Applied Energy 86 (2009) 2152–2161

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Gas turbine performance prognostic for condition-based maintenance

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A R T I C L E I N F O

Article history:
Received 2 May 2008
Received in revised form 9 February 2009
Accepted 10 February 2009
Available online 18 March 2009

Keywords:
Gas turbine
Engines
Performance prognostics
Remaining useful life
Regression

A B S T R A C T

Gas turbine engines experience degradations over time that cause great concern to gas turbine users on engine reliability, availability and operating costs. Gas turbine diagnostics and prognostics is one of the key technologies to enable the move from time-scheduled maintenance to condition-based maintenance in order to improve engine reliability and availability and reduce life cycle costs. This paper describes a prognostic approach to estimate the remaining useful life of gas turbine engines before their next major overhaul based on historical health information. A combined regression techniques, including both linear and quadratic models, is proposed to predict the remaining useful life of gas turbine engines. A statistic "compatibility check" is used to determine the transition point from a linear regression to a quadratic regression. The developed prognostic approach has been applied to a model gas turbine engine similar to Rolls-Royce industrial gas turbine AVON 1535 implemented with compressor degradation over time. The analysis shows that the developed prognostic approach has a great potential to provide an estimation of engine remaining useful life before next major overhaul for gas turbine engines experiencing a typical soft degradation.

1. Introduction

In gas turbine applications, maintenance costs, availability and reliability are some of the main concerns of gas turbine users. With conventional maintenance strategy engine overhauls are normally carried out in a pre-scheduled manner regardless of the difference in the health of individual engines. As a consequence of such maintenance strategy, gas turbine engines may be overhauled when they are still in a very good health condition or may fail before a scheduled overhaul. Therefore, engine availability may drop and corresponding maintenance costs may arise significantly. For gas turbine engines, one of the effective ways to improve engine availability and reduce maintenance costs is to move from pre-scheduled maintenance to condition-based maintenance by using gas turbine health information provided by engine diagnostic and prognostic analysis.

The performance of most physical assets degrades over time and follows certain failure patterns. Research reveals that there are at least six failure patterns actually occur in practice [1]. A gas turbine engine, as a physical asset, has its own features in performance degradations. Observations of gas turbine fouling in operations [2–4] show that performance degradation over time due to fouling is nearly linear with slight accelerated degradation rate. Observations of gas turbine non-recoverable degradation over time show that performance may degrade with nearly constant rate in some cases [5,6], slightly increasing rate [6] or decreasing rate [7] in others. Saravaramuttoo and MacIsaac [8] referred three types of failure, i.e. instantaneous, delayed time-dependent and purely time-dependent, to describe gas turbine failure/degradation and concluded that the rates of degradation for gas turbines are seldom known and not likely to be linear. Brothertom et al. [9] described the gas turbine degradation mode as bathtub type.

Different prognostic techniques and relevant issues were reviewed and investigated by many researchers such as Brotherton et al. [9], Bytington et al. [10], Roemer et al. [11], DePold and Gass [12], Roemer and Kacprzynski [13], Brotherton et al. [14] and Hess et al. [15] and these techniques are summarized as experience-based prognostics, model-based prognostics, evolutionary prognostics, neural networks, state estimator prognostics, rule-based expert systems, fuzzy logic based methods, etc. Linear trending of gas turbine degradation is one of the prognostic methods and has been effectively used for short term prediction of engine health; examples of which are those given in [16,17]. Such trending methods base on linear regressions over time and have the limitation that they may only be acceptable for short term health prediction. Initial investigation of gas turbine diagnostic and prognostic analysis taking into account combined linear and non-linear degradation over time is shown in [18]. The objective of the research in this paper is to further investigate the linear and/or a non-linear prognostic approach for the prediction of potential engine performance degradation into the future

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doi:10.1016/j.apenergy.2009.02.011

Nomenclature

Symbols

e	residual
$E()$	mean value
GPA	Gas Path Analysis
H	Influence Coefficient Matrix (ICM)
L	summation of squares of deviations
m_f	fuel flow rate (kg/s)
n	number of data points
N	gas generator rotational speed
P	total pressure (kPa)
$skew()$	Skewness
t	time
$t_{\alpha/2,n-2}$	upper (α/2) percentage point of the t-distribution with ($n-2$) degree of freedom
t_p	predicted pessimistic useful life
t_u	predicted useful life with a regression model
t_o	predicted optimistic useful life
T	total temperature (K)
$V()$	variance
$\vec{x}$	component health parameter vector
$\vec{z}$	gas path measurement parameter vector
β_0, β_1, β_2	regression coefficients
α	accumulated tail probability of t-distribution
ε	measure of difference between actual and predicted measurements; random error
η	isentropic efficiency
λ	*GPA* Index
μ	mean value
σ	standard deviation
ψ	prediction error or prognostic uncertainty
Δ	deviation

Subscript

1–9	engine gas path station numbers (shown in Fig. 7)

Superscripts

^	estimated
T	transpose
−1	inverse

by taking into account possible change of degradation patterns over time.

Gas turbine gas path diagnostics is an essential step towards effective prognostic analysis. Different gas path diagnostic techniques have been developed in the past. Typical ones are Gas Path Analysis (*GPA*) and its derivatives [19–26], neural networks [27–29], Bayesian Belief Networks [30], Genetic Algorithm [31–33], Fuzzy Logic [34–36], diagnostics using transient measurements [37,38], etc. This research field has been summarized by Li [39] and Singh [40].

The forecasting of engine degradation or engine prognostics is very challenging due to great uncertainty associated with gas turbine design, manufacturing, ambient and environmental condition, operating condition, duty missions, maintenance actions, etc. This study explores the incorporation of prognostic and statistical knowledge and develops a technical approach to predict the remaining useful life of gas turbine engines. The approach is then applied to a model offshore gas turbine application implanted with soft compressor degradation over time to show the effectiveness of the approach.

2. Gas path prognostic approach

2.1. Basic assumptions

Gas turbine degradation phenomenon is so complicated that no any single diagnostic and prognostic approach can cover all scenarios. Therefore, to make the diagnostic and prognostic approach described in this study applicable it is assumed that

(1) Only engine soft degradation associated with performance change (such as fouling and erosion) that develops gradually over time is discussed in this study.
(2) Engine operates at the standard *ISO* ambient condition and at maximum power throughout its life.
(3) Engine performance degradation follows a failure rate pattern shown in Fig. 1 where a constant failure rate last for a period of time followed by an increasing failure rate. This assumption also covers the scenario where only constant failure rate or increasing failure rate happens. Regular maintenance actions, such as online and off-line compressor washing, do not change engine degradation patterns.
(4) The uncertainty associated with the prognostic analysis is normally distributed around its true health and becomes larger into the future.
(5) Only major engine component degradations, such as compressor and turbine degradations, are included in the analysis and the degradation is described by the deviation of isentropic efficiency and flow capacity from their clean (un-degraded) value.
(6) Engine health analysis is carried out continuously from the beginning of its operation. However, the frequency of such analysis is dependent on the frequency of measurement data sampling.
(7) Frequent/recurrent maintenance actions such as on-line and off-line compressor washing are regularly carried out and do not change the fault patterns.

2.2. Gas path diagnostics

Degradation can be recognized as the deviation in performance from that when the engine was new. A non-linear *GPA* diagnostic approach used in this study is the one developed by Escher and Singh [25] and Li and Singh [26]. To assist the understanding of such diagnostic approach a brief description of the method is provided as follows.

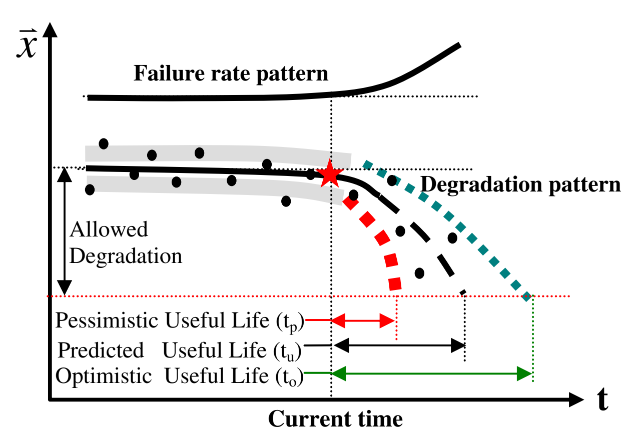

Fig. 1. Degradation and prognostic model.

At a given operating point and at certain time during operation, a linear relationship between gas path measurement deviation vector $\Delta\vec{z}$ and engine component health parameter deviation vector $\Delta\vec{x}$, Eq. (1), can be obtained from engine performance model $\vec{z} = f(\vec{x})$ by using a Taylor series expansion.

$$\Delta\vec{z} = H \cdot \Delta\vec{x} \tag{1}$$

where H is called the "*Influence Coefficient Matrix*" *(ICM)*. Therefore, engine performance degradation represented with $\Delta\vec{x}$ can be obtained with Eq. (2) if the number of measurements equals the number of health parameters, or Eq. (3) if the number of measurements is more than the number of health parameters.

$$\Delta\vec{x} = H^{-1} \cdot \Delta\vec{z} \tag{2}$$

$$\Delta\vec{x} = (H^T H)^{-1} \cdot H^T \cdot \Delta\vec{z} \tag{3}$$

The above method is called linear Gas Path Analysis (*GPA*). Due to that engine performance rarely deviates linearly with degradation and the linear approach may result in significant prediction errors in diagnostic analysis. This leads to the development of a non-linear *GPA* where the linear *GPA* is used iteratively until a converged solution is obtained (Newtom–Raphson method).

Accurate prediction of engine degradation with the *GPA* approach depends on *a priori* information of degraded components and therefore confusing solutions may be obtained if different degraded components are pre-assumed due to lack of such information. In order to isolate actually degraded component(s), a *GPA Index* λ defined in Eq. (4) is used to assess the accuracy of the prediction solutions.

$$\lambda = \frac{1}{1+\varepsilon} \tag{4}$$

where ε is a measure of the difference between the measured and predicted deviations of engine gas path measurements.

All engine gas path components may degrade during operation. To isolate the most severely degraded component(s) effectively, component fault cases (*CFC*) representing possible combination of degraded components that cover all the combinations of potential degraded components are assumed and the *GPA* diagnostic search is then applied to each of the fault cases. The cases with high *GPA* Indices indicate the most likely engine degradations. The details of the approach are described in [26].

2.3. Linear regression for prognostic analysis

Once the engine health is analyzed with the non-linear *GPA* at all individual moments in the past, engine future health could be predicted with the obtained historical engine health data.

In the context of this study, the forecasting methods to be used are the simple regression methods, such as linear and quadratic regressions. Regression analysis is a statistical tool that can produce predictions and provide explanation of data.

Based on the assumption that gas turbine engines would experience a long period of soft degradation from the beginning of its operation with a constant failure rate, Fig. 1, a linear regression is applied first to the historical data to produce a regression line for the purpose of prognostic analysis.

Suppose that the true relationship between engine health parameter x_i and time t is a straight line and that $x_{i,k}$ at each t_k is a random variable. The expected value of x_i for each value of t is presented by Eq. (5).

$$E(x_i|t) = \beta_{i,0} + \beta_{i,1} t \tag{5}$$

where $\beta_{i,0}$ and $\beta_{i,1}$ are unknown regression coefficients. It is assumed that each $x_{i,k}$ can be described by Eq. (6).

$$x_{i,k} = \beta_{i,0} + \beta_{i,1} t_k + \varepsilon_{i,k}, \quad k = 1, 2, \ldots, n \tag{6}$$

where $\varepsilon_{i,k}$ are random errors with zero mean and variance σ_i^2. The random errors $\varepsilon_{i,k}$ corresponding to different $x_{i,k}$ are also assumed to be uncorrelated and normally distributed.

Fig. 2 shows a typical scatter plot of historical engine health data over time and an estimated linear regression line. The value of $\beta_{i,0}$ and $\beta_{i,1}$ can be estimated by a least squares method to obtain a best fit to the data $x_{i,k}$ ($k = 1,2,\ldots,n$) where the sum L of the squares of the deviations of $x_{i,k}$, Eq. (7), from the true regression line is minimized.

$$L = \sum_{t=1}^{n} \varepsilon_{i,k}^2 = \sum_{k=1}^{n} (x_{i,k} - \beta_{i,0} - \beta_{i,1} t_k)^2 \tag{7}$$

More details of the method can be found in many books, such as [41]. The solution to Eq. (7) results in least squares estimators $\hat{\beta}_{i,0}$ and $\hat{\beta}_{i,1}$. Therefore, the estimated regression line is represented by Eq. (8).

$$\hat{x}_i = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} t \tag{8}$$

Note that each pair of ($x_{i,k}$, t_k) satisfies the relationship shown in Eq. (9).

$$x_{i,k} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} t_k + e_{i,k}, \quad k = 1, 2, \ldots, n \tag{9}$$

where $e_{i,k} = x_{i,k} - \hat{x}_{i,k}$ is called the *residual* describing the error in the fit of the model to $x_{i,k}$.

2.4. Quadratic regression model

In a situation where an increasing failure rate occurs linear regression is no longer applicable. Therefore, a quadratic regression could be a better solution for prognostic prediction. Fig. 3 shows a typical scatter plot of engine health data over time and a quadratic regression line to fit the data.

Similar to the linear regression, suppose that the true relationship between engine health parameter x_i and time t is a quadratic line and that $x_{i,k}$ at each t_k is a random variable. The expected value of x_i for each value of t is represented by Eq. (10).

$$E(x_i|t) = \beta_{i,0} + \beta_{i,1} t + \beta_{i,2} t^2 \tag{10}$$

where $\beta_{i,0}$, $\beta_{i,1}$ and $\beta_{i,2}$ are unknown regression coefficients that would have to be estimated. It is assumed that each $x_{i,k}$ can be described by Eq. (11).

$$x_{i,k} = \beta_{i,0} + \beta_{i,1} t_k + \beta_{i,2} t_k^2 + \varepsilon_{i,k}, \quad k = 1, 2, \ldots, n \tag{11}$$

where $\varepsilon_{i,k}$ are random errors with zero mean and variance σ_i^2. The random errors $\varepsilon_{i,k}$ corresponding to different $x_{i,k}$ are also assumed to be uncorrelated and normally distributed.

To find the coefficients ($\beta_{i,0}$, $\beta_{i,1}$ and $\beta_{i,2}$) of the regression line for n pair data ($x_{i,k}$, t_k), $k = 1,\ldots,n$, the least square estimator $\beta_{i,0}$, $\beta_{i,1}$ and $\beta_{i,2}$ are those values that minimize L, Eq. (12).

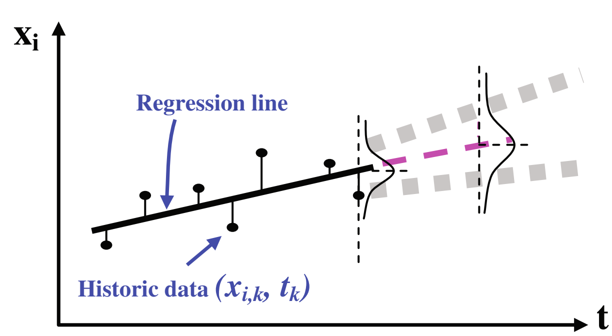

Fig. 2. Linear regression model.

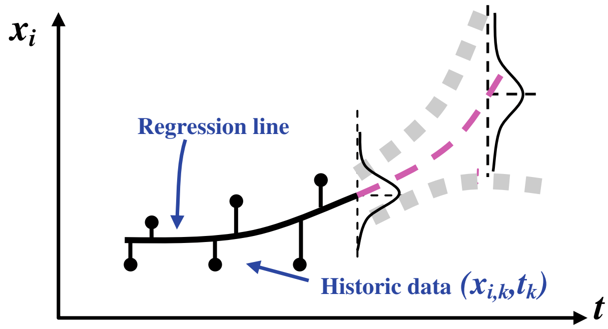

Fig. 3. Quadratic regression model.

$$L = \sum_{t=1}^{n} \varepsilon_{i,k}^2 = \sum_{k=1}^{n} (x_{i,k} - \beta_{i,0} - \beta_{i,1} t_k - \beta_{i,2} t_k^2)^2 \tag{12}$$

Therefore, the estimated regression line becomes Eq. (13)

$$\hat{x}_i = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} t + \hat{\beta}_{i,2} t^2 \tag{13}$$

Note that each pair of ($x_{i,k}$, t_k) satisfy the relationship shown in Eq. (14). More details of the method can be found in many books such as [42].

$$x_{i,k} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} t_k + \hat{\beta}_{i,2} t_k^2 + e_{i,k}, \quad k = 1, 2, \ldots, n \tag{14}$$

For both linear and quadratic regressions, the regression coefficients determine the quality of the regression lines, Eqs. (8) and (13). The reliability of the regression lines representing the true values of the health parameters depends on the accuracy of the measurement samples, the number of the measurement samples and the accuracy of the *GPA* diagnostic analysis.

2.5. Transition of regression methods

In gas turbine applications, the degradation pattern of a gas turbine engine over time is unknown. It could be linear, non-linear or the combination of both. Based on published information [2–9], it can be seen that the combined failure rate pattern shown in Fig. 1 is one of the typical degradation patterns of gas turbine engines. For such a degradation process, the engine degradation develops linearly with a constant failure rate during the first period of operation when engines experience soft and gradual degradation and is then followed by an increasing failure rate during the second period of operation. Therefore, the prognostic prediction is started with the linear regression mode. A compatibility check of monitored points around the regression lines is continuously conducted to determine if the quadratic regression model should be used to replace the linear regression model, Fig. 4. It is important to accurately determine a transition point where the prognostic model is switched from the linear regression model to the quadratic regression model in order to have an accurate prognostic assessment. When only linear degradation happens the linear regression model will be continuously used. When only non-linear degradation happens the prognostic analysis will turn to quadratic regression model soon after the beginning of the operation based on the compatibility check.

To determine the transition point for the transition from the linear regression to the quadratic regression, a compatibility check is proposed in this study and carried out continuously in the prognostic analysis to assess if current regression model fits actual failure rate pattern. If current regression model is valid, the variance of new observations of the health parameters should continue to be normally distributed around current regression line. Otherwise, a different failure rate pattern and corresponding regression model should be applied.

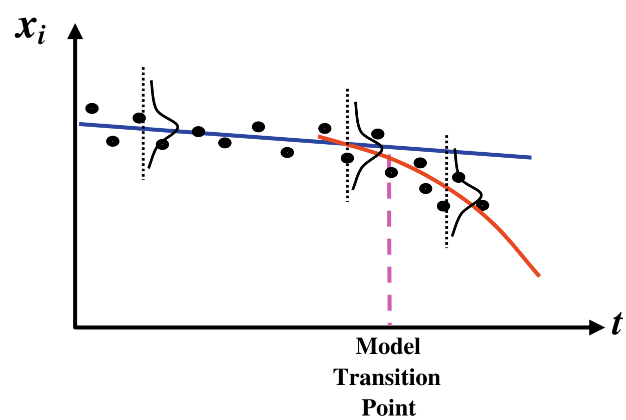

Fig. 4. Compatibility check for model transition.

In the proposed compatibility check, two statistical parameters are used in this study and they are Significance Level and Skewness. To understand the concept of the Significance Level, a null hypothesis is assumed, where the observations of the variance of the health parameters are normally distributed. The probability of rejecting the null hypothesis when it is true is called the Significance Level [41]. The Significance Level may vary from 0 to 1; a lower value of the Significance Level would indicate that the null hypothesis should be rejected and vice versa. A critical value of the Significance Level is application dependent and should be determined based on application statistics and past experience; a too small value would allow an engine to degrade too much while a too big value would overhaul an engine when it is still healthy. In this research, a critical value of 0.2 is chosen for the Significance Level in order to determine if the null hypothesis should be rejected. The approach and the software used to calculate the Significance Level is the Shapio–Wilk (S–W) statistic test [43] and the *SPSS for Windows* [44], respectively. In a case where new observation data shift away from the current regression line with the Significance Level becoming smaller and smaller, it indicates that the current regression model is no longer valid and a different regression model should be applied to fit the data.

The Skewness is the measure of symmetry of data in a statistic sense. Symmetric data should have a Skewness value near zero. A negative Skewness value (skewed to the left) indicates that data are bunched together above the mean but with a long tail below the mean, while a positive one (skewed to the right) indicates that data are bunched together below the mean but with a long tail above the mean. Fig. 5 illustrates the notion of Skewness where both probability density functions (PDFs) of the data have the same expectation and variance; the one on the left is positively skewed and the one on the right is negatively skewed.

The Skewness of random variable x_i is denoted as *skew(x_i)* and is defined in Eq. (15).

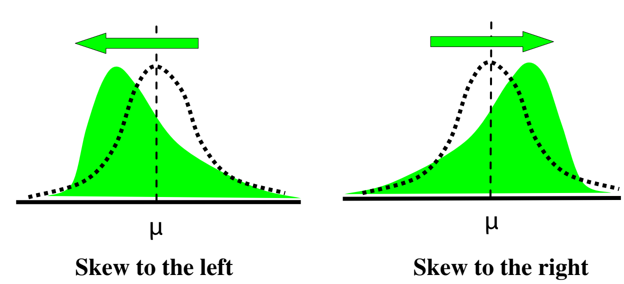

Fig. 5. Schematic demonstration of skewed data distribution.

$$skew(x_i) = \frac{E[(x_i - \mu_i)^3]}{\sigma_i^3} \tag{15}$$

where μ_i and σ_i are the mean value and standard deviation of data x_i, respectively. More details of the Skewness can be found in [45] and the software used to calculate the Skewness is the *SPSS for Windows* [44].

In a case where a regression line does not match the actual failure pattern, the difference between the data and the regression line, $(x_{i,k} - \beta_{i,0} - \beta_{i,1}t_k)$ or $(x_{i,k} - \beta_{i,0} - \beta_{i,1}t_k - \beta_{i,2}t_k^2)$, should be either negative with the data showing on the upper side of the regression line or positive with the data showing on the lower side of the regression line. Therefore, a continuous decrease or increase in the Skewness value indicates that a different regression model should be used to fit the data.

Critical value for the Significance Level and the Skewness should be defined in order to determine the transition point. However, such compatibility check is based on statistic information. Therefore the frequency of sampling over time and the number of total available data samples have significant influence on the calculated values of the Significance Level and the Skewness. Certain crisp criterion for the transition only becomes meaningful when the frequency of sampling over time and the amount of data samples are determined.

2.6. Prognostic uncertainty

Once a regression line, Eq. (8) or (13), has been established, it can be used to predict new or future health parameters. However, the prediction error or prognostic uncertainty represented by Eq. (16).

$$\psi_i = x_i - \hat{x}_i \tag{16}$$

is strongly associated with time into the future and can be regarded as a normally distributed random variable with a zero mean and a variance around the predicted health at a future time of interest. Such prognostic uncertainty is very difficult to estimate as it could be affected by many factors, such as engine design safety margins, manufacture tolerance, ambient and environmental conditions, operating conditions, mission duties, maintenance schedule etc. For example, an engine has to work with higher firing temperature in hot days than in cold days when the same power output is required. Therefore the engine performance may degrade faster in hot days. The manufacturing quality of gas turbine engines of the same fleet may also be different due to manufacturing tolerance and therefore "good" engines may degrade slower than "bad" engines because of different firing temperature required to provide the same power output. Due to the complexity of the degradation uncertainty, engine operating field data and experience may provide good information for the estimation of prognostic uncertainty.

To assist current prognostic study and demonstrate the idea of the whole prognostic system, a prognostic uncertainty model [41] based on the variance of historical data of an engine is adopted as follows.

Let $x_{i,k}$ be the future observation of an engine health parameter at time t and $\hat{x}_{i,k}$ be given by the fitted model of either Eq. (8) or (13). The variance of prediction error $\psi_i = (x_{i,k} - \hat{x}_{i,k})$ is assumed to have mean zero and variance estimated by Eq. (17).

$$V(\psi_i) = \hat{\sigma}_i \left[1 + \frac{1}{n} + \frac{(t - t_o)^2}{S_{tt}}\right] \tag{17}$$

where $\hat{\sigma}_i$ is the estimate of the standard deviation of $\hat{x}_{i,k}$ and

$$S_{tt} = \sum_{k=1}^{n} t_k^2 - \frac{1}{n}\left(\sum_{k=1}^{n} t_k\right)^2 \tag{18}$$

a $100(1-\alpha)\%$ prediction error on a future observation $x_{i,k}$ at time t is defined by Eq. (19).

$$\hat{x}_{i,k} \pm t_{\alpha/2,n-2} \cdot \sqrt{\hat{\sigma}_i^2 \left[1 + \frac{1}{n} + \frac{(t - t_0)^2}{S_{tt}}\right]} \tag{19}$$

where n is the number of measurement samples used in the estimation, $t_{\alpha/2,n-2}$ the upper $(\alpha/2)$ percentage point of the t-distribution with $(n-2)$ degrees of freedom and α the cumulated tail probability of the t-distribution. Such a prediction error is used as the estimate of the prognostic uncertainty into the future.

The prognostic uncertainty is of minimum width at time ($t = t_0$) and increases as the t value (time or running hours) moves away from current time into the future. The estimate of the prognostic uncertainty described above is based on historical uncertainty of engine health data inclusion of different existing influential factors such as design and manufacturing quality of an engine, ambient and environmental conditions, mission profiles, maintenance actions, etc. If these influential factors change in the future the prognostic uncertainty may also change accordingly and such changes are not considered in this study.

2.7. Determination of remaining useful life

Based on gas turbine historical data up to the current time of operation, gas turbine degradation into the future can be predicted with linear or quadratic regression with an upper and lower bound of prognostic uncertainty determined by Eq. (19), Fig. 1. For the sake of safety of gas turbine engines, gas turbine operators may only use either lower bound or upper bound to determine the remaining useful life depending on the direction of the variation of health parameters over time – for those health parameters decreasing over time, lower bound of prognostic uncertainty provides pessimistic prediction and is used to determine the remaining useful life, and vice versa. Therefore, the prediction procedure of remaining engine useful life is as follows:

- Allowed degradation for health parameters (thresholds) should be determined.
- The time period from current time to the intersection point between the predicted engine degradation line and allowed degradation line is the estimate of the predicted remaining useful life (t_u).
- The time period from current time to the intersection point between the lower prognostic uncertainty bound of the predicted engine degradation line (in case of health parameters decreasing over time) and allowed degradation line is the estimate of the predicted pessimistic remaining useful life (t_p).
- Similarly, a predicted optimistic remaining useful life (t_o) can be obtained but cause comparatively little worry to gas turbine users.
- The actual remaining useful life should be between the pessimistic and predicted engine remaining useful lives (t_p and t_u) if the prediction is satisfactory.

2.8. Integrated diagnostic and prognostic approach

To apply the above diagnostic and prognostic techniques to gas turbine applications, a diagnostic and prognostic approach, Fig. 6, is proposed and explained as follows:

Step 1: Apply the *GPA* diagnostic approach to detect engine degradation up to current time using available gas path measurements. Such *GPA* diagnostic approach is able to diagnose major engine gas path components, such as compressors and turbines.

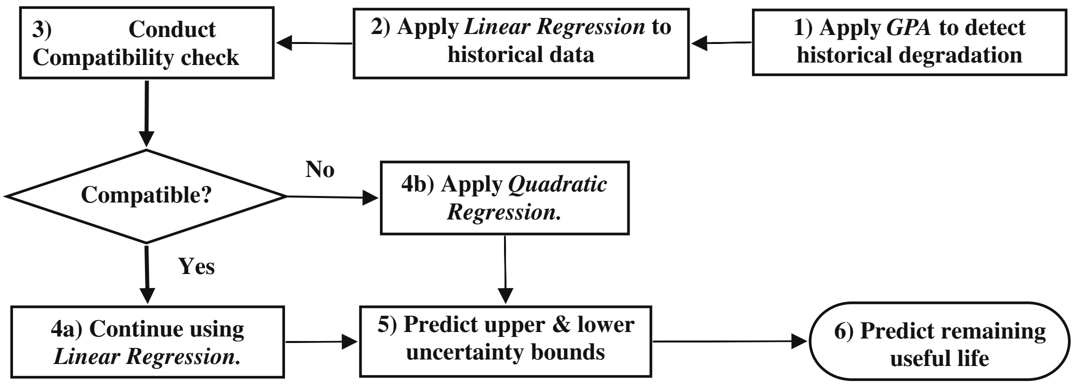

Fig. 6. Diagnostic and prognostics system for gas turbines.

The selected measurements should be uncorrelated gas path measurements that are sensitive to the degradation of these gas path component degradations. Due to the statistic nature of the approach, the more the amount of measurement samples the better prognostic results may be achieved.

Step 2: Apply the linear regression model to fit historical performance health data and predict future engine health parameters.

Step 3: Conduct Compatibility Checks to determine whether the regression model is compatible with the actual pattern of engine failure rate.

Step 4: (a) If good compatibility is demonstrated, the linear regression model will continue to be used. (b) Otherwise, the quadratic regression should be used instead.

Step 5: Prognostic uncertainty over time into the future is estimated in order to determine the upper and lower bounds of prognostic uncertainty of the prediction line.

Step 6: Allowable engine degradation specified with a threshold for each engine health parameter should be determined and the estimated engine remaining useful life, including the pessimistic useful life, can be obtained.

3. Application and analysis

The integrated diagnostic and prognostic approach described in the previous section is applied to a model industrial gas turbine engine simulated with gas turbine performance simulation software in order to demonstrate the effectiveness of the approach.

3.1. Performance simulation and diagnostics of a model engine

The model gas turbine engine used in this study is a two-shaft industrial gas turbine, similar to Rolls-Royce industrial AVON Mk 1535, that has one compressor, one burner, one compressor turbine and one power turbine. The basic performance parameters are as follows:

Total pressure ratio	3.33
Turbine entry temperature	869 (°C)
Exhaust mass flow rate	77.3 (kg/s)
Power output	15 (MW)
Heat rate	12,258 (kJ/kWh)

Cranfield University gas turbine performance and diagnostic software [26] is used to create an engine performance model and simulate the clean and degraded performance over time. The model engine configuration is shown in Fig. 7.

It is assumed that:

- The pattern of engine failure rate follows the one shown in Fig. 1.
- The degradation in this gas turbine occurs due to significant compressor degradation represented by the deviation of compressor flow capacity and isentropic efficiency. Due to that these two compressor health parameters are independent from one another a particular case of degradation where the degradation in flow capacity is double the degradation in compressor efficiency is simulated in this study.
- The engine degrades at a constant failure rate from the beginning of operation to 20,000 h of operation and then an increasing failure rate occurs. The engine reaches −3% degradation in efficiency and −6% degradation in flow capacity at 30,000 h of operation.
- The measurement noise has a normal distribution around true measurement values and the maximum level of measurement noise for different gas path parameters is shown in Table 1 [46].
- Diagnostic assessments are carried out for every 500 h of operation. However, due to the statistic nature of the analysis in concern more frequent data sampling will improve the prediction accuracy. This is due to the fact that the measurement noise can be assessed more easily and accurately and the obtained regression lines will provide better prediction of true values of health parameters.
- The engine is to be removed for an overhaul when the degradation in efficiency reaches −3%, or the degradation in flow capacity reaches −6%.

The available gas path measurements for diagnostic and prognostic analysis are chosen to be those shown in Table 2.

To demonstrate the proposed prognostic method, a typical compressor degradation developed over time is implanted into the model gas turbine engine (solid line in Figs. 8 and 9) and the corresponding degraded engine performance and gas path measure-

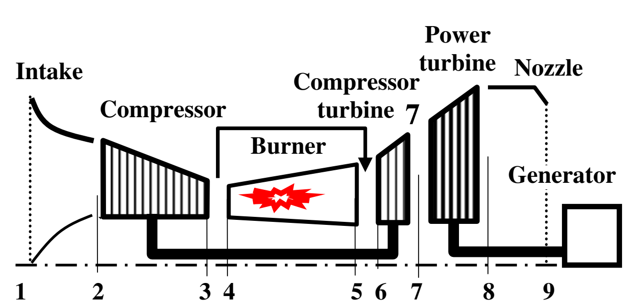

Fig. 7. Model engine configuration.

Table 1
Maximum measurement noise [46].

Measurement	Range	Typical error
Pressure	3–45 psia	0.5%
	8–460 psia	±0.5% or 0.125 psia whichever is greater
Temperature	−65–290 °C	±3.3 °C
	290–1000 °C	$\pm\sqrt{2.5^2 + (0.0075 \cdot T)^2}$
	1000–1300 °C	$\pm\sqrt{3.5^2 + (0.0075 \cdot T)^2}$
Fuel flow	Up to 250 kg/h	41.5 kg/h
	Up to 450 kg/h	34.3 kg/h
	Up to 900 kg/h	29.4 kg/h
	Up to 1360 kg/h	23.7 kg/h
	Up to 1815 kg/h	20.8 kg/h
	Up to 2270 kg/h	23.0 kg/h
	Up to 2725 kg/h	25.9 kg/h
	Up to 3630 kg/h	36.2 kg/h
	Up to 5450 kg/h	63.4 kg/h
	Up to 12,260 kg/h	142.7 kg/h

Table 2
Instrumentation set.

Measurement	Meaning
P_3	Compressor exit total pressure (kPa)
P_7	Compressor turbine exit total pressure (kPa)
T_7	Compressor turbine exit total temperature (K)
P_8	Power turbine exit total pressure (kPa)
T_8	Power turbine exit total temperature (K)
m_f	Fuel flow rate (kg/s)
N	Gas generator rotational speed (%)

ments are simulated. Then it is assumed that the implanted degradation is unknown to the diagnostic system and the *GPA* diagnostic system described in [26] is used to isolate and quantify engine component degradation over time. The predicted degradation plotted over time (dotted line in Figs. 8 and 9) representing the engine degradation history is used in the prognostic analysis to estimate potential engine remaining useful life.

3.2. Component diagnostic analysis using GPA approach

In diagnostic and prognostic analysis, the non-linear *GPA* is applied to all the engine historical data up to the current time to analyze the engine health degradation history. This includes isolating the degraded engine component(s) using the concept of fault cases and *GPA* Index and quantifying the component degradation [26]. Due to that the diagnostic analysis is not the focus of this paper,

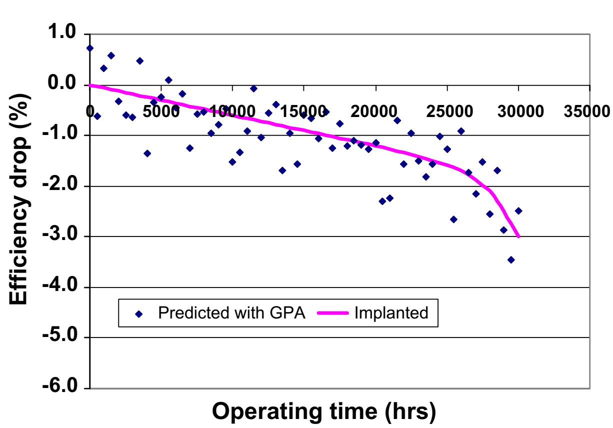

Fig. 8. Implanted compressor efficiency degradation and predicted degradation with *GPA*.

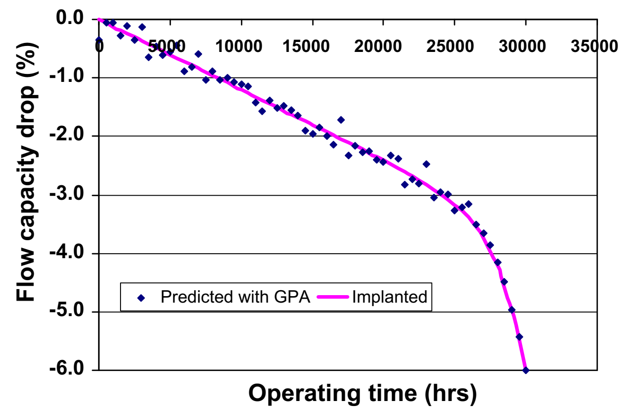

Fig. 9. Implanted compressor flow capacity degradation and predicted degradation with *GPA*.

the detailed component fault isolation and quantification is assumed to be done successfully while the interested readers may refer to [26] for more information of the process. Once the degradation analysis is done for all individual points, the predicted degradation for component health parameters over time can be plotted up to the current time. Figs. 8 and 9 show the predicted diagnostic results in dotted points in terms of the predicted degradation of compressor efficiency and flow capacity, respectively. As discussed in [26] the non-linear *GPA* is able to provide accurate diagnostic results if engine gas path measurements are accurate. Therefore the scattering of the points are due to the impact of measurement noise that contributes to the diagnostic prediction errors and the quantitative level of such prediction errors is more or less similar to the measurement noise of the gas path measurements. Due to the statistic nature of the prognostic method the amount and the accuracy of measurements samples and the accuracy of diagnostic analysis have great impact on the accuracy of prognostic analysis. After the historical diagnostic information become available, the proposed prognostic approach is then used as follows.

3.3. Applying linear regression model for prognostic analysis

As the first step of the prognostic analysis, the linear regression model is applied to the scattered data from the beginning of operation for both compressor efficiency and flow capacity degradation. Figs. 10 and 11 provide an example of applying linear regression to the scattered data of compressor efficiency and flow capacity drops when it is assumed that the moment after 15,000 operation hours is the current time.

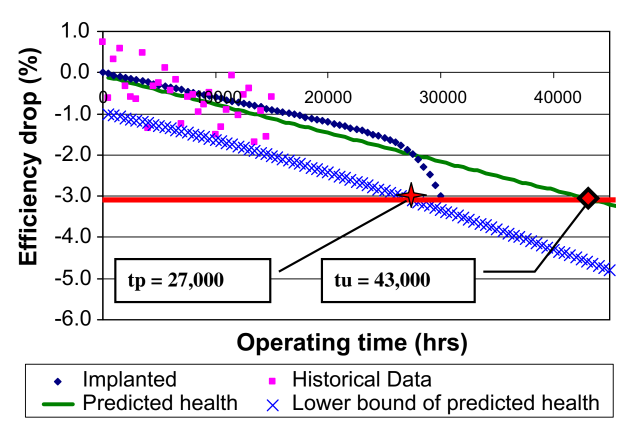

Fig. 10. Linear regression to scattered data of compressor efficiency at 15,000 h.

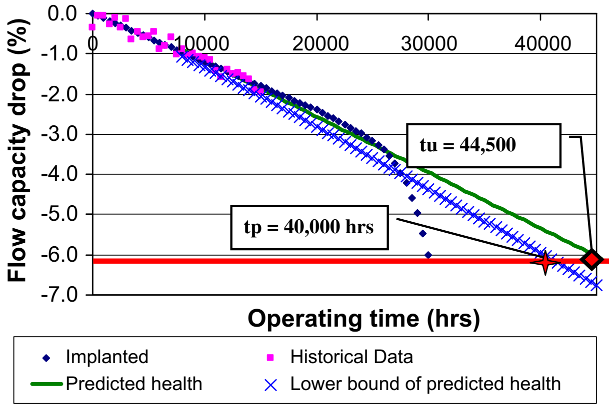

Fig. 11. Linear regression to scattered data of compressor flow capacity at 15,000 h.

Based on the assumption that the acceptable degradation is 3.0% for compressor efficiency and/or 6.0% for compressor flow capacity before a major overhaul, t_p (the pessimistic estimate of engine useful life) and t_u (the predicted engine useful life with assumed regression model) can be determined. For example in Fig. 10 where future degradation of compressor efficiency is predicted, t_p is around 27,000 h and t_u around 43,000 h. Therefore, with the prognostic prediction taking place at 15,000 h based on the compressor efficiency data, the predicted remaining useful life for the engine is roughly between 12,000 and 28,000 h. Similarly in Fig. 11 where future degradation of compressor flow capacity is predicted, t_p is around 40,000 h and t_u around 44,500 h. Therefore, the predicted remaining useful life of the engine is roughly between 25,000 and 29,500 h. It can be seen by the comparison in Table 3 that the predicted remaining useful life based on compressor efficiency data provides more conservative result due to greater scattering of the historical data. The significant difference between the predicted remaining useful life based on efficiency data and that based on flow capacity data is due to the significant difference in prognostic uncertainties. Although the lower prognostic uncertainty bound of the linear regression line for the compressor efficiency data covers the implanted remaining useful life (Fig. 10), it is very likely that the prediction of remaining useful life may not be reliable due to that the linear regression model does not take into account the situation where actual degradation pattern changes in the future, such as the case in Fig. 11.

3.4. Compatibility checks

Once the prognostic analysis starts, compatibility checks of new observation points are continuously conducted to determine whether the linear regression model is still compatible with actual failure rate pattern of the engine. If the regression model is still fit, the new observation points distribute normally around the linear regression line.

Fig. 12 shows the Significance Levels of compressor efficiency and compressor flow capacity degradation derived from the S–W tests from the beginning of operation until 25,000 h of operation, respectively. The Significance Level for compressor flow capacity and compressor isentropic efficiency degradation decreases over time. After 22,500 h, the significant decrease in the Significance Level for both the compressor efficiency and flow capacity drops below pre-defined threshold 0.2 indicating that the failure rate pattern has changed from a constant failure rate to an increasing failure rate.

Fig. 13 shows the Skewness from the beginning of operation until 25,000 h of operation. It shows that the absolute value of the Skewness for compressor flow capacity and compressor isentropic efficiency degradation increases over time. However, the level of increase of the Skewness in the compressor efficiency degradation data is not as significant as that of the compressor flow capacity degradation data; this may be due to large scattering of the compressor efficiency degradation data shown in Fig. 8. The continuous increase in the absolute value of the Skewness Level indicates the status of incompatibility of normal distribution of degradation data and suggests that the linear regression model does not fit the data any more after 22,000–25,000 h of operation when the Skewness increase significantly.

Based on both the Skewness and the Significance Level analysis, it can be concluded that the failure rate pattern has changed from

Table 3
Predicted remaining engine useful life at 15,000 h of operation.

	Remaining engine useful life at 15,000 h of operation	
	Pessimistic prediction considering prognostic uncertainty (t_p – 15,000)	Prediction with quadratic regression model (t_u – 15,000)
From compressor efficiency drop data (Fig. 10)	12,000	28,000
From compressor flow capacity drop data (Fig. 11)	25,000	29,500
Based on implanted degradation	15,000	

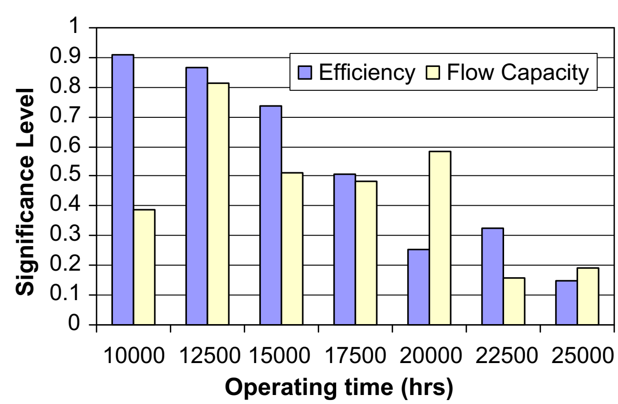

Fig. 12. Significance level of compressor efficiency and flow capacity degradation during engine operation.

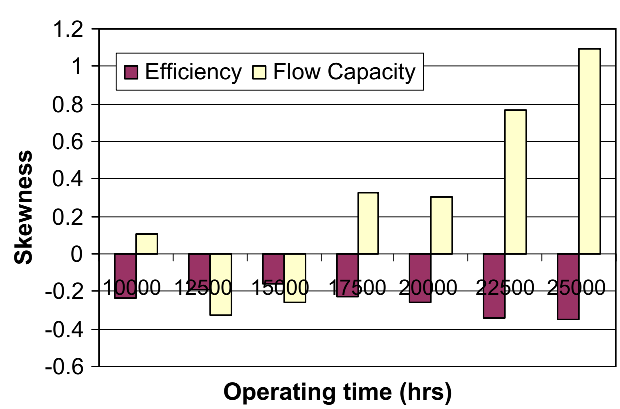

Fig. 13. Skewness levels of compressor efficiency and flow capacity degradation during engine operation.

constant to increasing rate pattern at some point within the range of 22,500–25,000 h of operation. Therefore, the quadratic regression model should be used to replace the linear regression model for further prognostic prediction after around 22,500 h of operation.

3.5. Applying quadratic regression for prognostic analysis

Based on previous analysis, the engine health prognostic analysis is carried out using the quadratic regression model from 22,500 h of operation onwards. Figs. 14 and 15 show an example of applying the quadratic regression model to the data of compressor efficiency and flow capacity degradation when it is assumed that 22,500 h of operation is current time and that the last 30 data points before the current time are used to produce the regression lines.

Similar to the practice using linear regression model, the remaining engine useful life can be estimated accordingly. In Fig. 14 where future degradation of compressor efficiency is predicted, t_p is around 26,000 h and t_u around 33,500 h. The predicted remaining useful life for the engine based on the compressor efficiency data is roughly between 3500 and 11,000 h. Similarly in Fig. 15 where future degradation of compressor flow capacity is predicted, t_p is around 29,500 h and t_u around 35,000 h. Therefore, the predicted remaining useful life of the engine based on the flow capacity data is roughly between 7000 and 12,500 h. A comparison

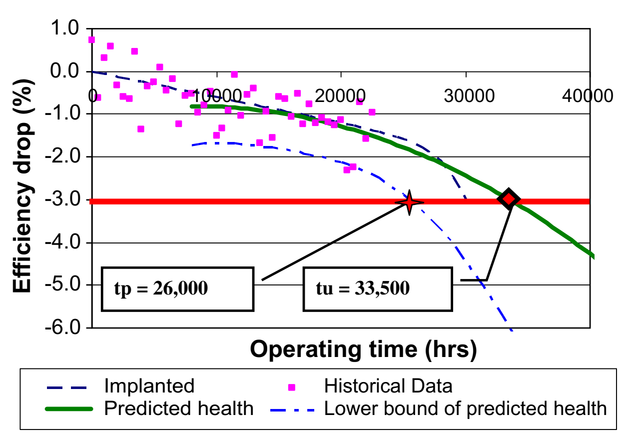

Fig. 14. Quadratic regression to scattered data of compressor efficiency at 22,500 h.

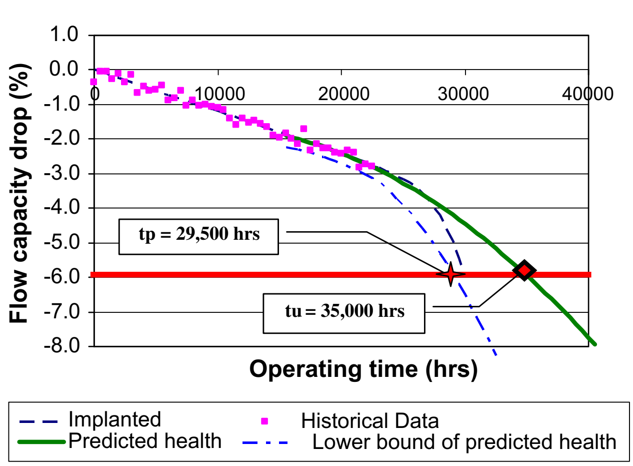

Fig. 15. Quadratic regression to scattered data of compressor flow capacity drop at 22,500 h.

Table 4
Predicted remaining engine useful life at 22,500 h of operation.

	Remaining engine useful life at 22,500 h of operation	
	Pessimistic prediction considering prognostic uncertainty (t_p – 22,500)	Prediction with quadratic regression model (t_u – 22,500)
From compressor efficiency drop data (Fig. 14)	3500	11,000
From compressor flow capacity drop data (Fig. 15)	7000	12,500
Based on implanted degradation	7500	

of the predicted remaining useful lives together with the implanted remaining useful life is shown in Table 4.

The prediction of remaining engine useful lives from both Figs. 14 and 15 are found to be satisfactory, as in both cases the implanted failure point is well between the predicted failure points using the quadratic regression model and the lower bound of prognostic uncertainty, Table 4. However, the prediction based on the compressor flow capacity data provides a narrower uncertainty interval than that based on the compressor efficiency data because of different levels of scattering of the data resulted from the diagnostic analysis using the *GPA* analysis. More conserved prediction of the remaining useful life is from the result based on the compressor efficiency degradation data due to its bigger data scattering.

The above diagnostic and prognostic analysis should be carried out continuously during engine operation and the predicted engine remaining useful life should be updated when new gas path measurements and new predicted engine health data are available. However, such prognostic information can be used as extra useful information for gas turbine operators for their maintenance planning and decision making to define more accurate time for plant shutdowns, scheduling of maintenance activities, and ordering of long lead-time spare parts.

4. Conclusions

In this study, a gas turbine prognostic approach based on statistic analysis has been proposed and applied to a model industrial gas turbine similar to a Rolls-Royce industrial AVON operating at a constant ambient and operating condition with implanted compressor degradation developed over time following an assumed failure rate pattern. In this approach, the varying linear and non-linear degradation patterns that may happen to gas turbine engines are considered in the prognostic analysis. A combined linear and quadratic regression model is introduced in the prognostic analysis to fit engine degradation data and provide satisfactory prediction of engine degradation into the future. For engine degradation following a typical failure rate pattern where a constant failure rate occurs from the beginning of operation followed by an increasing failure rate, linear regression model should be applied first and the quadratic regression model should be applied at the time when the changing failure rate occurs. A compatibility check using the Significance Level and the Skewness, a criterion for the determination of a transition point from linear to quadratic regression model, is introduced and proved to be useful in engine prognostic analysis. A prognostic uncertainty model based on the estimation of the variance of historical engine health data is introduced and the prognostic uncertainties are considered in the prognostic analysis in order to determine the prognostic uncertainty bounds and then the engine remaining useful life. The application of the proposed prognostic approach to the model gas turbine engine shows that the combined regression model is able to provide good fitting to the engine historical health data with varying fault patterns and provide satisfactory prediction of engine potential degradation into the future with the consideration of prognostic uncertainties. The test case shows that the proposed diagnostic and prognostic approach has a great potential to provide valuable estimation of engine remaining useful life and assist gas turbine users in their condition-based maintenance activities.

Acknowledgments

Special thanks to Chevron Thailand Exploration and Production that provided both the wonderful educational opportunity for the second author and the important engine information required to complete this research.

References

[1] Moubray J. Reliability-centred maintenance. 2nd ed. Oxford (UK): Butterworth-Heinemann; 1997.
[2] Haub GL, Hauhe WE. Field evaluation of on-line compressor cleaning in heavy duty industrial gas turbines. ASME 90-GT-107; 1990.
[3] Meher-Homji CB. Gas turbine axial compressor fouling – a unified treatment of its effects detection and control. ASME cogen-turbo conference, vol. 5; 1990. p. 179–90.
[4] Peltier RV, Swanekamp RC. LM2500 recoverable and non-recoverable power loss. ASME cogen-turbo power conference, Vienna, Austria; August 1995.
[5] Sasahara O. JT9D engine/module Performance Deterioration results from back to back testing; 1986.
[6] Flashbery LS, Haub GL. Measurement of combustion turbine non-recoverable degradation. ASME 92-GT-264; 1992.
[7] Crosby JK. Factors relating to deterioration based on Rolls-Royce RB211 in service performance. Turbomachin Perform Deteriorat 1986;37:41–7.
[8] Saravaramuttoo HIH, MacIsaac BD. Thermodynamic models for pipeline gas turbine diagnostics. ASME J Eng Power 1983(October):105.
[9] Brotherton T, Jahns G, Jacobs J, Wroblewski D. Prognosis of fault in gas turbine engines. In: Aerospace conference proceedings, 2000 IEEE, vol. 6; 2000. p. 163–71.
[10] Bytington CS, Roemer MJ, Galie T. Prognostic enhancements to diagnostic systems for improved condition-based maintenance. In: Aerospace conference proceedings, 2003 IEEE, vol. 7; 2003. p. 3247–55.
[11] Roemer MJ, Byington CS, Kacprzynski GJ, Vachtsevanos G. An overview of selected prognostic technologies with application to engine health management. ASME GT2006-90677; 2006.
[12] DePold HR, Gass FD. The application of expert systems and neural networks to gas turbine prognostics and diagnostics. J Eng Gas Turb Power 1999;121(October):607–12.
[13] Roemer MJ, Kacprzynski GJ. Advanced diagnostics and prognostics for gas turbine engine risk assessment. In: Aerospace conference proceedings, 2000 IEEE, vol. 6; March 2000. p. 345–53.
[14] Brotherton T, Grabill P, Wroblewski D, Friend R, Sotomayer B, Berry J. A testbed for data fusion for engine diagnostics and prognostics. In: Aerospace conference proceedings, 2002 IEEE, vol. 6; 2002. p. 3029–42.
[15] Hess A, Frith P, Suarez E. Challenges, issues, and lessons learned implementing prognostics for propulsion systems. ASME GT2006-91279, ASME Turbo Expo 2006, Barcelona, Spain; May 2006.
[16] Greitzer FL, Kangas LJ, Terrones KM, Maynard MA, Wilson BW, Pawlowski RA, et al. Gas turbine engine health monitoring and prognostics. The International Society of Logistics (SOLE) 1999 symposium, Las Vegas, Nevada, August 30 – September 2; 1999.
[17] Kacprzynski G, Fumina M, Roemer MJ, Caguiat D, Galie TR, McGroarty JJ. A prognostic modeling approach for predicting recurring maintenance for shipboard propulsion system. ASME 2001-GT-0218; 2001.
[18] Li YG, Nilkitsaranout P. A gas path diagnostic and prognostic approach for gas turbine applications. ASME GT2007-27275; 2007.
[19] Urban LA. Gas path analysis applied to turbine engine condition monitoring. AIAA-72-1082; 1972.
[20] Doel DL. An assessment of weighted-least-squares-based gas path analysis. J Eng Gas Turbines Power 1994;116:366–73.
[21] Borguet S, Leonard O. A generalized likehood ratio test for adaptive gas turbine performance monitoring. ASME J Eng Gas Turbines Power 2009;131.
[22] Romessis C, Kamboukos Ph, Mathioudakis K. The use of probabilistic reasoning to improve least squares based gas path diagnostics. J Eng Gas Turbines Power 2007;129:970–6.
[23] Volponi AJ. Gas path analysis: an approach to engine diagnostics. In: 35th symposium mechanical failures prevention group, Gaithersbury, MD; April 1982.
[24] Provost MJ. COMPASS: a generalized ground-based monitoring system. AGARD-CP-449, engine condition monitoring – technology and experience; October 1988.
[25] Escher PC, Singh R. An object-oriented diagnostics computer program suitable for industrial gas turbines. In: 21st (CIMAC) international congress of combustion engines, Switzerland; 15–18 May 1995.
[26] Li, YG, Singh R. An advanced gas turbine gas path diagnostic system – PYTHIA. ISABE-2005-1284, ISABE, Munich, Germany; September 2005.
[27] Denney G. F16 jet engine trending and diagnostics with neural networks. In: Proceedings of SPIE – the international society for optical engineering, vol. 1965; 1993. p. 419–22.
[28] Ogaji SOT, Singh R. Gas path fault diagnosis framework for a three-shaft gas turbine. IMechE J Power Energy 2003;217(Part A):149–57.
[29] Tan HS. Fourier neural networks and generalized single hidden layer networks in aircraft engine fault diagnostics. J Eng Gas Turbines Power 2006;128: 773–82.
[30] Romessis C, Mathioudakis K. Bayesian network approach for gas path fault diagnosis. J Eng Gas Turbines Power 2006;128:64–72.
[31] Zedda M, Singh R. Gas turbine engine and sensor fault diagnosis using optimization techniques. AIAA J Propulsion Power 2002;18(5):1019–26.
[32] Gulati A, Zedda M, Singh R. gas turbine engine and sensor multiple operating point analysis using optimization techniques. AIAA-2000-3716; 2000.
[33] Wallin M, Grönstedt T. A comparative study of genetic algorithms and gradient methods for rm12 turbofan engine diagnostics and performance estimation. ASME Turbo Expo GT2004-53591; 2004.
[34] Ganguli R. Application of fuzzy logic for fault isolation of jet engines. ASME Turbo Expo 2001-GT-0013; 2001.
[35] Martis D. Fuzzy logic estimation applied to newton methods for gas turbines. J Eng Gas Turbines Power 2007;129:88–96.
[36] Eustace R. A real-world application of fuzzy logic and influence coefficients for gas turbine performance diagnostics. ASME J Eng Gas Turbines Power 2008;130.
[37] Li YG. A gas turbine diagnostic approach with transient measurement. IMechE J Power Energy 2003;217(Part A):169–72.
[38] Surender VP, Ganguli R. Adaptive myriad filter for improved gas turbine condition monitoring using transient data. J Eng Gas Turbines Power 2005;127:329–39.
[39] Li YG. Performance-analysis-based gas turbine diagnostics: a review. IMechE J Power Energy 2002;216(Part A).
[40] Singh R. Advances and opportunities in gas path diagnostics. ISABE-2003-1008, 15th ISABE; 2003.
[41] Montgomery DC, Runger GC. Applied statistics and probability for engineer. 3rd ed. John Wiley & Sons, Inc.; 2002.
[42] Ross SM. Introduction to probability and statistics for engineers and scientists. John Wiley & Sons; 1987.
[43] SPSS Training Department. Time series analysis and forecasting with SPSS trends 9.0", SPSS Inc.; 1999.
[44] SPSS for Windows. Copyright SPSS Inc.; 1989–2001.
[45] Evans M, Hastings N, Peacock B. Statistical distributions. 3rd ed. New York: John Wiley & Sons Inc.; 2000.
[46] Dyson RJE, Doel DL. CF-80 condition monitoring – the engine manufacturing's involvement in data acquisition and analysis. AIAA-84-1412; 1987.