta X_{r_{inj}}$ with its corresponding accuracy bounds is shown in Fig. 6. The final step of the prognosis task is RUL estimation for the component.

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

Finally, accuracy bounds similar to the diagnostic accuracy bounds are implemented for the true ERUL. The true ERUL is determined by the injected degradation to the engine component parameters $\Delta X_{r_{inj}}$. As a result the comparison between estimated ERUL and true ERUL provides an insight to the performance capability of the proposed method. The ERUL represents the rate at which the component of the engine system 'consumes' its useful life according to the mode of operation.

3. Case Study Description

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

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

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

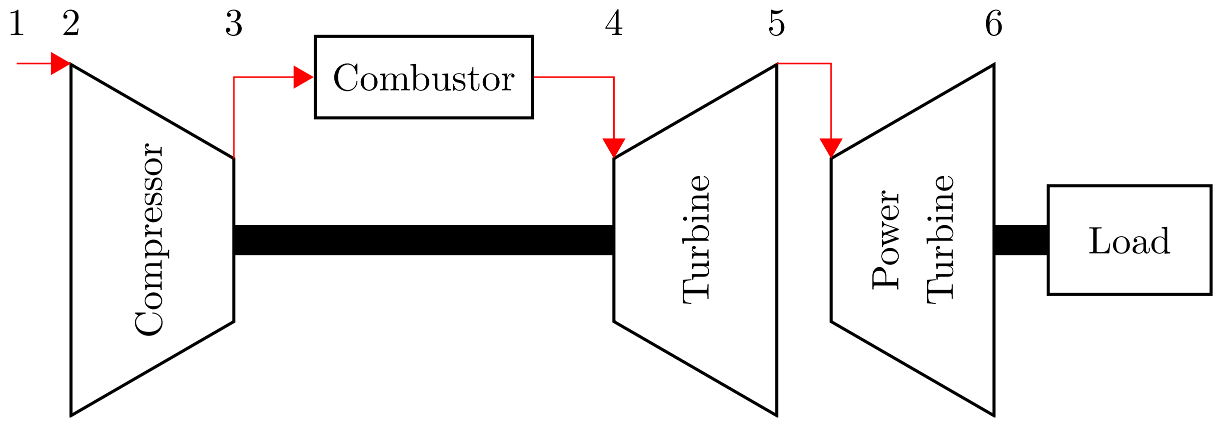

Figure 7: The engine model schematic layout representing a two shaft gas turbine.

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

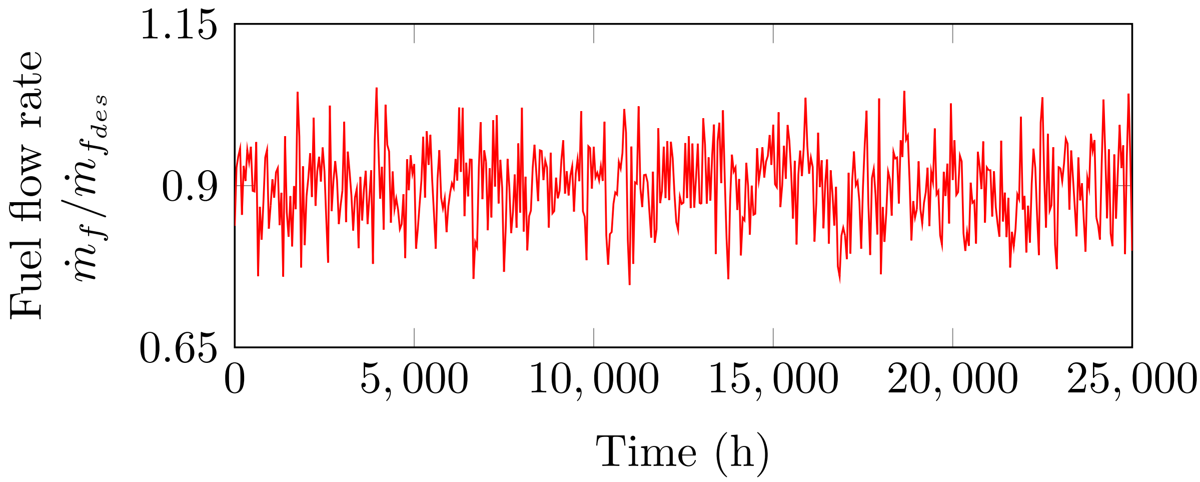

Figure 8: The variation of the fuel flow rate with respect to time.

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

Data implemented for the case studies are the *reference engine* degraded simulated measurements and the prognosis process is performed at various time instants. The degraded measurements are generated by injecting deviation signals in the component parameters of the *reference engine*. A summary of the 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)

In this study two test cases are carried out. The first case study objective is to assess the prediction accuracy for the proposed real-time adaptive diagnostic method. It follows that for the second case study the objective is to predict the evolution of the compressor degradation by implementing both the window-based analysis and the linear regression methods. Moreover, the comparison of the prognostic method with the one earlier developed by the authors will give an insight of the accuracy improvement by the variable window-width activation introduced. Towards this end the common metrics of PDF and ERUL are utilized for assessing the accuracy of the prognosis.

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

4. Results

4.1. Diagnosis

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

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

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

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

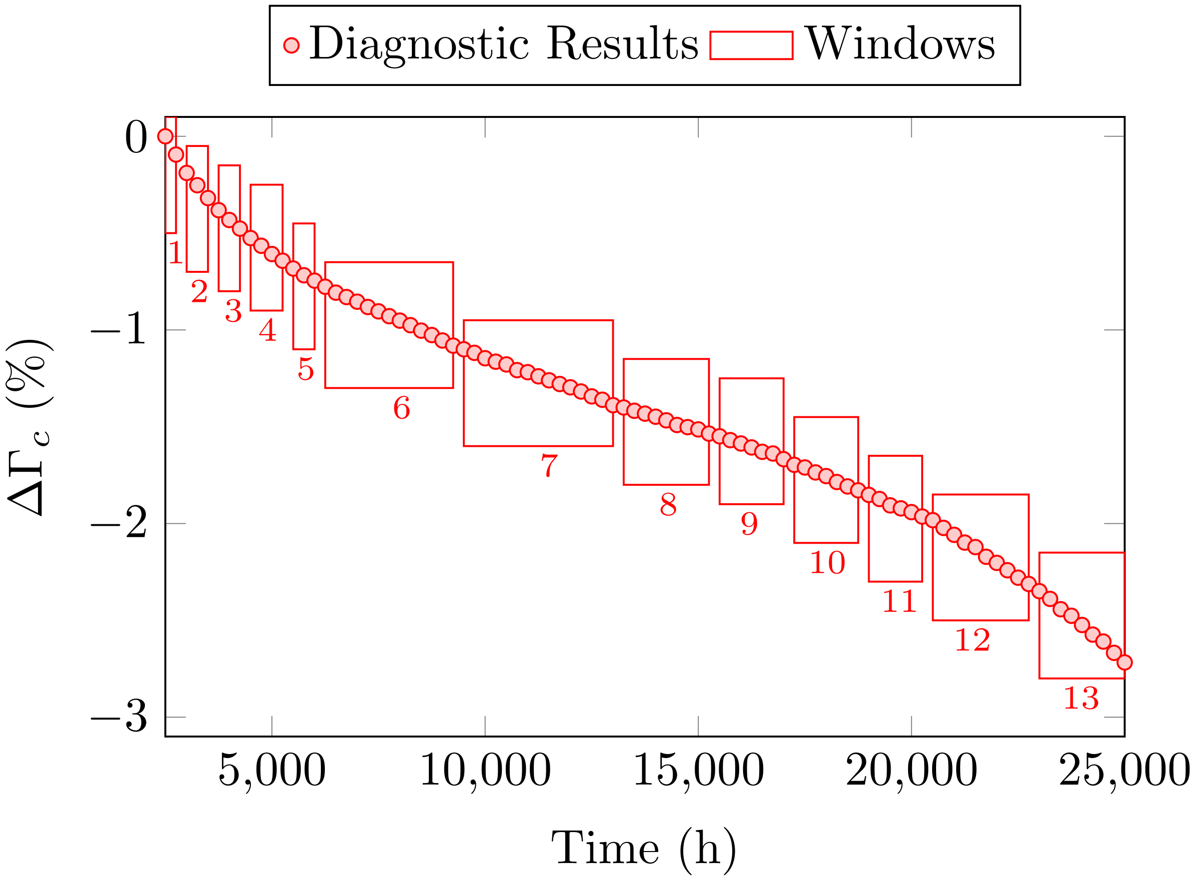

Figure 9: Predicted compressor degradation represented by the deviation of the mass flow capacity. Diagnostic information is splitted into 13 windows where their width is variable and dependent on the acceleration of degradation.

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

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

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

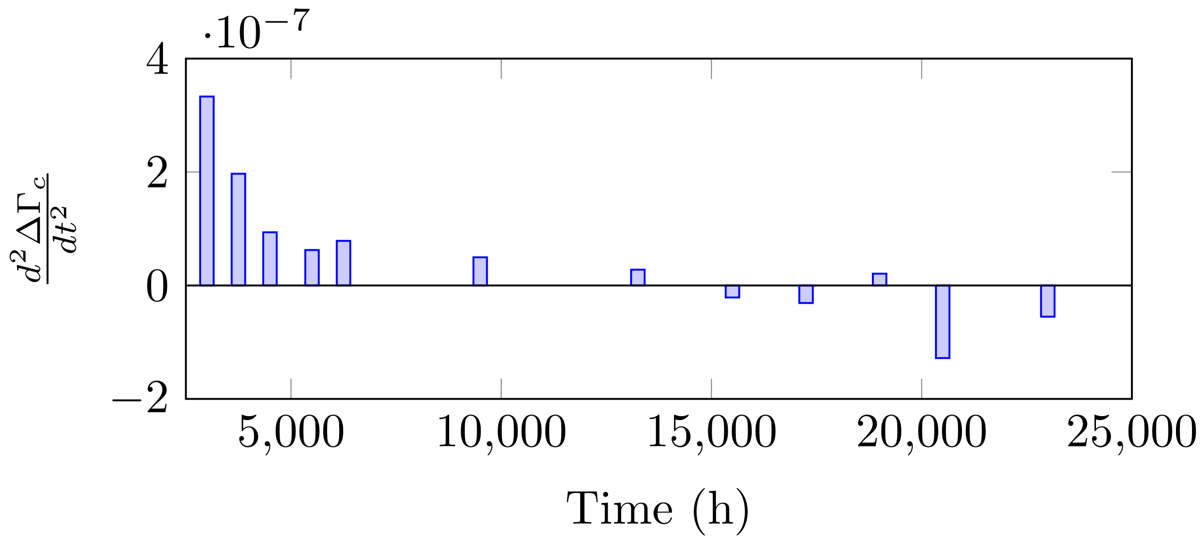

Figure 10: Acceleration of compressor degradation represented by deviation of the mass flow capacity.

4.2. Prognosis

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

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

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

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

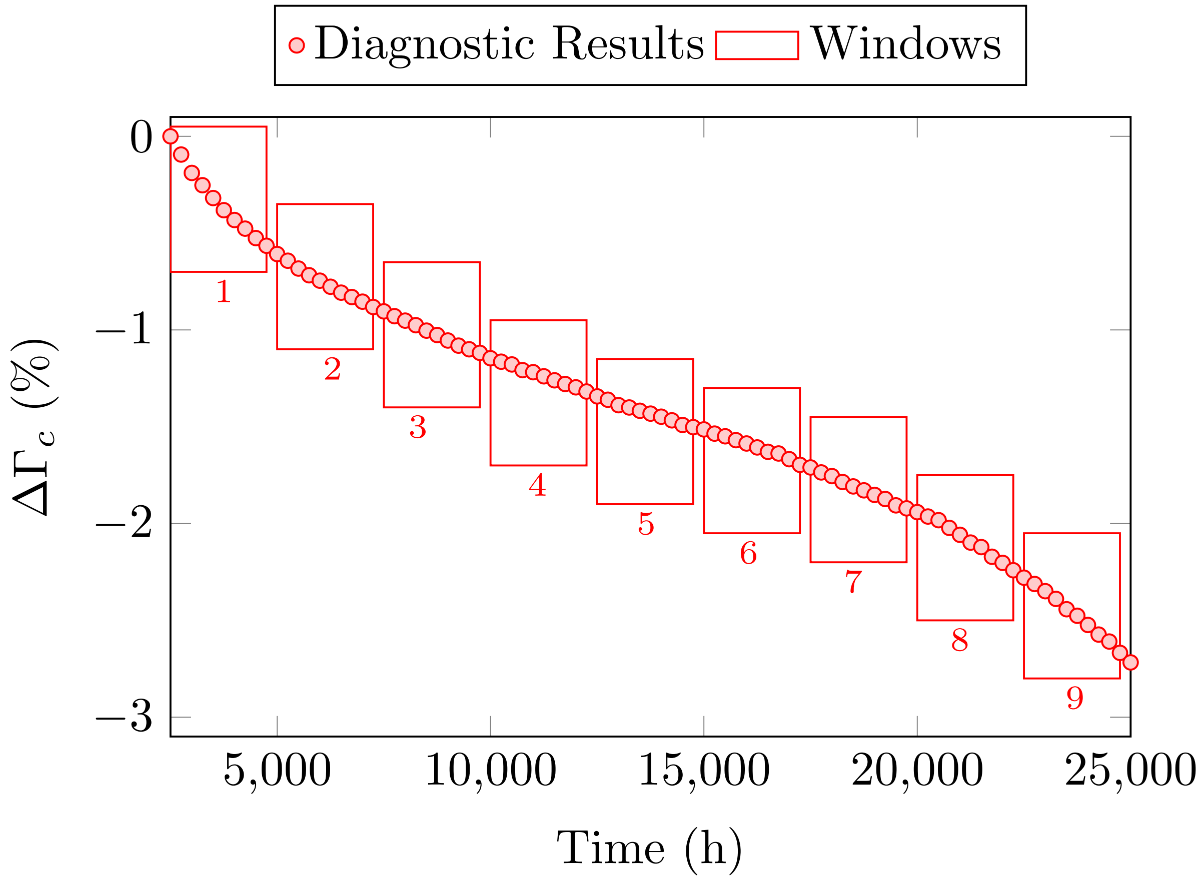

Figure 11: Predicted compressor degradation represented by the deviation of the mass flow capacity. Diagnostic information is splitted into 9 windows where their width is fixed.

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

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

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

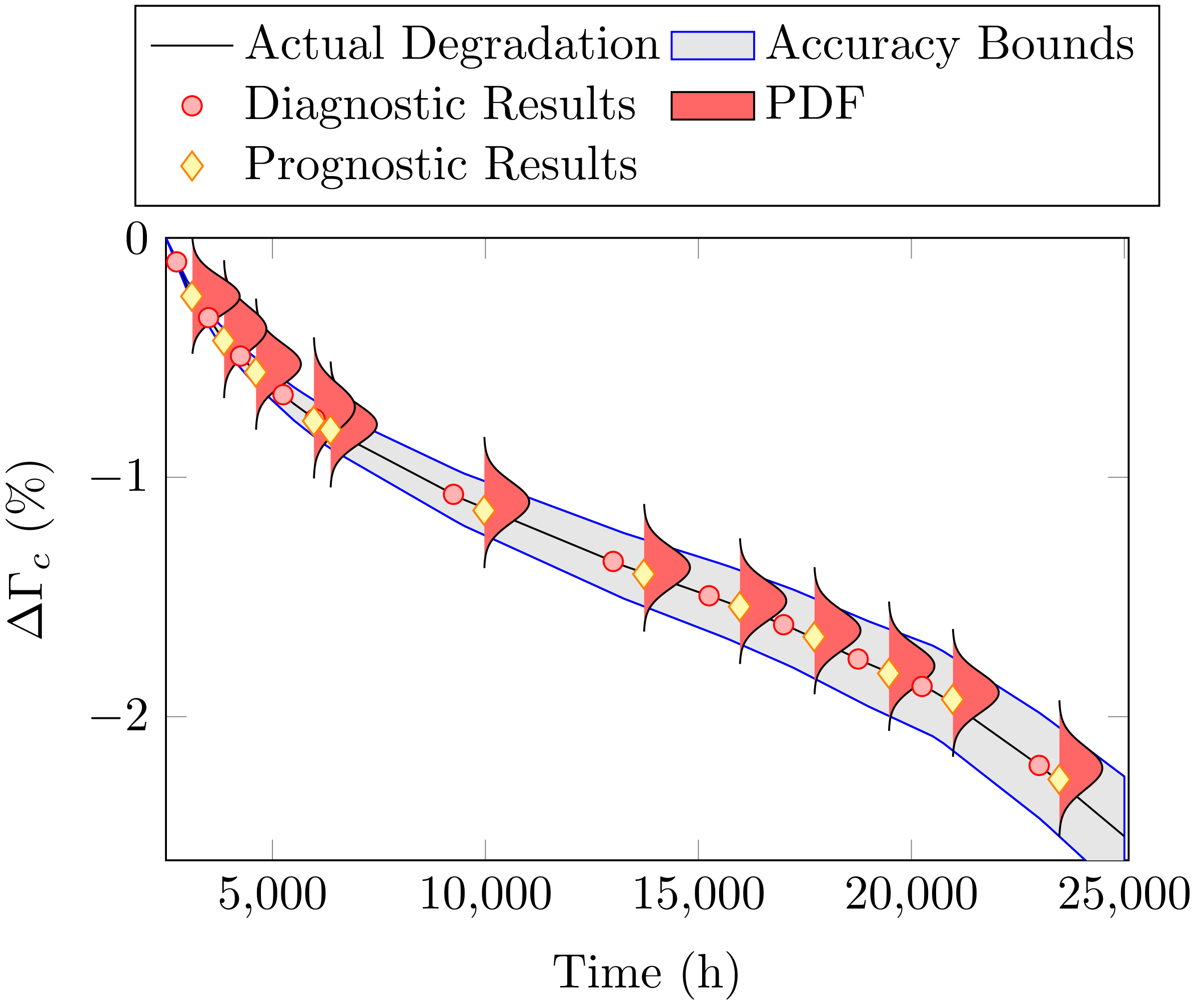

Figure 12: The deviation of compressor mass flow capacity as predicted by variable width window-based Method A.

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

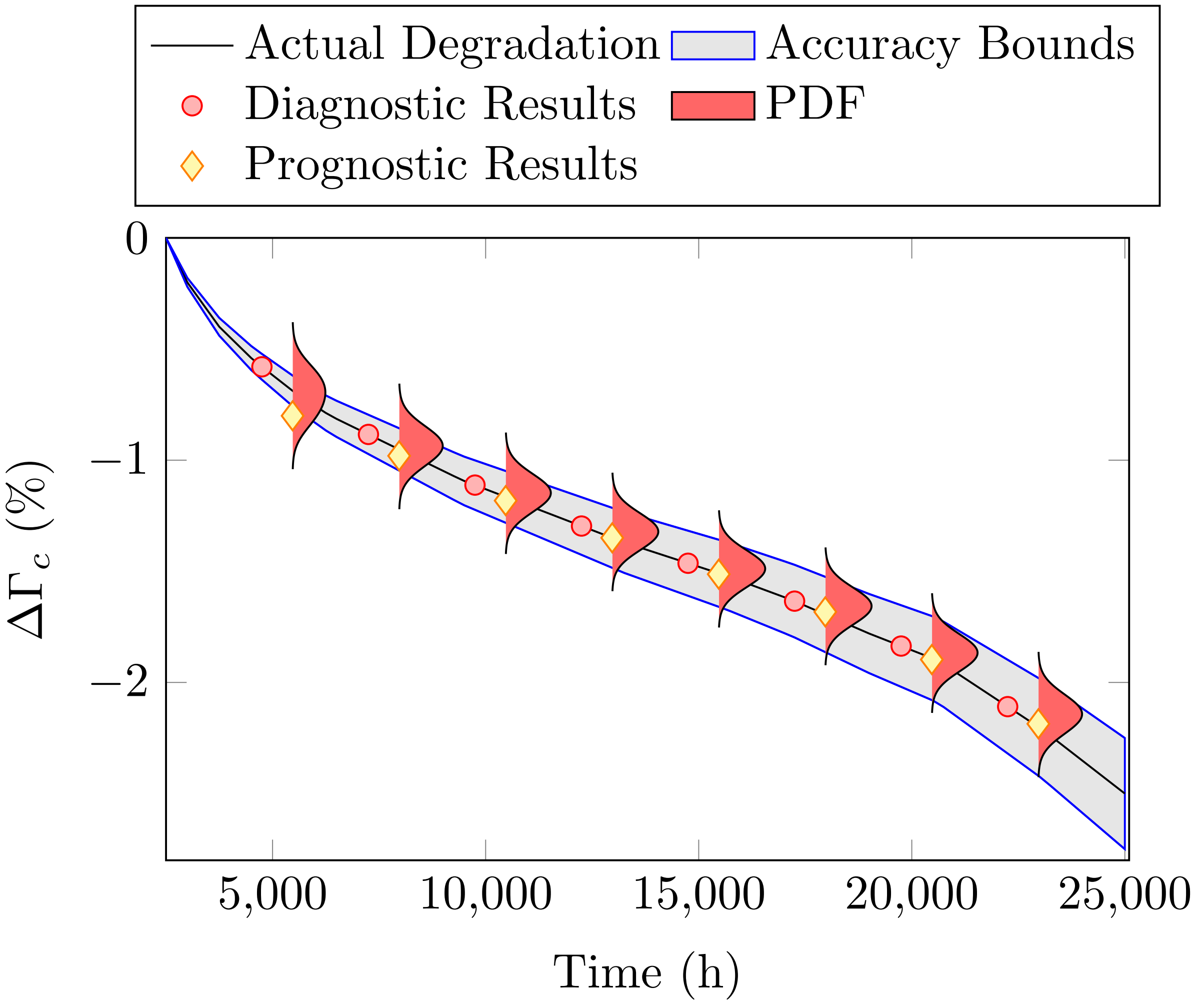

Figure 13: The deviation of compressor mass flow capacity as predicted by fixed width window-based Method B.

5. Conclusions

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

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

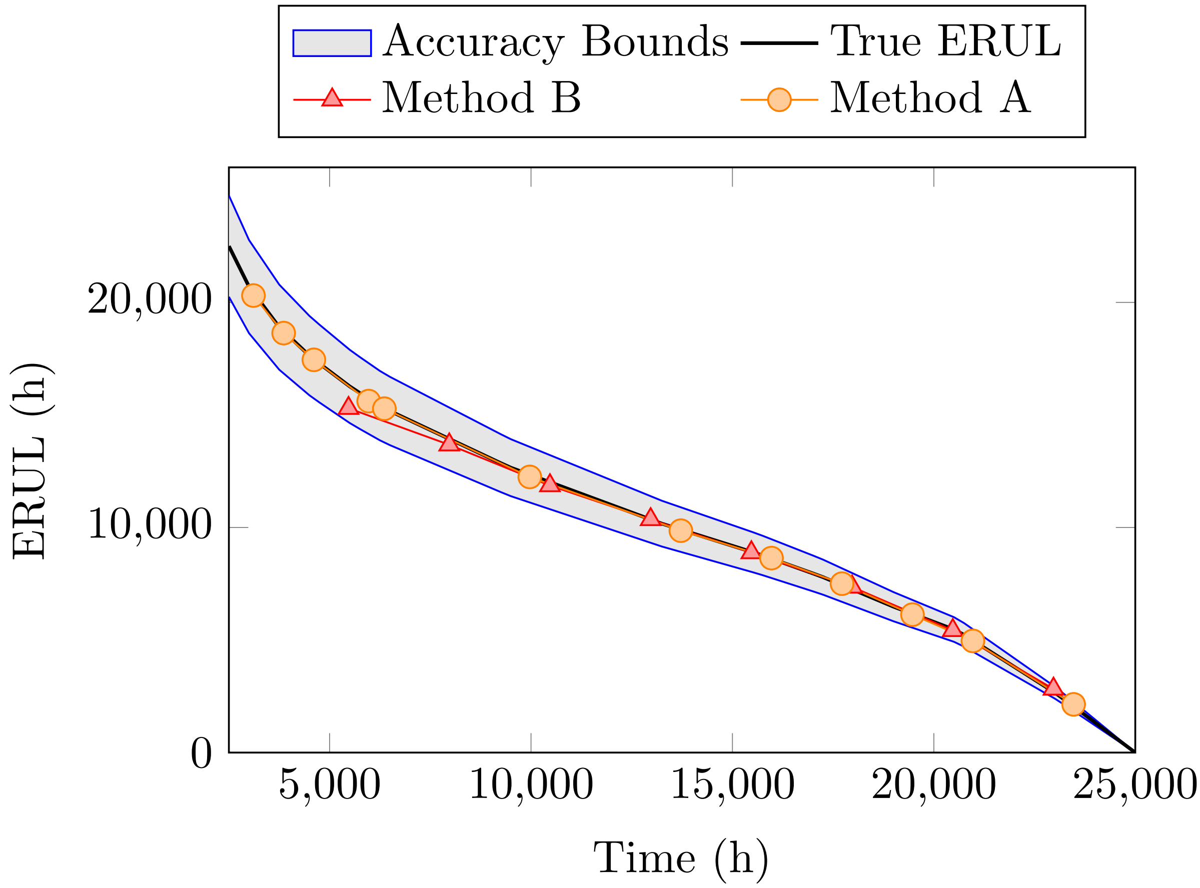

Figure 14: The predicted ERUL based on compressor mass flow capacity.

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

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

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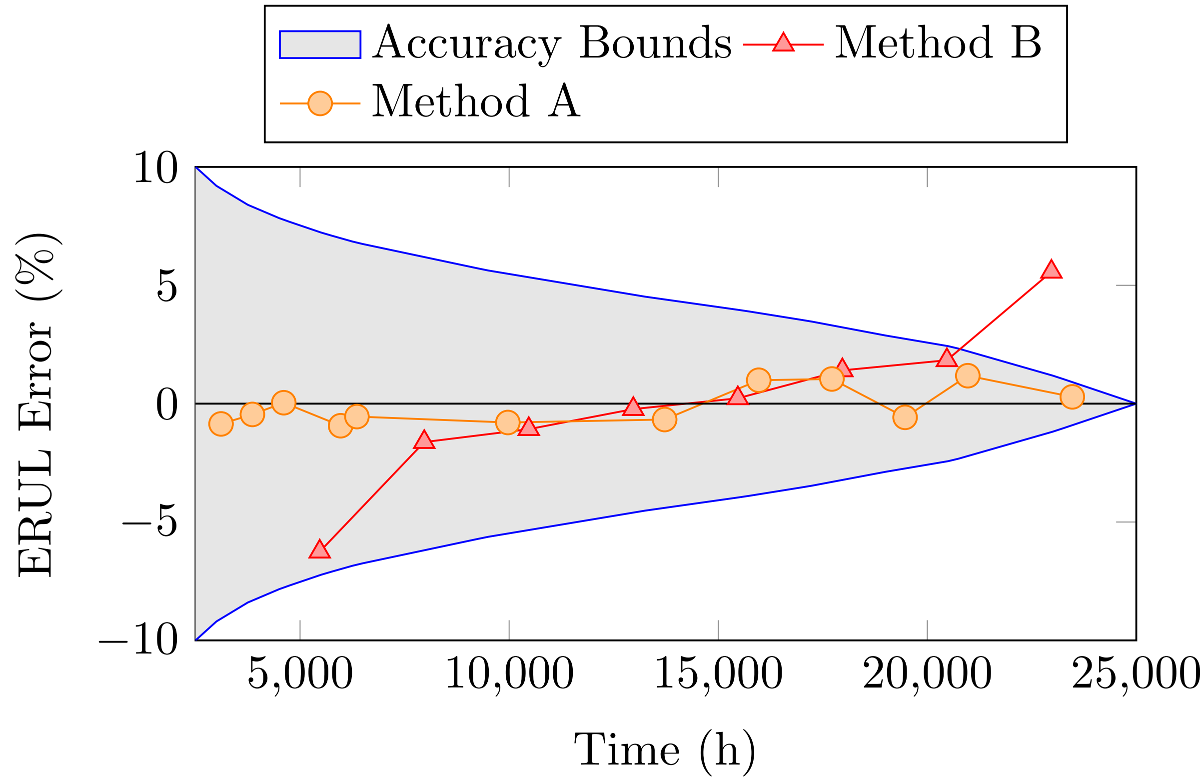

Figure 15: The predicted ERUL error based on compressor mass flow capacity.

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