International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Artificial Neural Network based Process History Data Model for Gas Turbine Compressor Systems

Shaiju M.R., Arun P., S. Jayaraj

Abstract*: Gas turbine-based power plants are found to play a vital role in electric power generation and act as spinning reserves for renewable electric power. A robust performance assessment tool is inevitable for a gas turbine system to maintain high operational flexibility, availability, and reliability at different operating conditions. A suitable simulation model of the gas turbine provides detailed information about the system operation under varying ambient and load conditions. This paper illustrates a systematic methodology for process history data-based modelling of a gas turbine compressor system. The ReliefF feature selection method is applied for the proper identification of the parameters influencing the compressor efficiency. Appropriate Artificial Neural Network (ANN) based models are developed for data classification and system modelling of the compressor. The model performance has been validated using actual plant operational data, and the standard deviation of the error in model output was found to be 0.38. A novel approach for suitable integration of data processing methods, machine learning tools and gas turbine domain knowledge has led to the development of a robust compressor model. The model has been utilized for the health assessment of an existing gas turbine compressor, demonstrated through an illustrative case study. The model has been found suitable for parametric analysis of compressor efficiency with operating hours, which is helpful for operational decision-making involving studies on the influence of part-load operation, compressor wash planning, maintenance planning etc.

Keywords*: Gas turbine, Compressor, Modelling, Artificial neural network, Principal component analysis, ReliefF algorithm.

I. INTRODUCTION

Incorporation of a large amount of renewable power is planned in the national grid of India from the current renewable power capacity of 70 GW to a target of 175 GW by the year 2022 [1]. Gas turbine-based power plants are expected to act as efficient backup power plants in scenarios involving large-scale diffusion of renewable power. Large-scale integration of renewable energy in the central grid necessitates high operational flexibility, availability, and reliability of the existing gas turbine combined cycle power plants for the stable operation of the grid [2]. The performance monitoring of gas turbine systems has an increased significance in recent times due to their demanding activities of fast start-up and shut downtimes and increased periods of part-load operation. The gas turbine components involve a complex mechanical assembly, and purely mathematical model-based performance analysis of these non-linear machines is a difficult task.

The flexibility and efficient operation of a gas turbine module can be improved with the help of performance-based health monitoring tools. A recent review of performance analysis and fault diagnosis of gas turbine module has outlined various approaches in this domain[3]-[5]. The reliability and availability of gas turbine module can be improved by the application of various performance analysis tools. Importance of gas turbine health assessment, health prediction techniques, gas path assessment and its significance have also been discussed in [5]-[7]. Qualitative and quantitative model-based methods can be employed for fault diagnosis. Different model development approaches and their significance are also discussed in [8]-[10]. A model-based fault detection system makes use of residuals, which are generated by comparing the actual output with the model output.

The compressor is one of the key components of the gas turbine-based power plant. The performance of the compressor depends on operating conditions such as loading level, speed, atmospheric conditions like temperature, humidity etc. Performance analysis of compressor is, therefore, a hard task because of the ever-varying operating conditions. Correction curves are essential to estimate the performance of a compressor at various working conditions [11]. Design curves such as compressor maps may not always be available with gas turbine customers resulting in imprecise performance analysis of the system. A suitable compressor simulation model is required for analysing the performance at different working conditions. Design curves and related parameters are necessary for formulating the thermodynamic process model, which are not readily available to the gas turbine customers. Hence it is often preferable to adopt a 'process history-based model' in place of a conventional thermodynamic model. Process-history based modelling techniques use a significant amount of process history data for the creation of a suitable compressor simulation model. The process-history model gains knowledge from past data [12]-[14].

Manuscript published on November 30, 2019.
* Correspondence Author
Shaiju M.R.*, Research Scholar, Mechanical Engineering Department., NIT Calicut, India. Email: shaijumr@gmail.com
Arun P., Associate Professor, Mechanical Engineering Department, NIT Calicut , India. Email: arun.p@nitc.ac.in
S. Jayaraj, Professor, Mechanical Engineering Department, NIT Calicut , India. Email: sjayaraj@nitc.ac.in

Process-history data-based fault detection and diagnosis can replace the process-model based methodologies . Advancements in computer processor speed, data acquisition methods, and soft computing tools give tremendous scope for process data-based model development. The input data to the process history-based method are different sensor output values received from the gas turbine compressor. These high dimensional process history data are used for the creation of a process model. Hence the model can suitably accommodate the effects of installation, modification and overhaul[15]-[17].

The first step of model development is the identification of input and output parameters required for compressor model creation. The inputs are various sensor measurements related to the compressor, which affect the performance of the compressor such as inlet temperature, speed, humidity etc. Selection of the parameter is based on the systematic literature review and domain knowledge [15],[18]. The output parameters are the critical parameters which indicate the performance of the compressor. After identification of input and output parameters, relevant data must be collected for the selected period of interest. Feature selection process removes irrelevant features from the identified input parameters. A comparative study of feature selection methods is described in [19],[20]. Feature selection reduces the measurements and storage requirements of data and also the training and utilisation time involved. Principal feature selection reduces the dimensionality of the feature set by selecting a subset of the original features which comprises all essential information of the original feature set. Principal component analysis and regression are the basis of principal feature selection methods [21],[22].*ReliefF* algorithm is a filter-based feature selection method, which helps to choose a subset of features from the original feature set[23]-[25]. This method picks a subset of the initial features rather than obtaining a mapping that uses all the initial features . The advantage of identifying this subset of features could be in saving the cost of capturing and storing additional parameters and reduction in measurement noise.

The accuracy of compressor model prediction is enhanced if the data of selected input and output features are suitably classified into different categories based on the applicable operating range. This classified input and output features can be used for the creation of the corresponding regression model. Different classifier development methods are described in [26]. An Artificial Neural Network (ANN) may be used for classification of inputs into a set of target categories. ANN classifier is preferred because of its intrinsic ability to get more accurate results and its convenient implementation. The accuracy of the classifier performance mainly depends on the accuracy and significance of the training data. Using ANN classifier, the data are categorised into different classes, based on different loading patterns such as base-load and part-load operation. Model development is the process of finding a relation between input parameters and output parameters, and it can be achieved by regression analysis. Regression analysis estimates how the value of the dependent feature changes when any of the independent features value changes. Again, Artificial Neural Network (ANN) is one of the preferred tools for nonlinear regression analysis.

Performance analysis of compressor is challenging due to 'off-design' operating conditions and continuous part-load operation of the machine. Most of the compressor models for performance analysis are thermodynamic models and based on design conditions. This paper provides a systematic illustration of process history-based model development for the performance analysis of an industrial gas turbine compressor system. A novel integrated method incorporating feature selection, data classification and system modelling using an ANN based approach is described. A representative case study of application where the model has been utilized for the health assessment of a typical gas turbine compressor operating in a combined cycle power plant is also presented.

II. COMPRESSOR MODEL

Gas turbine power plant integrates different sub-components, and the basic schematic diagram of the plant is shown in Figure 1.Gas turbine module comprises an axial flow compressor to meet the high pressure and high flow requirements of the working fluid. Axial flow compressor has multistage aerofoil rotary blades positioned on the rotor to pressurise the fluid [11],[15]. In gas turbine module, compressor consumes up to 65% of the power produced by the turbine. It indicates that even a 1% increase in compressor power consumption leads to about 2% reduction in net power output. Hence compressor performance is critical for the gas turbine cycle. Degraded compressor consumes more energy, and reduces output power and overall cycle performance. The compressor performance depends on parameters such as the inlet guide vane angle, inlet filter differential pressure, shaft speed and environmental conditions like atmospheric temperature and humidity. Any simulation model capable of analysing the performance of the compressor must incorporate the influence of such internal and external parameters. The model must be able to forecast the performance of the axial flow compressor under various working environments such as "off-design" as well as "design" conditions. Process-history techniques use a large amount of process history data for the creation of a compressor model. The process-history model acquires knowledge from past performance. The data for the past performance is collected for an entire operating range of the input parameters. Hence the model can accommodate the effects of overhauling, installation, and modification for the whole operating range. The input parameters to the process history method are different sensor readings received from the gas turbine components.

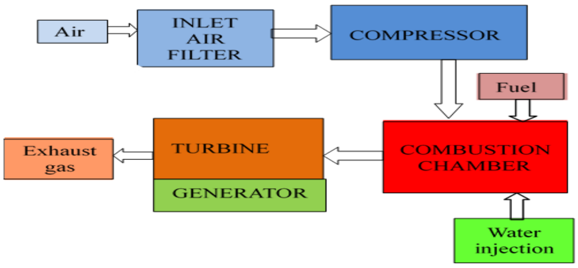

Fig. 1. Schematic diagram of gas turbine module

Retrieval Number: D8299118419/2019©BEIESP
DOI:10.35940/ijrte.D8299.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

A. Feature selection

The first step in process modelling is the identification of input and output parameters required for compressor model creation. Identification of input and output parameters are based on the literature review and the process domain knowledge. Feature selection is the process of removing redundant features from the identified measured parameters. Feature selection leads to a reduction in storage requirements, a decrease in processing time for training and related computations. The present work focuses mainly on the selection of a subset of features that are useful to build an efficient compressor model. Removal of redundant and irrelevant features ensures an increase in the effectiveness of the simulation model. *ReliefF*algorithm is a filter-based feature selection method, which helps to choose a subset of features from the original feature set. This method uses the concept of nearest neighbours to derive feature statistics that indirectly account for interactions. The *ReliefF* algorithm calculates a proxy statistic for each feature that can be used to estimate feature relevance to the target concept. It can determine the rank and weight of each feature to the target. A subset of features can be selected from a feature set based on the rank and weight of each feature [23],[25]. Hence *ReliefF*algorithm is adopted in this work as a tool for identification and removal of extraneous features.

For illustrating the approach, the actual operating data of a typical GE Frame 9E 115MW gas turbine compressor has been taken for model development and related performance analysis. The model output parameter is the critical parameter, which indicates the performance of the compressor. In this study, compressor isentropic efficiency (η_c) is taken as the model output parameter, which is evaluated by the following equation:

$$\eta_c = \frac{T_1}{T_2-T_1}\left[\left(\frac{P_2}{P_1}\right)^{\frac{\gamma-1}{\gamma}} - 1\right] \quad (1)$$

whereT_1 is compressor inlet temperature, T_2 is compressor discharge temperature, $P_1$is compressor inlet pressure, P_2 is compressor discharge pressure and $\gamma$is specific heat ratio. For the compressor model, compressor efficiency being fixed as an output feature, 11 input features are identified based on domain knowledge. Total 1000 sets of samples are collected for the entire operating range of each feature at steady-state conditions. The *ReliefF*feature selection method is applied to this data set for the identification of the influence of each input feature on compressor isentropic efficiency. The results of feature selection, the weight, and rank of each input features are given in Table.I. Based on this, three shallow weight input features (particulate matter, cumulative rainfall, inlet pressure) are discarded, and the new data set is created with only eight input features. In the next step, principal feature selection is adopted as a tool for identification and removal of the redundant features.

Principal feature selection uses Principal Component Analysis (PCA) for selection of the subset. It is a two-step multivariate regression method. In the first step, a PCA of normalised values of input features is performed. PCA is a statistical method, which can estimate the variance of the input features [21],[22]. It calculates a set of loading vectors to estimate the variance of the input data. From this, the importance of each input feature on orthogonal vectors is estimated. In the present case, PCA is applied to the new data set with the identified eight input parameters, and the first five principal components can map the data set with an accuracy of 99.9% as shown in Figure 2.

Table I. Weight and rank of the identified input features

Sl. No.	Input feature	Weight	Rank
1	Inlet filter differential pressure	0.59	4
2	Inlet guide vane position	0.64	3
3	Generator frequency	0.06	8
4	Bellmouth differential pressure	1.05	1
5	Generator output power	1.03	2
6	Inlet temperature	0.51	5
7	Humidity	0.09	7
8	Operating hours	0.09	6
9	Cumulative rainfall	0.04	10
10	Inlet pressure	0.02	11
11	Particulate matter	0.04	9

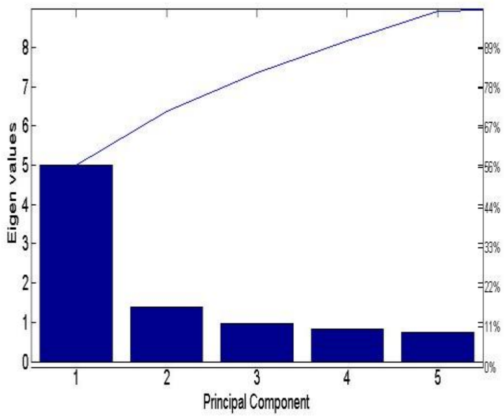

Fig. 2. Principal components analysis

The estimated correlation matrix indicated that no redundant features are present in the eight input features. After performing PCA on input features, in the second step, the regression of the orthogonal vectors scores and the output feature can be estimated. Using the two-step multivariate regression method, the importance of each feature on the compressor efficiency has been calculated. The regression coefficients of PCA scores and compressor efficiency are estimated by the regression feature selection method. The importance of each input feature on compressor efficiency is also calculated. From the above analysis, it is clear that all eight input features have a significant impact on compressor efficiency. Feature selection method evaluates the weight of each input features and ranks the features based on their influence on compressor efficiency. The weight of each input feature indicating the influence on compressor efficiency is illustrated in Figure 3.

Retrieval Number: D8299118419/2019©BEIESP
DOI:10.35940/ijrte.D8299.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

The most significant feature influencing compressor efficiency is observed to be the bellmouth differential pressure and the least significant feature is generator frequency (proportional to the speed). This is expected as in normal operating range for a synchronised generator; the speed is almost constant. These selected features have been used for compressor model development.

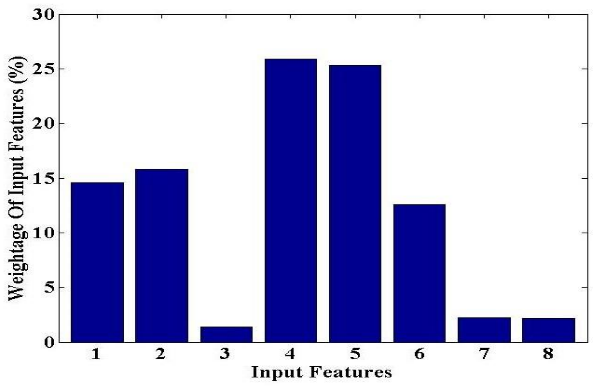

Fig. 3. Influence of input features on compressor efficiency

B. Data classification

The classification of data identified as the input and output features into suitable categories is vital for the performance of the compressor model. The 'appropriately classified' input and output features need to be used for the creation of the system model. Recorded data of the eight selected input features between one major inspection and the next major inspection of the compressor has been utilized for the building the system model. The data includes the operating range under varying ambient conditions and different loading patterns. An Artificial Neural Network model is developed to classify the data into different target categories. The performance of the classifier depends on the accuracy and significance of the training data and the training process. Using the ANN classifier, the data is classified into different classes based on various operating conditions. The data set is divided into three categories, and 600 data sets/samples are used to develop the ANN classifier. A two-layer feed-forward network with hidden sigmoid neurons and a linear output neuron is used for the development of the classifier [26],[27]. The sample data have been used for the training and weight adjustment of the neural network. The classifier has been tested and validated, with 30% of the sample data. The developed ANN classifier has been successful in classifying the input data into the appropriate categories. The classifier has been tested with a set of 993 samples, which were not used for training purpose. The classifier performed with an accuracy of 99.7%, and the classifier performance as indicated by the confusion matrix is given in Figure 4.

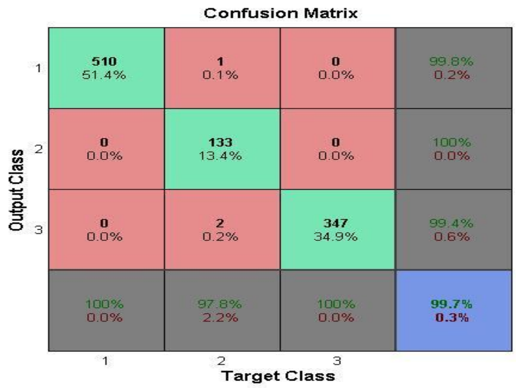

Fig. 4. Confusion matrix of classifier

The ANN classifier has been successful in classifying the data into different categories based on the pattern of the eight input values. The structure of the ANN classifier is finalised by considering the accuracies in training, testing, and validation. The developed ANN classifier is a two-layer feed-forward network with linear output neurons and sigmoid hidden neurons. The network has 8 input neurons, 16 hidden neurons, and 3 output neurons. The structure of the ANN classifier is illustrated in Figure 5.

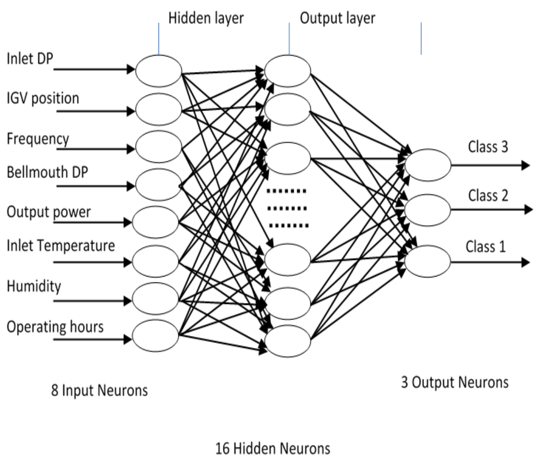

Fig. 5. Structure of the ANN classifier

C. Model development

The performance of the compressor is found to be governed by the values of the eight input variables or operating conditions. An apt compressor simulation model needs to accommodate the performance of the system under different operating values of all these parameters. A process history-based model is expected to incorporate the effects of installation, modification, and overhaul. An ANN-based approach is found beneficial for creating the process history data-based model of the compressor, which is a complex nonlinear system [28]-[37]. The model can predict the output feature from the identified input features. The optimisation algorithm adopted for training the network is the Levenberg-Marquardt method. Separate models have been developed for each category of data to improve the accuracy and robustness of the model. As discussed in the previous section, the data is classified into three categories based on the compressor operating pattern[38].

ANN-based modelling is applied to each class, and ANN models are developed corresponding to the specified category. Category 1 data is used for training, testing and validation of model 1. Since separate ANN-based regression models are generated, the accuracy of the model as indicated by the R-value is quite high. The R-value of the trained network is 0.98, as shown in Figure 6. The ANN model structure is developed by considering the error values in the training, testing and validation data sets. The model 1 is a two-layer feed-forward network with a sigmoid function for hidden neurons and linear output neuron. The network has 8 input neurons, 9 hidden neurons and 1 output neuron. The structure of the ANN model 1 is given in Figure 7.

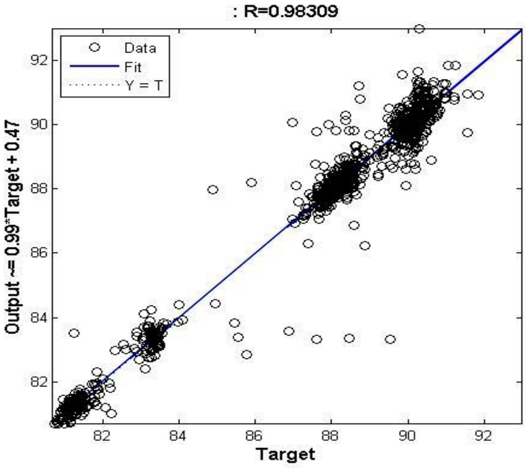

Fig. 6. R-value of ANN Model 1

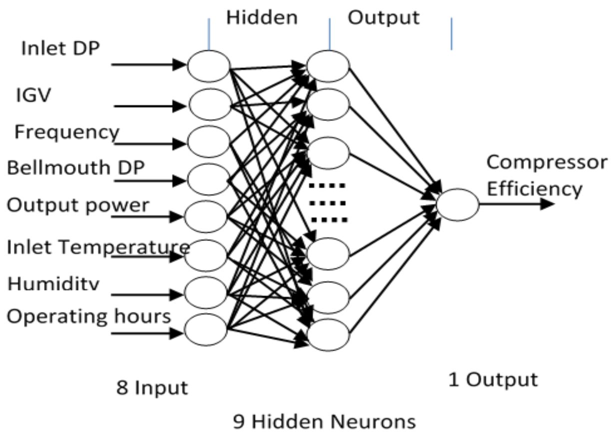

Fig. 7. Structure of the ANN Model 1

Similarly, category 2 and category 3 data are used for developing model 2 and model 3, respectively. All three models are tested with the corresponding training dataset, and error of compressor efficiency is calculated in each case. The standard deviation of error is 0.34 and error histogram of model 1 is shown in Figure 8. The error distribution and standard deviation of the three models are found to be within the acceptable range.

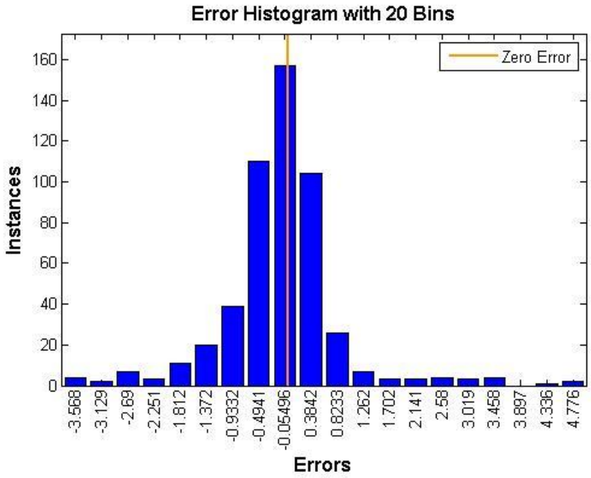

Fig. 8. Error histogram of ANN Model 1

The main steps involved in compressor modelling are the collection of input data, classifying the data and data-feed to the corresponding model[39],[40]. The classifier suitably classifies the input data based on the pattern of the eight input values and supplies to the corresponding ANN model. The model estimates the compressor efficiency from the eight input variables and feeds to the output module. The schematic diagram of compressor modelling is shown in Figure 9. This output data indicates the normal performance of the compressor under various working conditions. The deviation between the model output and actual plant output can be used to analyse the compressor performance.

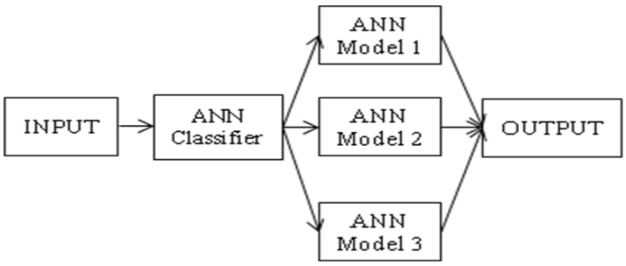

Fig. 9. Schematic diagram of the compressor model

III. VALIDATION OF COMPRESSOR MODEL

The compressor model was validated using a set of 860 samples of various working conditions of the compressor. These data, previously not used for the training were fed to the classifier; which classified and transferred it to the corresponding ANN model. After processing the input parameters, compressor efficiency was generated as the model output. The error (Actual value – Model output) of compressor efficiency was estimated by comparing the actual compressor efficiency and that obtained as model output. The error of the compressor model computed for different sample sets is shown in Figure10. The standard deviation of output error of the compressor model is 0.38, which is well within the acceptable range. Figure 11 shows the parity plot of compressor efficiency prediction and the R^2 value of prediction is observed to be 0.974. The flowchart of the process history based compressor model development is shown in Figure 12.

Retrieval Number: D8299118419/2019©BEIESP
DOI:10.35940/ijrte.D8299.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

This generic algorithm can be used for model development of any gas turbine compressor.

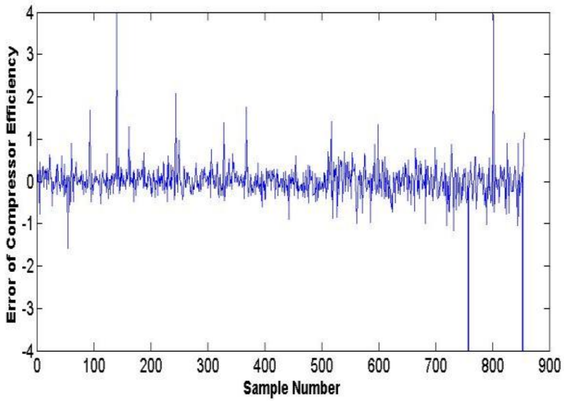

Fig. 10. The error of compressor efficiency prediction

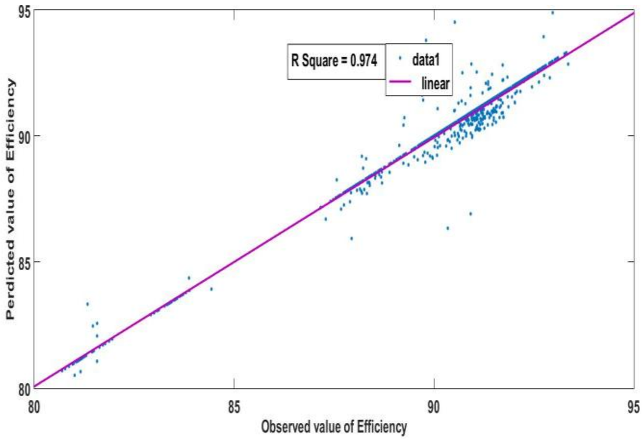

Fig. 11.Parity plot of compressor efficiency prediction

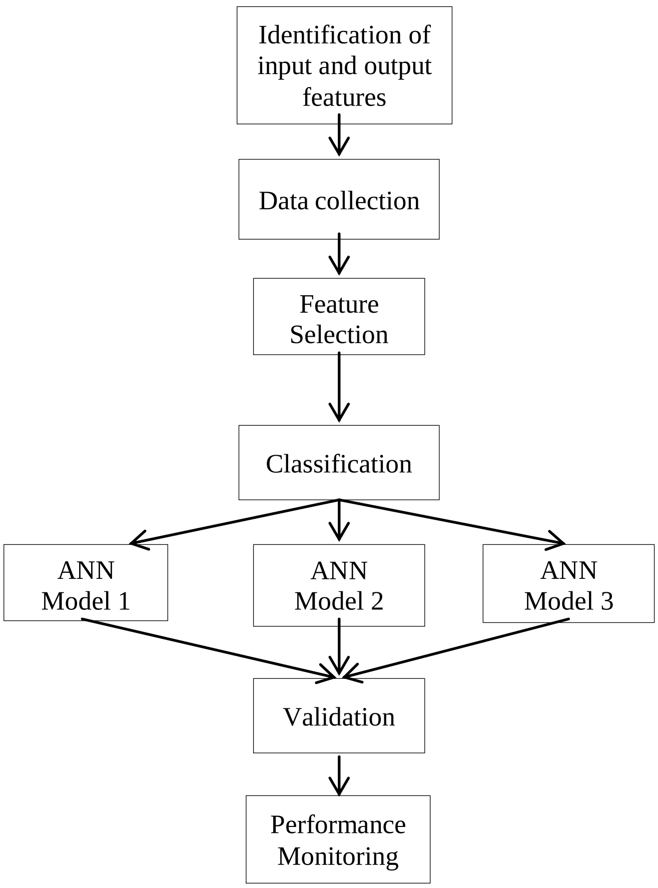

Fig.12. Flowchart of compressor model development

Identification of input and output features is the first step of the process. Process history data collection is carried out for the entire operating range of the input and output features. This pre-processed data have been clustered into a specific category, and a classifier is developed for this classification. Regression models have been developed for each category input features to improve the accuracy of the model. The compressor model can predict the compressor efficiency from the eight operating parameters for the different operating ranges. It has been demonstrated that the ANN model can successfully map the non-linear relationship between the eight input variables with the output variable. The model is validated with actual plant data, and the accuracy of the model is acceptable for different applications.

The training data used for the creation of the model is taken during the normal operating condition. In the normal operating conditions, the model compressor efficiency and actual plant compressor efficiency will be the same. The validated compressor model can further be used for the performance monitoring of the compressor.

IV. CASE STUDY

The gas turbine customers can use the developed compressor model for different practical applications such as performance analysis, assessment of the effectiveness of online and offline compressor wash, an estimate of compressor fouling rate etc. The results of these assessments are useful for maintenance planning, inventory management and other commercial decisions. The model-based approach can accommodate site-specific effects such as installation, modification and overhauling effects. Hence the information extracted from the operating data and the model developed are helpful for efficient and reliable operation of the system. The validated compressor model has been used for offline monitoring of a running compressor used in the combined cycle plant with GE Frame 9E operated by the power generation company NTPC Ltd. India.

A. Performance analysis

A model is a suitable tool for different decision-making process related to the compressor such as the effect of part load, compressor wash planning and other maintenance planning activities. Variation of the compressor efficiency with operating days can be easily obtained from the model. It gives a clear indication of compressor performance degradation with respect to working hours. The predicted compressor efficiency for different loading and operating days are estimated from the model, and it is shown in Figure 13. The plot shows compressor efficiency against working days at a constant speed, inlet temperature and humidity. The reduction in compressor efficiency after 90 operating days at baseload is 2.1%.

The compressor efficiency at base-loadis around 6% more than the efficiency at minimum operating load, with the other parameters remainingconstant. Along with part-load operation, operating days also have a significant impact on compressor efficiency. The combined effect of part-load operation and operating days on compressor efficiency is shown in Figure 14.

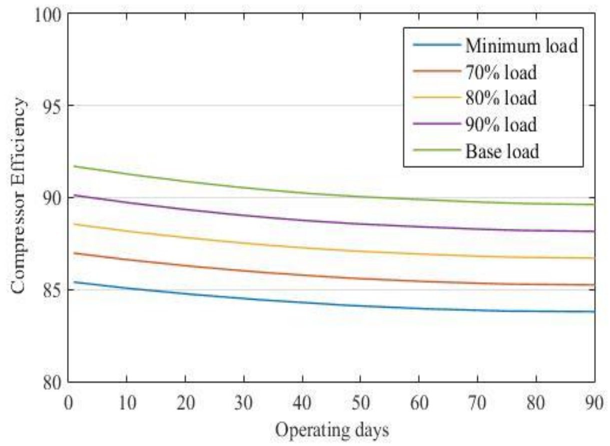

Fig. 13. Predicted compressor efficiency against operating days

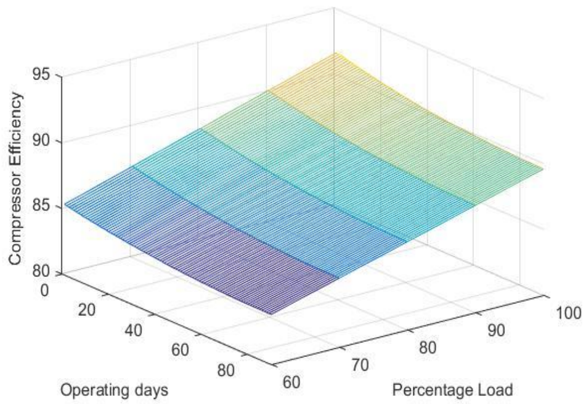

Fig. 14. Predicted compressor efficiency for different loads

The compressor efficiency decreases with an increase in operating days and increases with increase in operating load. The maximum compressor efficiency is at the initial period with base-load condition. The compressor efficiency after 90 days at minimum operating load is 7.8% less than the maximum value. This prediction of compressor efficiency helps in cost analysis and decision making regarding offline compressor wash and other maintenance activities.

B. Health assessment

Health monitoring system of compressor uses residual for analysis, which is the difference between the plant compressor efficiency (derived from the measured plant data) and the predicted compressor efficiency (obtained from the model). The model uses eight input variables for prediction of compressor efficiency. The pattern of residual indicates the performance and health condition of the compressor. The compressor efficiency residual pattern of the GE Frame 9E compressor, based on the developed model is shown in Figure 15. The model has been used for the calculation of the residual of compressor efficiency for 110 days, and the variation has been plotted against the operating days. The figure shows a gradual decrease in the residual of compressor efficiency over the days of operation. In the absence of a fault in the system, the residual of compressor efficiency tends to zero for the days under observation. The gradual decrease in the residual of compressor efficiency indicates that there is a fault or abnormality in the compressor system.

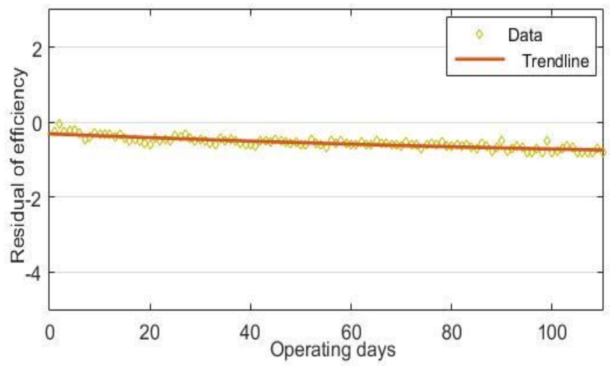

Fig. 15. Residual of compressor efficiency variation

Performance tests conducted at the rated operating condition revealed that the abnormality was due to a faster rate of fouling of the compressor system. From the residual of compressor efficiency graph, it was clear that 0.8% more drop-in compressor efficiency in 100 days was due to the elevated rate of fouling. The variation of efficiency is more predominant with the part-load operation and inlet temperature, hence quantifying the fouling effect is a difficult task. The compressor model can assess the fouling effect and estimate the losses. In the compressor, the fouling rate mainly depends on the effectiveness of the inlet air filtration system, particulate matter in the atmosphere and the operating hours of the compressor. On detailed assessment, it was observed that the rate of increase in differential pressure of the inlet filter was slow, which indicated that the performance of the inlet air filtration system was not effective. Hence the ANN-based model of the system facilitated the predictive health assessment of the compressor.

C. Compressor wash assessment

Offline compressor wash removes recoverable part degradation of the compressor and improves compressor performance. The effectiveness of a compressor wash can be assessed with the compressor model. The pattern of residual of compressor efficiency derived from the model is useful for compressor wash assessment. Residual of compressor efficiency is the difference between the actual compressor efficiency and the model predicted compressor efficiency. The residual patterns of the GE Frame 9E compressor, after different compressor wash, are shown in Figure 16.

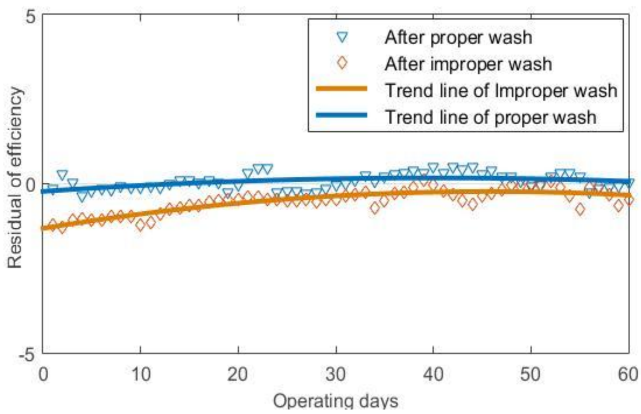

Fig. 16. Compressor wash effectiveness assessment

The model has been used for the calculation of the residual of compressor efficiency for 60 days, and the variation has been plotted against the operating days.

In case1, the residual of efficiency is almost zero for entire operating days, so that the model predicted value is matching with actual efficiency. Hence the offline compressor wash was proper. In case 2, the residual of efficiency is less than zero indicates that actual efficiency is less than the expected. The offline compressor wash was found to be less effective than expected. Hence the model can be used as a tool for compressor water was effectiveness assessment.

V. CONCLUSION

A systematic approach for the development of process history-based model for gas turbine compressor system has been presented in this paper. The simulationmodel of the gas turbine helps in studying the plant parameters under different ambient conditions and load patterns. A generic methodology has been developed incorporating the*ReliefF*algorithm and principal feature selection methods.

Artificial Neural Networks (ANN) classifier of 99.7% accuracy was developed and used for classification of the identified input parameters. A compressor model has been created from the process history data of a representative GE Frame 9E gas turbine module, and ANN has been further used as the modelling platform. The model performance was validated with data corresponding to varied operating conditions, and the standard deviation of the error in model output (compressor efficiency) was found to be 0.38. Feature selection and classification of data improved the effectiveness of the developed ANN model. Proper integration of domain knowledge and machine learning techniques thus leads to an acceptable and accurate model. The model is found to be a useful tool for performance assessment of gas turbine compressor at steady-state conditions. Residual of compressor related parameters can be used for the health assessment of the compressor. This has been demonstrated through an illustrative case study. The proposed methodology and the developed model can be an appropriate tool for different decision-making process related to the compressor such as efficient operation, part-load operation, compressor wash planning, maintenance planning etc.

REFERENCES

1. MNRE - National Wind-Solar Hybrid Policy 2018, (2018).https://mnre.gov.in.
2. Gülen, S. C. Gas Turbine combined cycle fast start: the physics behind the concept ,*PowerEng* 117.6 (2013): 40-49.
3. Kurz, Rainer, and Klaus Brun. Degradation in gas turbine systems,*J.Eng. Gas Turbines Power* 123.1 (2000): 70-77.
4. Zwebek, A. I., and P. Pilidis. Degradation effects on combined cycle power plant performance—Part III: Gas and steam turbine component degradation effects,*J. Eng. Gas Turbines Power* 126.2 (2004): 306-315.
5. Kurz, Ranier, and Klaus Brun, Gas Turbine Tutorial-Maintenance And Operating Practices Effects On Degradation And Life ,*Proceedings of the 36th Turbomachinery Symposium. Texas A&M University. Turbomachinery Laboratories*, 2007.
6. E. Schmid, Operational Flexibility Enhancements of Combined Cycle Power Plants, *Siemens AG*. (2008)..
7. Kurz, Rainer, Klaus Brun, and MeronWollie, Degradation effects on industrial gas turbines,*Journal of engineering for gas turbines and power* 131.6 (2009): 062401.
8. Y.G. Li, P. Nilkitsaranont, Gas turbine performance prognostic for condition-based maintenance, *Appl. Energy*. 86 (2009) 2152–2161.
9. Y.K. Lee, D.N. Mavris, V. V. Volovoi, M. Yuan, T. Fisher, A Fault Diagnosis Method for Industrial Gas Turbines Using Bayesian Data Analysis, *J. Eng. Gas Turbines Power*. 132 (2010) 041602.
10. Li, Yi-Guang., Gas turbine performance and health status estimation using adaptive gas path analysis, *Journal of Engineering for Gas Turbines and Power* 132.4 (2010): 041701.
11. M.P. Boyce, *Gas Turbine Engineering Handbook*, 2011.
12. E. Giacomazzi, The importance of operational flexibility in gas turbine power plants, *EAI Energia, Ambient. e Innov*. 6 (2013) 6.
13. Venturini, Mauro, and Dirk Therkorn., Application of a statistical methodology for gas turbine degradation prognostics to alstom field data ,*Journal of Engineering for Gas Turbines and Power* 135.9 (2013): 091603.
14. M. Taan, E. Tsoutsanis, M. Muhammad, Z. a. Abdul Karim, Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review, *Appl. Energy*. 198 (2017) 122–144.
15. G. F. C. Rogers, H. Cohen,P. V. Straznicky,A.C. Nix, and H.I.H.Saravanamutto. *Gas Turbine Theory* Seventh Edition,2017 .
16. T.A. Lemma, A Hybrid Approach for Power Plant Fault Diagnostics-Studies in Computational Intelligence 743, *Springer*, 2018.
17. V. Venkatasubramanian, R. Rengaswamy, S.N. Kavuri, A review of process fault detection and diagnosis part II: Qualitative models and search strategies, *Comput. Chem. Eng*. 27 (2003) 313–326.
18. ASME, ASME PTC 22-2005 Gas Turbines,2005.
19. Y. Kuang, A Comparative Study on Feature Selection Methods and Their Applications in Causal Inference, Lund University 2009.
20. Bolón-Canedo, Verónica, Noelia Sánchez-Maroño, and Amparo Alonso-Betanzos, A review of feature selection methods on synthetic data, Knowledge and information systems 34.3 (2013): 483-519.
21. Abdi, Hervé, and Lynne J. Williams., Principal component analysis, *Wiley interdisciplinary reviews: computational statistics* 2.4 (2010): 433-459.
22. Jolliffe, Ian, Principal component analysis,*Springer Berlin Heidelberg*, 2011.
23. M. Robnik-Šikonja, I. Kononenko, An adaptation of Relief for attribute estimation in regression, Mach. Learn. Proc. Fourteenth Int. Conf. 5 (1997) 296–304.
24. Spolaôr, Newton, et al, ReliefF for multi-label feature selection, 2013 *Brazilian Conference on Intelligent Systems*. IEEE, 2013.
25. Urbanowicz, R. J., Meeker, M., La Cava, W., Olson, R. S., & Moore, J. H. (2018). Relief-based feature selection: Introduction and review. Journal of biomedical informatics, 85, 189-203.
26. C.M. Bishop, Pattern Recognition and Machine Learning, 2006.
27. Haykin, Simon. Neural Networks and Learning Machines, *3/E. Pearson Education India*, 2010.
28. R. Bettocchi, M. Pinelli, P.R. Spina, M. Venturini, Artificial Intelligence for the Diagnostics of Gas Turbines—Part II: Neuro-Fuzzy Approach, *J. Eng. Gas Turbines Power*. 129 (2007) 720.
29. R. Bettocchi, M. Pinelli, P.R. Spina, M. Venturini, Artificial Intelligence for the Diagnostics of Gas Turbines—Part I: Neural Network Approach, *J. Eng. Gas Turbines Power.* 129 (2007) 711.
30. Fast, Magnus, Mohsen Assadi, and Sudipta De., Condition based maintenance of gas turbines using simulation data and artificial neural network: a demonstration of feasibility, *ASME Turbo Expo 2008: Power for Land, Sea, and Air. American Society of Mechanical Engineers*, 2008.
31. Panov, V. Gasturbolib: Simulink library for gas turbine engine modelling, *ASME Turbo Expo 2009: Power for Land, Sea, and Air. American Society of Mechanical Engineers*, 2009.
32. Palmé, Thomas, et al., Different condition monitoring models for gas turbines by means of artificial neural networks,*ASME Turbo Expo 2009: Power for Land, Sea, and Air. American Society of Mechanical Engineers*, 2009.
33. Fast, M., M. Assadi, and S. De., Development and multi-utility of an ANN model for an industrial gas turbine, *Applied Energy* 86.1 (2009): 9-17.
34. Kulikov, Gennady G., and Haydn A. Thompson, eds. Dynamic modelling of gas turbines: identification, simulation, condition monitoring and optimal control. Springer Science & Business Media, 2013.
35. Asgari, Hamid, XiaoQi Chen, and RaazeshSainudiin., Modelling and simulation of gas turbines, IJMIC 20.3 (2013): 253-270.
36. Asgari, Hamid, et al., Artificial neural network–based system identification for a single-shaft gas turbine, *Journal of Engineering for Gas Turbines and Power* 135.9 (2013): 092601.
37. M.I. Ibrahimy, M.R. Ahsan, O.O. Khalifa, Design and Optimization of Levenberg-Marquadt based Neural Network Classifier for EMG Signals

to Identify Hand Motions, *Meas. Sci. Rev.* 13 (2013) 142–151.
38. D. Abbott, Applied Predictive Analytics, 2014
39. Shaiju M. Raghavan, ArunPalatel, and JayarajSimon, Health Assessment of Gas Turbine Compressor Using Process History Based Modelling Approach, *ASME GTINDIA 2015*-1240, pp. 1–6, 2015.
40. Talaat, Mohamed, M. H. Gobran, and M. Wasfi., A hybrid model of an artificial neural network with thermodynamic model for system diagnosis of electrical power plant gas turbine, *Engineering Applications of Artificial Intelligence* 68 (2018): 222-235.

AUTHORS PROFILE

Shaiju M.R. Deputy General Manager, NTPC Ltd. Research Scholar, National Institute of Technology, Calicut. The research area ispower plant performance assessment and health monitoring using machine learning, application of artificial intelligence in power plant.He has eighteen years' experience in power plant operation and maintenance. He is currently working asDGM (Operation and Maintenance) 1967MW Combined Cycle Power Project, (6xGE 9FA Gas Turbines and 3xGE D11 Steam Turbines), Ratnagiri, Maharashtra, India. January 2003 – May 2016: Sr.Manager (Operation and Maintenance), NTPC Limited, 360MW Rajiv Gandhi Combined Cycle Power Project (2x115 MW GE Fr9E Gas Turbines and 1x130MW BHEL Steam Turbine), Alappuzha, Kerala, India.May 2002 – January 2003: Engineer (Operation and Maintenance), NTPC Limited, 2000MW Simhadri Super Thermal Power Station, AP, India Email: shaijumr@gmail.com.

Arun P. Associate Professor,Mechanical Engineering Department, National Institute of Technology Calicut.PhD in Energy Science and Engineering from IIT Bombay. Research areas are mathematical modelling and optimal thermal design of various energy systems, energy management in thermal systemsand renewable energy utilization.December 2007-June 2010, Assistant Professor, Mechanical Engineering Department, NIT Surat (Sardar Vallabhbhai National Institute of Technology, Surat, Gujarat).July 2004-December 2007, Teaching Assistant, Department of Energy Science and Engineering, IIT Bombay. He has membership in Professional Societies such as Institution of Engineers (India), American Society of Mechanical Engineers, International Solar Energy Society
Email:arun.p@nitc.ac.in

S. Jayaraj Professor,Mechanical Engineering Department, National Institute of Technology Calicut. PhD in Computational fluid dynamics from IIT Kanpur. Research areas are thermophoretic augmentation of aerosol particle deposition, studies on fully closed and partially open enclosures, design of nuclear fuel elements, cooling of electronic equipment, fluid flow and heat transfer studies in heat pipes, computational fluid flow and heat transfer, conjugate heat transfer and boundary layer analysis, ANN applications in thermal systems, design and analysis of energy systems, energy conservation and management., alternative energy utilization, refrigeration and air-conditioning, multiphase flow studies.
Email:sjayaraj@nitc.ac.in