VOL. 11, NO. 22, NOVEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

GAS TURBINES HEALTH PROGNOSTICS: A SHORT REVIEW

Tamiru A. L., Fakhruldin M. H., Mohd Amin A. M. and Ainul A. M.
Mechanical Engineering Department, Universiti Teknologi Petronas, Bandar Seri Iskandar, Perak, Malaysia
E-Mail: tamiru.lemma@petronas.com.my

ABSTRACT

Gas turbines are used in oil platforms, floating liquid natural gas (FLNG) plants, and land based distributed power plants to generate power. In Malaysia, as much as 40% of the total electricity (e.g. an estimated 783 MW in Peninsular Malaysia, 289 MW in Sarawak, and 42 MW in Sabah) comes from gas turbine driven power plants. Some of the challenges in gas turbine operations are stringent safety and emission control requirements, urgent need to reduce life cycle cost, and the need to sustain high efficiency regardless of operating conditions, changing fuel cost, electricity tariff and electricity demand. The idea that got attention and intended to address these issues is the concept of integrated approach to remaining useful life prediction and operation scheduling. The purpose of the present paper is to review the literatures specific to gas turbine prognostics. The reviewed methods include regression methods, physics based models, computational intelligence (artificial neural network and fuzzy systems, evolutionary-based method), and hybrid approaches. As it turned out, (i) there is no readily available method that can be used to integrate reliability information into a prognostics model, (ii) the benchmark data from NASA is the only available information that can be used to test new algorithms, (iii) commercial softwares like Gate Cycle, PROSIS, and GSP have been used to generate data for diagnostics and prognostics studies, (iv) thermoeconomic or exergetic approach seems to be less applied to prognostics.

Keywords: gas turbine, remaining useful life, prognostics, physics based models, computational intelligence.

INTRODUCTION

Stationary gas turbines are widely used as mechanical drives and to provide electrical power. They operate on Brayton cycle with the compression and expansion processes following nonideal behavior, i.e. entropy changes different from zero. They are expected to have alternative means to control the emission of NOx and other greenhouse gases. In a tyical design, Figure-1, a gas turbine might be featured by modular design and comprised of a multi-stage axial compressor, combustion chamber, core turbine and main turbine. The core turbine drives the compressor while the main turbine is intended to run the generator shaft.

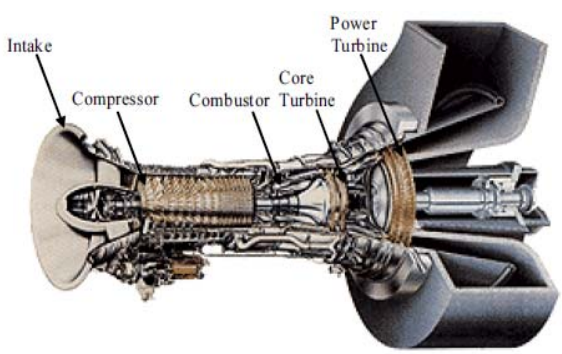

Figure-1. Typical two-shaft aero-derivative gas turbine with power turbine [1].

Gas turbine efficiency is likely to deteriorate due to fouling, corrosion, erosion, foreign object damage, tip clearance, or operation related issues. The performance drop will lead to wastage of the primary energy, an increase in the emission of greenhouse gases, and high maintenance cost. The emerging field of prognostics is believed to be ideal to address the highlighted issues as well as the challenges related to stringent safety and emission control requirements, urgent need to reduce life cycle cost, and the need to sustain high efficiency regardless of operating conditions, changing fuel cost, electricity tariff and electricity demand. The purpose of the present paper is to review the literatures specific to gas turbine prognostics. The reviewed methods include regression methods, physics based models, computational intelligence (artificial neural network and fuzzy systems, evolutionary-based method), and hybrid approaches. Prognostics is ideal to reduce maintenance costs through early detection of malfunctions. It might also lead to reduced down time, improved planning, and better management of assets [2]. In proactive maintenance, the capacity to accurately predict performance degradation through prognostics is considered an important element. Prognostics enables forward estimation of the time to failure, hence allowing prolonged time in-service.

THE CONCEPT OF PROGNOSTICS

Prognostics refer to prediction of the conditions at some future time [3]. For prognostics to work, the onset of failure has to be detected first. This can be realized analysing either a single parameter or a multiple-of parameters. According to ISO 13381-12004(E), prognostics requires methods for trend extrapolation, fault tree analysis, risk assessment, failure initiation models, and failure mode and effect analysis.

ARPN Journal of Engineering and Applied Sciences

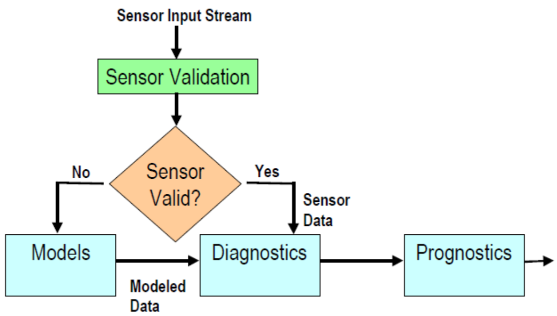

Figure-2. Structure of a prognostic system [4].

Figure-2 shows the diagnostics and prognostics system architecture as suggested by Greitzer *et al.* [4]. Similar or perhaps either simple or complicated designs can also be gotten from [5-8]. After the fault is detected and diagnosed, the next step is prognostics in which the time to failure or remaining useful life is estimated. Even though this might be done based on experts knowledge, the proven approach is to use some elements of modeling combined with experts knowledge. In terms of information required, the designer may rely on monitored data, operation data, manufacturers' data, historical data, or company test data.

METHODS APPLIED TO PROGNOSTICS

Accurate prediction of time to failure or remaining useful life is only possible through full knowledge of the maintenance actions taken in the past and historical failure data. Once the data is acquired, a systematic approach still needs to be searched to define a suitable performance indicator. But then the maintenance data is often difficult to acquire and integrate with time serious model. Regardless, there have been many reported methods, some proposing to adopt fusion of data sources and exploitation of a multiple of modeling algorithms. In the sequel, the popular methods are considered for further study.

Prognostic data

Prognostics uses a specific modeling method. In general, the selection of a particular method is dictated by the type of signal available for measurement and the expected outcome. It has been observed that, prognostics has been researched around the following set of signals.

- Oil debris/ condition monitoring [5].
- Vibration signals[5, 9].
- Thermodynamic or gas path signals [2, 6, 7, 10-13].
- Lube oil temperature and pressure monitoring[14].
- Crack or defect [5] information.
- Gas leak [4].
- Signals for the fuel supply system [11].
- Blade tip clearance data [15-17].

Vibration, oil debris, lube oil temperature, and lube oil pressure are often considered to monitor bearing conditions. The gas path signals, on the other hand, are mostly intended for performance deterioration due to fouling [6, 18], erosion, corrosion, or foreign object damage (FOD). The suggested guideline is that the parameter for trending should be independent of operating conditions[18]. Otherwise, data normalization might be needed.

Regression models

Once the engine performance in the past is analyzed by using the thermodynamic methods, gas turbine remaining useful life (RUL) could be predicted exploiting the historical data. The forecasting methods to be used might be as simple as linear, quadratic or exponential regression.

p-th order model [16, 18]:

$$\mathrm{RUL}(t;\theta) = \theta_0 + \theta_1 t + \theta_2 t^2 + ... + \theta_p t^p + \varepsilon \qquad (1)$$

One parameter double exponential smoothing[6, 18]:

$$\begin{cases} S_T = \alpha.RUL_T(t;\theta) + (1-\alpha)S_{T-1} \\ S_T^{[2]} = \alpha.S_T + (1-\alpha)S_{T-1}^{[2]} \end{cases} \qquad (2)$$

$$RUL_{T+\tau}(t;\theta) = \left(2 + \frac{\alpha\tau}{1-\alpha}\right)S_T - \left(1 + \frac{\alpha\tau}{1-\alpha}\right)S_T^{[2]} \qquad (3)$$

In Equation (1) - (3), θ_0 to θ_p are unknown regression coefficients, ε signifies the modeling and measurement error, α is the smoothing parameter. The regression parameters can be estimated through the method of least squares. Ariyur and Jelinek [14] suggested sliding window in the context of linear regression, which makes their approach different and ideal to filter measurement noise. This idea has been applied to prognostics using lube oil temperature signal.

In the research reported by Davison [13], the progression of a gas turbine failure was assessed by the life ratio which is defined as the ratio of distance between healthy and current state, and healthy operation to failure state, equation (5).

$$\varphi = \frac{\lambda_O}{\lambda_{EFP}} = \frac{\sqrt{(T_{03}/T_{06})^2_{O_n} + (p_{01}/p_{03})^2_{O_n}}}{\sqrt{(T_{03}/T_{06})^2_{EFP_n} + (p_{01}/p_{03})^2_{EFP_n}}} \qquad (5)$$

Where, λ_O is life ratio distance for operating point; λ_{EFP} is life ratio distance for expected failure point. The life ratio data is fitted to a suitable function and extrapolated to tell the remaining time before repair is required. Davison studied turbine behaviour prediction for five fault cases: degrading turbine, inlet blockage, degrading compressor, bleed, and outlet blockage. The performance measures applied for RUL prediction varies from researcher to researcher. Hanachi *et al.* [19] showed the use of efficiency ratio instead of life ratio, φ.

VOL. 11, NO. 22, NOVEMBER 2016 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

Bayesian method

One of the methods proposed for prognostics model development is the method of Bayesian forecasting. This method allows the calculation of prior and posterior probabilities and uncertainty bounds [12]. It is purely a stochastic approach. As such, the method is fundamentally based on the modeling of observed data by probability density functions, in which the new performance is first predicted and latter updated when the measurement data is available. Because of the predictor and corrector steps, it might also be considered similar to Kalman filter. Bayesian method has been applied to civil aerospace gas turbines [20] and compressor turbine system[8]. Various versions of Bayesian method were reported: Bayesian Forecasting Method and Comparison [18], state space combined with Bayesian method [21], Bayesian Hierarchical Model (BHM) [20], Bayesian forecasting and dynamic linear models (DLMs) [22], . Bayesian method has been extended by including time-varying noise model. In other models the error is assumed to be constant.

Computational intelligence

Some prognostics studies have employed computational intelligence methods to enhance on automation, quality of analysis, self learning, and decision making capabilities of the resulting prognostics method. Timely alerting of incidents are also reported to be better served by CI methods. In a recent study, Nieto *et al*. [23] used particle swarm optimization (PSO) combined with support vector machines (SVM). PSO was used to optimize the SVM parameters. The conclusion stated that PSO-SVM model can accurately model the RUL. The methods in this category include ANN, fuzzy systems, and evolutionary methods. They are generally considered data-driven except in a situation where hybrid designs are adopted in which one of the methods might be based on physical principles. ANN have good approximation characteristics of nonlinear functions. They are self-adaptive and require less assumption in the construction of a model. They have been applied by many researchers [2, 4, 10, 24]. Some of the merits reported for ANN include improvement in detection time and accuracy [2]. It was observed that ANN have been tested for the following kind of signals:

- Thermodynamic or gas path[2].
- Tip clearance [17].
- Fuel system [25].

The data feed to ANN can be average, standard deviation value [2], raw data, or normalized data. Some advantages of ANN are adaptation, fault tolerance, pattern classification, parallel processing, and feature extraction [17].

Hybrid methods

There is ample evidence that a combination of methods have been adopted to predict remaining useful life of a gas turbine. In the outcome reported by DePold *et al.* [2], a robust design for diagnostics and prognostics was realized by integrating ANN with statistical methods, Kalman filter, Bayesian based decision making and rule based analysis. Ghiocel and Altmann [26] illustrated the hybridized use of stochast-neuro-fuzzy systems.

Crack propagation based methods

Prognostics using physics based models refer to the use of crack propagation rate models and cumulative damage theory to predict remaining useful life of a system under certain loading conditions. One of the popular models in this category is the Paris-Erdogan law [27]. This law relates the stress intensity factor (SIF) with the crack propagation rate. Integration of this equation provides the number of cylces before the part is considered failed.

The application of mechanistic models to prognostics was demonstrated in the work of Kumar *et al*. [28] and Orchard and Vachtsevanos [29]. The main challenge in the application of crack propagation models is the formulation of SIF models for different loading and complex subject geometry.

Bearing life model

In the work of Orsagh *et al*. [5], available sensor information such as rotor speed, vibration, lube system information are linked with fatigue-based damage accumulation models. In the same study, remaining useful life assessment was done based on stochastic version of Yu-Harris bearing life equations. At the core of the method is the model for spall progression rate intended to explain remaining useful life of the bearing.

Benchmark data for prognostics test

Gate Cycle, PROSIS, GSP are some of the commercially available software that can be used to generate data for reference model development and validation. Other than that the data provided by NACA prognostics data repository is the only available information that can be exploited for prognostics system design and testing. It has been used in [21].

Data fusion techniques

The sensory data available for prognostics might be many. Hence data fusion methods are required to exploit the data to the maximum. In a simplest example, data fusion could mean combining rotating speed with the monitored vibration signals [5, 10]. In a complicated case, however, it might amount to processing thermodynamic measurements, vibration signals, lube oil temperatures and pressures, and experience based knowledge. In the study reported by Xu *et al*. [30], comentropy theory was applied for the same purpose. Data fusion provides (i) more accurate and robust estimation of remaining useful life, (ii) reduced false alarm rates in early fault detection, and (iii) better confidence level in predicting remaining useful life [10]. It was observed that data fusion was carried out at different levels [5]: sensory signal processing, diagnostics, incorporation of experienced knowledge. The need for data fusion was also emphasized in many research papers[3, 25, 31].

DISCUSSION

Several methods have been applied to the design of gas turbine prognostics and useful life predictions. Some of them are analytical approach, artificial neural networks, support vector machines, Dempster-Shafer regression, Bayesian Method, regression models, Kalman filters, state-space models, principal component analysis, independent component analysis and expert systems. As for typical features, for instance, the analytical method may use performance maps for each component in the gas turbine. The first challenge in applying this method is handling the effect of measurement errors and operations in transient conditions. The Bayesian approach, on the other hand, is a fully data based method and has the advantage in that it provides probability distributions. The other main observations resulted from the review process are as summarized below.

- There are several published literature addressing gas turbine diagnostics and prognostics, but then no published research is available on (i) gas turbines mostly working at part load (a behavior common in combined or cogeneration systems), and (ii) a framework that integrates prognostics with reliability prediction to benefit from the advantages of both. Therefore, it is important to investigate the nature of performance /health degradation in gas turbines operating at part load, and assess the effect to the design of prognostics and reliability prediction.
- The concept of data fusion has been applied at three levels: (i) feature-level, (ii) decision-level, and (iii) data-level. Decision-fusion using fuzzy set theory has been applied in the work of Zein-Sabatto *et al*. [7]. As reported by Liu *et al*. [32], few researches targeted the development of data-level fusion models.
- Prognostics and useful life prediction has been mainly carried out using either thermal efficiency or power output. However, it was observed that other parameters like specific fuel consumption and temperatures can also be applied [33]. In some cases prediction error lower that 2% have also been reported.
- Adopting Bayesian methods in the construction of ANN and fuzzy models. Reported studies show that the probabilistic nature of this methods were not well emphasized. This has lead to the perception that CI methods – even though nonlinear in nature – might not be straight forward to deal with uncertainty hence limiting their use in prognostics studies.

Finally, the study in gas turbine power plants prognostics seems very limited as evidenced by the applications reported so far. Even though signals commonly classified as gas-path signals, lube system signals, vibration signals, etc. are available, due to unavailability of a unified approach, only part of it is exploited for prognostic studies.

CONCLUSIONS

The purpose of this paper is to provide a short review on the methods widely used in gas turbine health prognostics. Accordingly, several ideas have been identified. Finally, it was concluded that

- Paucity of a benchmark data has limited the method selection solely to model-based methods.
- A pragmatic way would be integrating prognostics with diagnostics, and reliability.
- Data fusion has to be considered to allow reliable prognostic outcome.

Future work would concentrate on application of some of the methods to prognostics system design.

ACKNOWLEDGEMENTS

The authors are grateful to the support provided by Universiti Teknologi Petronas. The work is partially supported by Ministry of Higher Education (MOHE) Malaysia under grant number FRGS/2/2014/TK01/UTP/03/2.

REFERENCES

[1] S. Ogaji and R. Singh, "Artificial Neural Networks in Fault Diagnosis: A Gas Turbine Scenario," in Computational Intelligence in Fault Diagnosis, V. Palade, L. Jain, and C. Bocaniala, Eds., ed: Springer London, 2006, pp. 179-207.

[2] H. R. DePold and F. D. Gass, "The Application of Expert Systems and Neural Networks to Gas Turbine Prognostics and Diagnostics," Journal of Engineering for Gas Turbines and Power, vol. 121, pp. 607-612, 1999.

[3] T. Brotherton, P. Grabill, D. Wroblewski, R. Friend, B. Sotomayer, and J. Berry, "A testbed for data fusion for engine diagnostics and prognostics," in Aerospace Conference Proceedings, 2002. IEEE, 2002, pp. 6-3029-6-3042 vol.6.

[4] L. J. K. Frank L. Greitzer, Kristine M. Terrones,, B. W. W. Melody A. Maynard, Ronald A. Pawlowski,, and a. N. B. B. Daniel R. Sisk, "Gas Turbine Engine Health Monitoring and Prognostics," presented at the International Society of Logistics (SOLE), Las Vegas, Nevada, 1999.

[5] R. F. Orsagh, J. Sheldon, and C. J. Klenke, "Prognostics/diagnostics for gas turbine engine bearings," in Aerospace Conference, 2003. Proceedings. 2003 IEEE, 2003, pp. 3095-3103.

[6] C. S. Byington, M. Watson, M. J. Roemer, T. R. Galic, and J. J. McGroarty, "Prognostic enhancements to gas turbine diagnostic systems," in Aerospace Conference, 2003. Proceedings. 2003 IEEE, 2003, pp. 3247-3255.

[7] S. Zein-Sabatto, J. Bodruzzaman, and M. Mikhail, "Statistical approach to online prognostics of turbine engine components," in Southeastcon, 2013 Proceedings of IEEE, 2013, pp. 1-6.

[8] J. Hu, L. Zhang, L. Ma, and W. Liang, "An integrated safety prognosis model for complex system based on dynamic Bayesian network and ant colony algorithm," Expert Systems with Applications, vol. 38, pp. 1431-1446, 3// 2011.

[9] C. Yan, H. Zhang, and L. Wu, "Fault Prognosis of Steam Turbine Generator Set by Trend Analysis of Frequency," in Future Power and Energy Engineering (ICFPEE), 2010 International Conference on, 2010, pp. 63-66.

[10] M. J. Roemer, G. J. Kacprzynski, and R. F. Orsagh, "Assessment of data and knowledge fusion strategies for prognostics and health management," in Aerospace Conference, 2001, IEEE Proceedings., 2001, pp. 2979-2988 vol.6.

[11] K. Kim, "Fault diagnosis and prognosis for fuel supply systems in gas turbine engines," Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, vol. 223, pp. 757-768, March 1, 2009 2009.

[12] M. A. Zaidan, A. R. Mills, and R. F. Harrison, "Bayesian framework for aerospace gas turbine engine prognostics," in Aerospace Conference, 2013 IEEE, 2013, pp. 1-8.

[13] C. R. Davison, "Health Monitoring and Prognosis for Micro Gas Turbine Engines," PhD, Department of Mechanical and Materials Engineering, Queen's University, 2005.

[14] K. Ariyur and J. Jelinek, "Aeroengine Prognostics via Local Linear Smoothing, Filtering and Prediction," SAE Technical Paper, 2004.

[15] L. Hao, Y. Jinsong, Z. Ping, and L. Xingshan, "A review on fault prognostics in integrated health management," in Electronic Measurement & Instruments, 2009. ICEMI '09. 9th International Conference on, 2009, pp. 4-267-4-270.

[16] N. Goel, A. Kumar, V. Narasimhan, A. Nayak, and A. Srivastava, "Health risk assessment and prognosis of gas turbine blades by simulation and statistical methods," in Electrical and Computer Engineering, 2008. CCECE 2008. Canadian Conference on, 2008, pp. 001087-001092.

[17] L. C. Jaw, "Neural networks for model-based prognostics," in Aerospace Conference, 1999. Proceedings. 1999 IEEE, 1999, pp. 21-28 vol.3.

[18] A. Cavarzere and M. Venturini, "Application of Forecasting Methodologies to Predict Gas Turbine Behavior Over Time," Journal of Engineering for Gas Turbines and Power, vol. 134, pp. 012401-012401, 2011.

[19] H. Hanachi, J. Liu, A. Banerjee, and Y. Chen, "A framework with nonlinear system model and nonparametric noise for gas turbine degradation state estimation," Measurement Science and Technology, 2015.

[20] M. A. Zaidan, R. F. Harrison, A. R. Mills, and P. J. Fleming, "Bayesian Hierarchical Models for aerospace gas turbine engine prognostics," Expert Systems with Applications, vol. 42, pp. 539-553, 1// 2015.

[21] J. Sun, H. Zuo, W. Wang, and M. G. Pecht, "Application of a state space modeling technique to system prognostics based on a health index for condition-based maintenance," Mechanical Systems and Signal Processing, vol. 28, pp. 585-596, 4// 2012.

[22] H. Lipowsky, S. Staudacher, M. Bauer, and K.-J. Schmidt, "Application of Bayesian Forecasting to Change Detection and Prognosis of Gas Turbine Performance," Journal of Engineering for Gas Turbines and Power, vol. 132, pp. 031602-031602, 2009.

[23] P. J. García Nieto, E. García-Gonzalo, F. Sánchez Lasheras, and F. J. de Cos Juez, "Hybrid PSO–SVM-based method for forecasting of the remaining useful life for aircraft engines and evaluation of its reliability," Reliability Engineering & System Safety, vol. 138, pp. 219-231, 6// 2015.

[24] T. Brotherton, G. Jahns, J. Jacobs, and D. Wroblewski, "Prognosis of faults in gas turbine engines," in Aerospace Conference Proceedings, 2000 IEEE, 2000, pp. 163-171 vol.6.

[25] G. Andrew, A. Dana, G. Andrew, and A. Dana, "Artificial intelligence for real time diagnostics and prognostics of gas turbine engines," in 33rd Joint Propulsion Conference and Exhibit, ed: American Institute of Aeronautics and Astronautics, 1997.

[26] G. Dan and A. Joshua, "Critical modeling issues for prediction of turbine performance degradation - Use of a stochastic-neuro-fuzzy inference system," in 19th AIAA Applied Aerodynamics Conference, ed: American Institute of Aeronautics and Astronautics, 2001.

[27] P. Paris and F. Erdogan, "A Critical Analysis of Crack Propagation Laws," Journal of Basic Engineering, vol. 85, pp. 528-533, 1963.

[28] A. Kumar, A. Srivastava, N. Goel, and A. Nayak, "Model based approach and algorithm for fault diagnosis and prognosis of coated gas turbine blades," in Advanced Intelligent Mechatronics (AIM), 2010 IEEE/ASME International Conference on, 2010, pp. 800-805.

[29] M. E. Orchard and G. J. Vachtsevanos, "A particle filtering-based framework for real-time fault diagnosis and failure prognosis in a turbine engine," in Control & Automation, 2007. MED '07. Mediterranean Conference on, 2007, pp. 1-6.

[30] X. Jiuping, W. Yusheng, and X. Lei, "PHM-Oriented Integrated Fusion Prognostics for Aircraft Engines Based on Sensor Data," Sensors Journal, IEEE, vol. 14, pp. 1124-1132, 2014.

[31] R. J. Hansen, D. L. Hall, and S. K. Kurtz, "A New Approach to the Challenge of Machinery Prognostics," Journal of Engineering for Gas Turbines and Power, vol. 117, pp. 320-325, 1995.

[32] K. Liu, N. Z. Gebraeel, and J. Shi, "A Data-Level Fusion Model for Developing Composite Health Indices for Degradation Modeling and Prognostic Analysis," IEEE Transactions on Automation Science and Engineering, vol. 10, pp. 652-664, 2013.

[33] N. Puggina and M. Venturini, "Development of a Statistical Methodology for Gas Turbine Prognostics," Journal of Engineering for Gas Turbines and Power, vol. 134, pp. 022401-022401, 2011.