A COMPARATIVE STUDY ON ANOMALY DETECTION OF THE COMBUSTION SYSTEM IN GAS TURBINES

Jiao Liu
School of Energy Science and Engineering
Harbin Institute of Technology
Harbin, Heilongjiang, China
Telephone: (240)825-7497
liujiaohit@hotmail.com

Myeongsu Kang
Center for Advanced Life Cycle Engineering (CALCE)
University of Maryland
College Park, MD, USA
mskang@umd.edu

Jinfu Liu, Zhongqi Wang, Daren Yu*
School of Energy Science and Engineering
Harbin Institute of Technology
Harbin, Heilongjiang, China
jinfuliu@hit.edu.cn, wangzhongqi@hit.edu.cn, yudaren@hit.edu.cn

Michael G. Pecht
Center for Advanced Life Cycle Engineering (CALCE)
University of Maryland
College Park, MD, USA
pecht@umd.edu

Abstract: Due to the fact that the combustion system, the core component of gas turbines, works in the highly adverse environmental conditions of high temperature and high pressure, it frequently faces malfunctions, causing catastrophic accidents. Hence, anomaly detection plays an important role in helping the combustion system run safely and economically. In recent decades, some methods have been published on anomaly detection of the gas turbine combustion system. However, there are few studies that compare these methods. The aim of this paper is to review and provide analytical results of the anomaly detection methods. An overall assessment of the merits or weaknesses of the generic methods is provided by testing the methods with actual gas turbine operating data. Additionally, some possible research development of the anomaly detection of the gas turbine combustion system is presented in this comparative study.

Key words: Anomaly detection; gas turbine; combustion system; health management

---

* Corresponding author.

Introduction: The technology of gas turbines has improved significantly over the past 50 years. As the efficiency of gas turbines increases, the combustion system, the core component of the gas turbine, is subjected to severe thermal stress [1] and requires costly maintenance [2]. Prognostics and health management (PHM) can be used to solve these problems. Implementation of PHM can help gas turbines run safely and economically by improving their reliability, safety, and availability, while reducing the operational costs.

The gas turbine combustion system works in the highly adverse environmental conditions of high temperature, high pressure, and high speed. Malfunction of the combustion system is often followed by catastrophic accidents. Anomaly detection plays an important role in PHM systems, and usually focuses on detecting abnormal deviation from its nominal behavior and detecting fault timely. Therefore, anomaly detection of combustion system in gas turbines is particularly significant.

Typical faults in gas turbine combustion system include fuel uneven distribution, fuel supply channel damage or leak, nozzle carbon deposition, nozzle jam, components burn through, and so on. These faults may cause abnormal combustion chamber outlet temperature. A gas turbine combustion system is usually installed with several combustion chambers of the same structure. These chambers are equally arranged in the circumferential direction. Outlet temperature of the normal combustion chamber is almost same, while the outlet temperature of the malfunction combustion chamber is different from the others. However, the combustor outlet temperature is very high, and conventional sensors cannot work in such harsh environments for a long time.

The owners usually take advantage of the exhaustive gas temperature (EGT) to monitor the performance of the combustion system. The EGT provides the most relevant information about the state of the hot components, which is measured by several thermocouples distributed equally at the outlet of the gas turbine. See Figure 1. All exhaust thermocouple readings are almost identical when the unit is in normal operation, while some exhaust thermocouple readings are different from the others when the combustion system malfunctions. The EGT spread, the difference between different thermocouples, can be treated as an indicator in anomaly detection of combustion system. But there are many problems to be considered. The malfunction of the combustion system is not the unique factor causing uneven temperature spreads. In normal operation, some other factors can also cause uneven temperature spreads [3], including operation conditions, ambient conditions, thermocouple position error, and manufacturing tolerances. At the same time, the hot gas rotates following by blades and the degree of rotation will vary with operation conditions. The hot gas from different combustion chambers mixes in the turbine, which reduces the amplitude of the EGT spreads compared with the spreads at the exit from the combustion chambers. Therefore, anomaly detection of gas turbine combustion systems is complex.

Many studies have been published on anomaly detection of gas turbine combustion systems. The research can be divided into two categories, including spread-based method and model-based method. In this paper, these methods are reviewed. The merits or weaknesses of the generic methods are discussed by testing the methods with actual gas turbine operating data. The paper presents some possible research developments in the anomaly detection of gas turbine combustion systems.

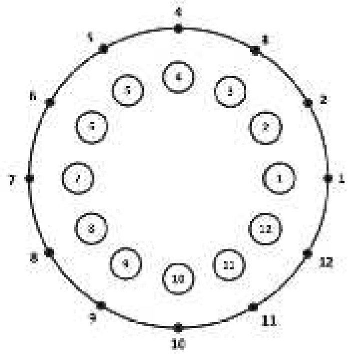


Figure 1: Combustion Chambers and Thermocouples Distribution

Method Review

Spread-based Method: The EGT profile is almost equal when the combustion system is in normal operation, while the EGT profile is uneven when there is a fault. This is an important feature of the EGT. Based on this feature, the spread-based method monitors the spread, the difference between different thermocouples, to identify the status of the system. The spread is small when the combustion system is in normal operation, while the spread is big when there is a fault. The spreads-based method is intuitive, so it is commonly applied in industry. The monitoring system introduced in Ref [4, 5] shows that the system monitors not only direct temperature but also variation in the exhaust gas distribution from the average value. Large variation can indicate combustion problems. In Ref [6], in addition to detecting the variation, combustion anomaly detection method also monitors the maximum EGT, median EGT and average EGT as supplements. Gulen et al. [7] introduce a heavy-duty industrial gas turbine real-time online performance diagnostic system. In the system, excessive and sudden changes or consistent upward trends in the ratio of the maximum EGT to the average value indicate the potential combustor problems.

The spread-based method utilizes unevenness of the fault EGT profile to monitor the performance of the combustion system. As mentioned above, some factors, operation conditions, ambient conditions, thermocouple position error, manufacturing tolerances, can also cause uneven temperature spreads. To remove the influence of the factors, the average EGT value is usually treated as the representative of operation conditions and ambient conditions in these methods. The value after subtracting or dividing by the average EGT value is taken as the monitoring indicator. Obviously, this kind of method is not very accurate. The average EGT value is roughly representative, and the relationship between the average EGT value and operation conditions and ambient condition is more complex. As one of the most widely used monitor systems, the MARK VI system [8] produced by GE makes a correction. It defines a parameter S, allowable exhaust temperature dispersion, which is the function of the average EGT value T_4^* and the compressor outlet temperature T_2^* , as shown in Eq. (1), where (100) means the equation should be added to 100 °F under the condition of variable operation condition.

$$S = \left(60 + 0.145 T_4^* - 0.08 T_2^* \Big|_{300}^{725} \right)\Big|_{50}^{170} + (100) \qquad (1)$$

The method calculates temperature differences between the maximum EGT and the three minimum EGTs. The higher the ratio of the temperature differences to the allowable exhaust temperature dispersion, the greater the possibility of the failure. However, some factors are still not considered, such as thermocouple position error, manufacturing tolerances, and the gas rotation. In practice, the operators have found the solution to lack adequate sensitivity, i.e., the hot components have been damaged seriously once the alarm is generated [9].

Model-based Method: The model-based method take advantage of an EGT model to detect anomaly in the gas turbine combustion system. The model may be built either from prior physical knowledge of the gas turbine (physical model) or from some prior identification based on a set of training data (data-driven model). The model-based method mainly contains two approaches.

The first one can be described as Figure 2, and the residuals are usually an indicator. The EGT model is built in normal operation. The output of model is the estimated EGT value. If estimated EGT value and actual EGT value are almost same, their residuals will be stable. Contrarily, if estimated EGT value and actual EGT value are totally different, their residuals will increase. The abnormalities are then identified by corresponding high residuals. The factors affecting EGT value in normal operation are taken into account by the model. Therefore, building an accurate model is the key problem in the model-based method.

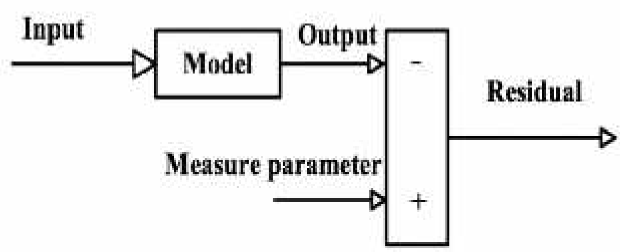


Figure 2: Diagram of Model-based Method

In combustion system anomaly detection methods, artificial neural network (ANN) is usually used to build the EGT model [10-12]. Artificial neural networks [13] are computational models inspired by the neural structure of the brain that are capable of machine learning and pattern recognition. Due to their high connectivity and parallelism, ANNs can link, in a non-linear way, a multi-dimensional input space with a multi-dimensional output space, allowing very high computational speed. Based on data, ANN does not need to consider a complex physics principle. Tarassenko et al. [10] present an EGT model of normality based on ANN and make use of the spatial correlations in the EGT profile. When a fault develops in one of the combustion chambers, there is a local effect on the temperature profile; only a small number of contiguous thermocouples are significantly affected whilst the rest of the profile is largely unchanged. The model of normality is therefore constructed by learning the function relating the temperature values from the four thermocouples opposite it. Song et al. [14] and Yılmaz [15] evaluate the relationship between EGT and operational parameters based on a multiple linear regression. The operational parameters Song et al. consider include low-pressure turbine outlet pressure, high-pressure rotator speed, high-pressure compressor outlet temperature and outlet pressure, and low-pressure rotator speed.

Yılmaz proposes that the fuel flow, thrust-specific fuel consumption, and take-off margin temperature are determined to be the most significant operational parameters. Kumar et al. [16] compare the statistical and neural network approach. As one of the breakthrough technologies in machine learning, deep learning has begun to be applied in anomaly detection of combustors. Stacked denoising autoencoder, one of the deep network architectures, has been used to improve combustor anomaly detection [17].

There are some EGT physical models to be proposed. Korczewski [18] describes an EGT physical model based on thermal and flow processes in gas turbines. Zhang [19] considers the gas rotating and mixing in the gas turbine and presents an EGT physical model. Medinaet al. [22] present an EGT model based on both basis function expansion and the Brayton cycle.

The second model-based method utilizes the parameters of EGT model as an indicator. The system can be described by the following equation

$$y_t = F(\theta_t,\ X_t) + v_t \tag{2}$$

where y_t and the variables X_t are observed, v_t is white noise independent of X_t, and the parameter vector is θ_t.

The parameter vector θ_t characterizes the system, which can be identified based on measurements. We can have a nominal model denoted by θ_t for such a system. Slight deviations of the actual system from its nominal behavior θ_t indicate early fault of the system [20].

Based on this opinion, a new indicator is presented in Ref [21]. Two main factors affecting the EGT value in normal operation are considered, including the operating and ambient conditions, and the structure deviation of different combustion chambers caused by processing and installation errors. Moreover, some studies focus on the parameter estimation and detection. Medina, P. et al. [22] analyzes the parameters with statistical techniques and with wavelets to detect abrupt changes in combustion chambers. The estimation is known to be biased because of the noisy input. M. Basseville et al. [23] present an asymptotic local approach for change detection to solve the problem.

Experiment: To assess the merits and weaknesses of the generic methods, two cases are presented in this section. The operating data come from the Taurus 70 gas turbine produced by Solar Turbines. The gas turbine has 12 combustion chambers and 12 thermocouples to measure the EGT. The gas turbine operated 14,407 min in normal operation, as can be seen in Figure 3. The normal operation data are used as the training set. In the first case, the fault data comes from actual operation. Figure 4 shows the fault EGT data in the first case. In the second case, the fault data is constructed by normal data. The 7th exhaust thermocouple reading downs 10 ºC slowly at 500 min, as shown in Figure 5. The training set is used to determine the threshold of the indicator. The other data is used to detect if the indicator exceeds the threshold. If the threshold is not exceeded, it means the system is normal. Otherwise, the system has an anomaly.

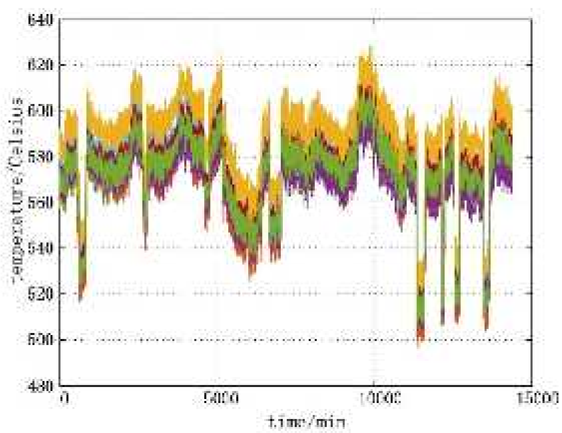


Figure 3: EGT in Normal Operation Condition

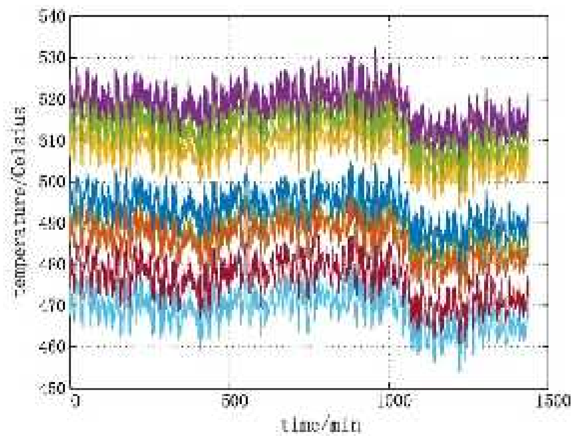


Figure 4: Fault Data in Case 1

In this section, the method introduced in Ref [5] is applied as the typical spread-based method. The detection indicator is variation in the exhaust gas distribution from the average value. The method introduced in Ref [10] is applied as the typical model-based method. The two models are, respectively, an ANN model and a physical model. In this paper, a three-layer ANN model is built. The output signal is an EGT value, and the input signals are EGT values of the four thermocouples opposite it. The neural node number in the hidden layer is 20. The detection indicator is the model's residuals.

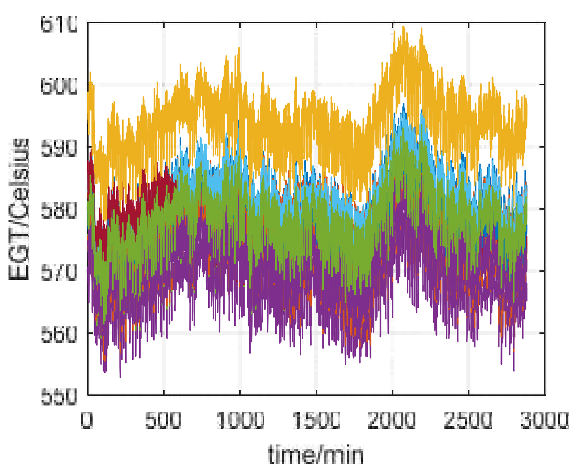


Figure 5: Fault Data in Case 2

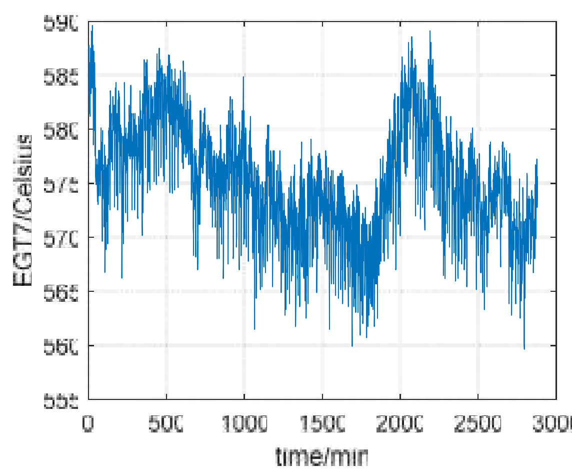


Figure 6: 7^{th} Thermocouple Reading in Case 2

The detection results are shown in Figure 7 to Figure 11. As we can see in Figure 7 and Figure 10, the spread-based method can detect the fault in the combustion system, but it is powerless to detect slight faults. In comparison, the model-based method performs much better. It can detect both serious and slight faults. However, it still has problems.

Figure 8 reflects the model accuracy. The residual of training data has some sudden change because of operation condition changes. It causes a wider threshold and then affects the detection sensitivity. As shown in

Figure 12, if the fault also happens at 500 min, but at a much slower deterioration rate, the model-based method is not sensitive as expected. It means the model could be modified more accurately to further improve the detection sensitivity.

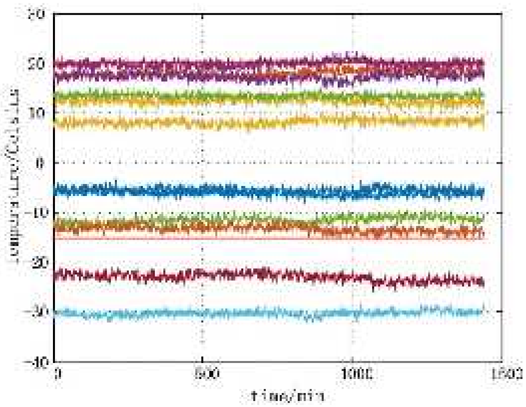


Figure 7: Spread-based Method Detection Result in Case 1

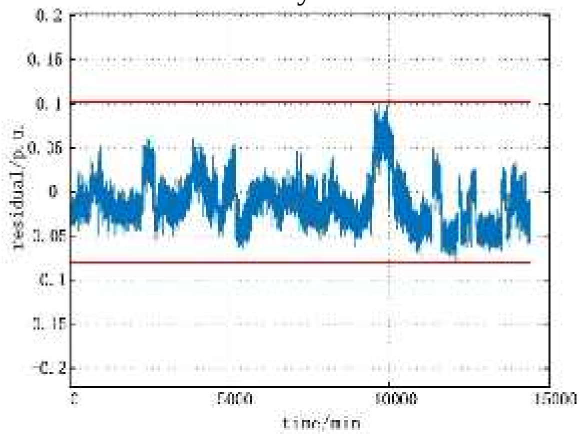


Figure 8: Model-based Method Training Data Detection Result in Case 1 (4^{th} thermocouple)

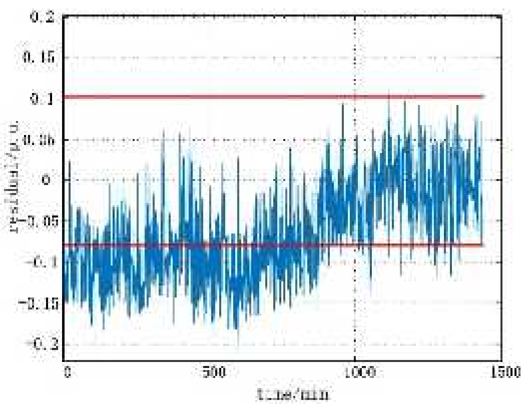


Figure 9: Model-based Method Detection Result in Case 1 (4^{th} thermocouple)

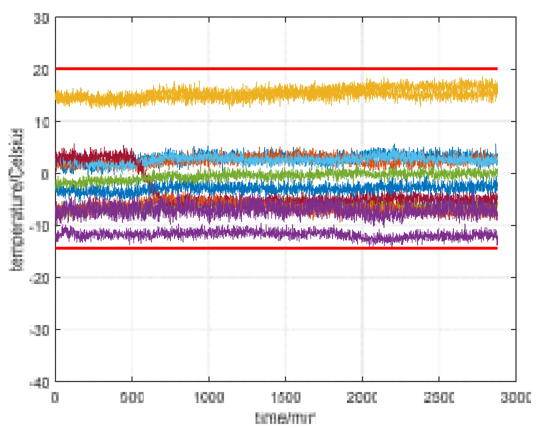
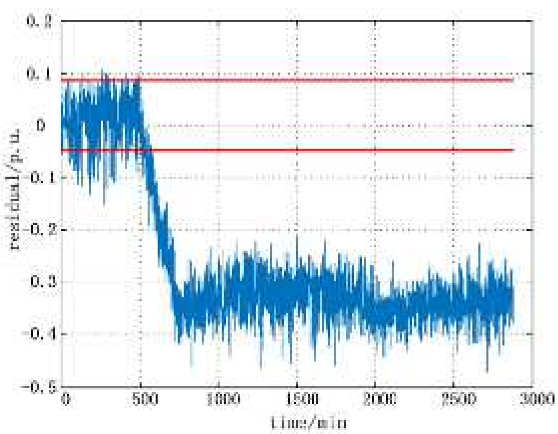


Figure 10: Spread-based Method Detection Result in Case 2



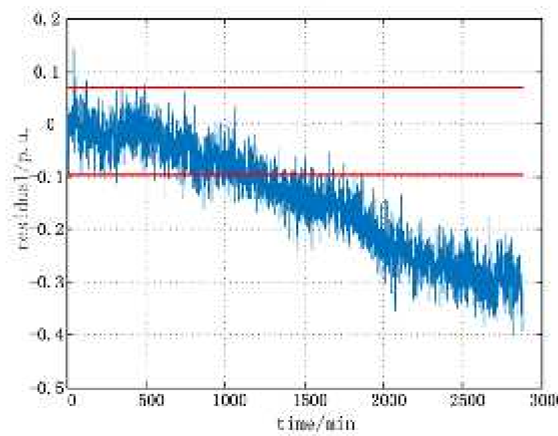


Figure 11: Model-based Method Detection Result in Case 2 (7^{th} thermocouple)

Figure 12: Model-based Method Detection Result in Case 3 (7^{th} thermocouple)

Conclusions: The vulnerability of combustion chambers in gas turbines motivated researchers to develop and advance various anomaly detection methods and tools. In this paper, a review of spread- and model-based methods was presented with a description of their pros and cons. Although the spread-based method was easy to realize in real applications, it was not suitable to detect anomalies in gas turbines operating under non-stationary conditions. Instead, the spread-based method was generally suitable for an over-temperature alarm. The model-based method has become an alternative for the detection of anomalous behavior of thermodynamics in combustion chambers. This was mainly because the model-based method has been more effective for facilitating anomaly detection under non-stationary conditions rather than the spread-based method. However, the performance of the model-based method depends on the accuracy of the model that represents the normal behavior of gas turbine combustors. The model-based method can be improved in some aspects. For instance, the fundamental understanding of the failure mechanisms of combustion chambers can improve the accuracy of the model. Likewise, the inclusion of prior physical knowledge in the data-driven model can be a potential research direction that can enhance the accuracy of the model and be used for anomaly detection.

Acknowledgment: The authors would like to thank China Scholarship Council for supporting the first author of this paper while studying abroad. Likewise, this work was supported in part by the over 100 CALCE members of the CALCE Consortium.

References:

[1] Jiang H, Ren J, Xueying L I, et al. Status and Development Trend of the Heavy Duty Gas Turbine. Proceedings of the Chinese Society of Electrical Engineering, 2014, 34(29): 5096-5102.

[2] IATA, Airline Maintenance Cost Executive Commentary, 2011, International Air Transport Association, Montreal, Canada.

[3] Knowles, Martin, Gas Turbine Temperature Spread Monitoring Detection of Combustion System Deterioration, ASME 1994 International Gas Turbine and Aeroengine Congress and Exposition. American Society of Mechanical Engineers, 1994.
[4] Hamilton, PE Patrick, and D. Ha. Exhaust gas temperature capabilities now in system 1 software. Product Update 25.1, 2005: 88-89.
[5] General Electric Company, Heavy Duty Gas Turbine Monitoring & Protection, 2015, General Electric Company, Nevada, United States.
[6] Miller, K. W., Iasillo, R. J., & Lemmon, M. F. 2015. U.S. Patent No. 20,150,267,591. Washington, DC: U.S. Patent and Trademark Office.
[7] Gulen, S. Can, Patrick R. Griffin, and Sal Paolucci. Real-time on-line performance diagnostics of heavy-duty industrial gas turbines. Journal of engineering for gas turbines and power, 2002, 124(4): 910-921.
[8] YU L, JIN J. Study on Deflection Laws of 9FA Gas-Turbine Exhaust Temperature Field. Electric Power Construction, 2009, 3: 026.
[9] Liu, J., The Research for Exhaust Temperature Anomaly Detection in Gas Turbine, 2014, M.S. thesis, Harbin Institute of Technology, Harbin, China.
[10] Tarassenko, L., Nairac, A., Townsend, N., Buxton, I., and Cowley, Z., Novelty Detection for the Identification of Abnormalities, Int. J. Syst. Sci., 2000, 31(11), pp. 1427–1439.
[11] Patsimo Systems, Case Study of Anomaly Detection on a GE LM2500+ Gas turbine done by Patsimo Systems.
[12] Kenyon, A. D., V. M. Catterson, and S. D. J. McArthur. Development of an intelligent system for detection of exhaust gas temperature anomalies in gas turbines. Insight-Non-Destructive Testing and Condition Monitoring, 2010, 52(8): 419-423.
[13] Haykin, S., Neural Networks - A Comprehensive Foundation, 2nd Ed., 1999, NJ, USA: Prentice Hall International.
[14] Song, Y. X., Zhang, K. X., and Shi, Y. S., Research on Aeroengine Performance Parameters Forecast Based on Multiple Linear Regression Forecasting Method, J. Aerosp. Power, 2009, 24(2), pp. 427–431.
[15] Yılmaz, I, Evaluation of the Relationship Between Exhaust Gas Temperature and Operational Parameters in CFM56-7B Engines, Proc. Inst. Mech. Eng., Part G, 2009, 223(4), pp. 433–440.
[16] Kumar, Amar, et al. Gas turbine engine operational data analysis for anomaly detection: Statistical vs. neural network approach, Electrical and Computer Engineering (CCECE), 2013 26th Annual IEEE Canadian Conference on. IEEE, 2013.
[17] Yan W, Yu L. On accurate and reliable anomaly detection for gas turbine combustors: A deep learning approach, Proceedings of the Annual Conference of the Prognostics and Health Management Society. 2015.
[18] Korczewski, Z., Exhaust Gas Temperature Measurements in Diagnostic Examination of Naval Gas Turbine Engines, Pol. Marit. Res., 2011, 18(2), pp. 37–43.
[19] Q.ZHANG. Contribution a` la surveillance de proce´de´s industriels. Thesis, Univ. Rennes I, Dec. 1991.
[20] Zhang, Qinghua, Michèle Basseville, and Albert Benveniste. Early warning of slight changes in systems and plants with application to condition based maintenance. Diss. INRIA, 1992.

[21] Jinfu, Liu, et al. Early Fault Detection of Hot Components in Gas Turbines. Journal of Engineering for Gas Turbines and Power, 2017, 139(2): 021201.
[22] Medina, P., Saez, D., and Roman, R., On Line Fault Detection and Isolation in Gas Turbine Combustion Chambers, ASME Turbo Expo 2008: Power for Land, Sea, and Air, ASME Paper No. GT2008-51316.
[23] Basseville, M., Benveniste, A., Mathis, G., & Zhang, Q, Monitoring the combustion set of a gas turbine. In Proc. Safeprocess, 1994, 94, pp. 397-402.