An Interference Optimization – Induced Electrical Turbine Fault Prediction and Analysis Method

P. SENTHILKUMAR[1], KASMARUDDIN CHE HUSSIN[2], MOHAMAD ZAMHARI TAHIR[3], T. PADMAPRIYA[4], S. V. MANIKANTHAN[5]

[1]Maha Barathi Engineering College,
Kallakurichi,Tamil Nadu,
INDIA

[2]Faculty of Entrepreneurship and Business,
Universiti Malaysia Kelantan,
MALAYSIA

[3]Faculty of Business and Management,
DRB-HICOM University of Automotive Malaysia,
Pahang,
MALAYSIA

[4]Melange Publications,
Puducherry,
INDIA

[5]Melange Academic Research Associates,
Puducherry,
INDIA

Abstract: - Predicting electrical turbine faults is decisive for consistent operation and power generation output. Based on the operative cycles of the electrical turbine, the faults are predicted to prevent power generation interruptions. This paper introduces an Interference Optimization-based Fault Prediction Method (IO-FPM) for serving smooth operation purposes. In this method, the inferred optimization using classifier tree learning is induced for segregating the operating cycles of the turbine. The maximum and minimum threshold conditions for turbine operation using resistance and magnitude of the blades are accounted for each operation cycle. The classifier performs segregation based on low and high thresholds for predicting failure cycles. Such cycles are altered using pre-maintenance intervals and mechanical fault diagnosis at an early stage. This prevents turbine failure regardless of external influencing factors.

Key-Words: - Classifier Tree Learning, Electrical Turbine, Fault Prediction, Threshold Condition, power generation, operating cycle, failure cycle.

Received: October 11, 2022. Revised: September 26, 2023. Accepted: November 7, 2023. Published: December 5, 2023.

1 Introduction

Electrical turbine fault detection is a process that detects the errors and faults that occur in an application. Many methods are used for fault detection in wind power plants. The fault detection method provides necessary information for the quality improvement process in wind power plants, [1]. The structure healthy condition monitoring (SHCM) technique is used in power plants to identify the structural aspects of turbines. SHCM technique gathers information which is related to electrical turbines that reduce the latency in the detection process. SHCM technique detects the healthy condition range of turbines that produce data for consequence and fault detection processes, [2]. A support vector machine (SVM) based fault detection method is also used in wind power plants. The main goal of SVM is to detect the actual cause of faults in power plants. The SVM algorithm evaluates the vibrations, conditions, working capability, and behavioral patterns of electrical turbines. The SVM algorithm method improves the accuracy of electrical turbine fault detection which enhances the performance range of the power plants, [3], [4].

Optimization-based methods are also used for fault detection in wind power plants. The optimization method is mainly used to improve the effectiveness and feasibility range of wind power plants, [5]. A principal component analysis (PCA) is used as a hybrid turbine fault detection method in power plants. The PCA uses a feature selection technique to select the features which contain faults. The fault features are optimized and used for the fault detection method which reduces the data dimension level in the computation process. The PCA-based method reduces the overall optimization problems in the fault detection process, [6], [7]. A novel convolutional neural network (CNN) model is used for fault detection in power plants. The CNN model uses a feature extraction method that extracts the important features from turbine monitoring systems. The extracted features produce the necessary data for the fault detection process. The CNN model trains the datasets that extract features to reduce the complexity of fault detection. The CNN model improves the accuracy of fault detection which improves the performance and significance range of wind power plants, [4], [8].

2 Related Works

The study, [9], proposed a fault detection method for wind turbines based on a backpropagation (BP) neural network and a pair-copula model. The pair-copula model is implemented here to analyze the input variables of turbines. Real-time data is produced via a pair-copula model which provides relevant data for the calculation process. The BP neural network is used here to reduce energy consumption in the fault detection process. The proposed method detects the exact faults that occur in wind turbines.

The study, [10], designed an integrated fault diagnosis method for wind turbines. A feature extraction technique is used in the method which extracts the important features which contain defect signatures. The designed method analyses the data which are provided by extraction and enhances the effectiveness level of the systems. It is used as a defect diagnosis that reduces latency in the fault detection process. The designed method improves the performance and feasibility range of wind turbines.

The study, [11], introduced an optimized artificial neural network (ANN) based operating characteristics prediction approach. The main aim of the approach is to predict the characteristics of gas turbine combustors. ANN is mainly used here to predict the root mean square error (RMSE) ratio in wind turbines. RMSE contains optimal operating characteristics for further processes. Experimental results show that the introduced approach increases the accuracy of the prediction process.

The study, [12], developed a new deep-learning model for the maintenance prediction process in wind turbines. A supervisory control and data acquisition (SCADA) technique is used here to address the critical issues in wind turbines. SCADA is used to identify the abnormal conditions, problems, and threats that are presented in turbines. SCADA increases the energy-efficiency level of the systems, [13]. The developed model improves the effectiveness and significance range of wind turbines, [14].

The study, [15], proposed a new combined method for fault detection in wind turbine systems. Firefly algorithm (FA), chaos map (CM), and extreme learning machine (ELM) are combined to detect faults in turbines. The combined method calculates the actual relationship between problems and causes. The combined method detects the faults at high speed which reduces the latency in the detection process. The proposed method archives high-performance range in wind turbine systems.

The study, [16], introduced an adaptive cyclostationary blind deconvolution (ACYBD) based weak fault detection method for wind turbines. Instantaneous energy slice bi-spectrum (IESB) is also implemented in the method to identify the frequency parameters of turbines. The ACYBD collect necessary signals and noise signal for the fault detection process. The proposed method maximizes the accuracy in fault detection which improves the flexibility range of wind turbines.

The study, [17], designed a two-stage anomaly decomposition scheme using multi-variable correlation extraction for wind turbines. The designed scheme is a wind turbine fault detection method that identifies the effective faults in turbines. An auto encoder is used in the method which detects the faults based on the frequencies. The actual behavioural patterns of the turbines are identified which provide relevant data for detection. The designed method increases the performance and feasibility level of wind turbine systems.

The study, [18], proposed a genetic algorithm (GA) based mathematical model for wind turbine systems. The proposed method is mainly used to analyze the type-I fuzzy logic controlled (FLC) faults in turbines. The actual power loss reason is identified via a mathematical model that reduces the energy consumption in the computation process.

The main aim of the method is to improve the voltage profile of turbines. The proposed model improves the significance and reliability range of wind turbine systems.

3 Proposed Prediction Method

The proposed fault prediction method is designed to maintain smooth operation and consistent power generation output in electrical turbines. Figure 1 presents an illustration of the proposed prediction method.

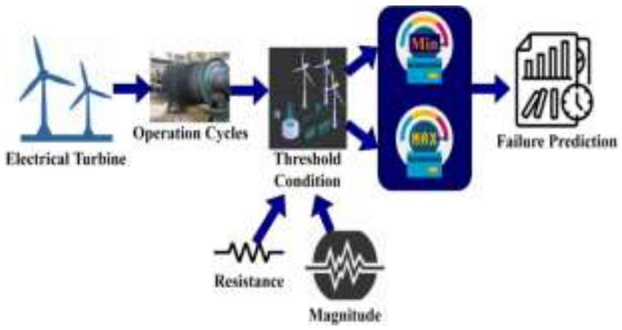

Fig. 1: Proposed Prediction Method Illustration

The proposed IO-FPM computes two outputs for improving electrical turbine operations namely resistance and magnitude of the blades. Using these values, the minimum and maximum thresholds are identified to achieve accurate fault prediction. Instead, if any failure or faults are identified from the instance, the operation cycles are altered for better operation purposes. Therefore, the two values are responsible for segregating low and high thresholds for predicting failure cycles using classifier tree learning and achieving failure-less operation. The resistance and magnitude values of the blades are computed for classifying operating cycles for the turbine to identify threshold conditions. From this continuous process, the faults in the electrical turbine are identified for smoothening turbine operation cycles. The variables OP_{c_n}, C_{opt} are used to represent the number of operation cycles in the electric turbine. The threshold condition is computed using the proposed method and faults are identified to prevent turbine failures. Assume that E^T means the active electrical turbine and its requirements r_q are analyzed to reduce faults. Initially, the processing of electrical turbine $p(E^T)$ is computed as in equation (1)

$$p(E^T) = \left(OP_{c_n}\left[C_{opt} \oplus r_q\right]\right) \tag{1}$$

Such that,

$$T_{tf} = \sum_{i=1}^{OP_{c_n}} T_{thr} - \left(1 - \frac{T_{tp}}{T_{\exists}}\right) \forall p(E^T) = C_{opt} = thr_{Cd} \;\; OP_{c_n} = C_{opt} \;(or)\; OP_{c_n} < C_{opt} \;\} \tag{2}$$

As per equation (1) and (2), the variable T_{tf} denotes the time for identifying turbine faults, T_{tp} is the time for electrical turbine processing, T_{thr} is the time for identifying maximum and minimum threshold conditions and $T_{\exists}$ means the total computing time. The variable thr_{Cd} is used to represent the maximum or minimum threshold condition using the proposed method. In equation (1), the condition $OP_{c_n} \leq thr_{Cd}$ is satisfied by the active electrical turbine to improve the turbine efficiency in any time interval, the operation cycles rely on a wide range of users and a large amount of resources to meet the user requirements. The faults are predicted using the IO-FP method for reducing power generation interrupts. The threshold condition is identified to reduce the faults and failures F in the electrical turbine. The electrical turbine operation C_{opt} and power generation output Δ_o are computed using the proposed method. The good condition operation cycles are identified and monitored for maintaining consistent operation. Therefore, the turbine failure is identified based on a threshold condition $T_F(thr_{Cd})$ is given as

$$T_F(thr_{Cd}) = OP_{c_n}\left(C_{opt} + \Delta_o - F\right) \tag{3}$$

Such that,

$$C_{opt} \in OP_{c_n} \leq T_F(thr_{Cd}) \; and, T_F(thr_{Cd}) \in T_{\exists} < T_{tf} \;\} \tag{4}$$

Based on equations (3), (4), and (5), the turbine failure is identified for smooth operation using the proposed method, and classifier tree learning is prominent for segregating the operating cycles for the turbine.

4 Classifier Tree Learning

The proposed method is designed to identify the faults in the electrical turbine. The existing electrical turbine processing is matched with the active electrical turbine for similarity analysis. For this instance, to compute whether the threshold condition is to meet the maximum turbine efficiency and accurate failure prediction, it is important to compute the resistance and magnitude of the blades for each operation cycle. The deployed operation cycles are responsible for maintaining consistent operation from the active electrical turbine. The input operation is based on minimum and maximum threshold conditions for identifying failures. In this computation, the operation received (ϵR) by the turbine is expressed as

$$\epsilon R = \frac{\{(thr_{Cd})_{max} - (thr_{Cd})_{min}\}}{F} + T_{\exists} \quad (5)$$

Where $(thr_{Cd})_{max}$ and $(thr_{Cd})_{min}$ are the maximum and minimum thresholds identified in different instances. The variables ρ_{res} and ρ_{mag} represent the probability of resistance and magnitude of the blades observed from the instance. It is to be accounted for that not all operation cycles can be associated with both res and mag. Now, the final power generation output for the conditions $C_{opt} > \frac{res}{mag}$ and $C_{opt} \leq \frac{res}{mag}$ is derived as in equations (6) and (7). There are some failures or faults that occur in turbines due to physical and operational problems of the operation cycles. Therefore, these failures affect the ϵR at any instance, for which the final power generation output $\complement^{pgo}$ is computed as

$$\complement^{pgo^1} = \epsilon R_1 \; \complement^{pgo^2} = \epsilon R_2 - \left(\frac{res}{mag}\right)_1 - \left(\frac{C_{opt}}{F}\right)_1 \; \complement^{pgo^3} = \epsilon R_3 - \left(\frac{res}{mag}\right)_2 - \left(\frac{C_{opt}}{F}\right)_2 \; \vdots \; \complement^{pgo^T} = \epsilon R_T - \left(\frac{res}{mag}\right)_{T-1} - \left(\frac{C_{opt}}{F}\right)_{T-1} \; \}, C_{opt} > \frac{res}{mag} \quad (6)$$

$$\complement^{pgo^1} = \epsilon R_1 - F \; \complement^{pgo^2} = \epsilon R_2 - \left(\frac{res * mag}{OP_{cn}}\right)_1 - F \; \complement^{pgo^3} = \epsilon R_3 - \left(\frac{res * mag}{OP_{cn}}\right)_2 - F \; \vdots \; \complement^{pgo^T} = \epsilon R_T - \left(\frac{res * mag}{OP_{cn}}\right)_{T-1} - F \; \}, C_{opt} \leq \frac{res}{mag} \quad (7)$$

The above equation (6) and (7) computes the final power generation output for predicting failures following the maximum threshold. Here, the threshold condition is the uncertain measure, for which accurate and appropriate computation is required for the diagnosis of mechanical faults. Based on the min and max threshold conditions, the early failure prediction is easily achieved. The active electrical turbine handling depends on the threshold condition. The classification learning process is illustrated in Figure 2.

The classification first identifies C_{opt} and $F \; \forall OP_{cn}$ in the $\in R$ for identifying $C_{Opt} \in T_{\exists}$ alone. In this classification the output OP_{cn} is identified for thresholds of max and min. These classifications respond to the next cycle or operation failure across different $C_{opt} \in T_{\exists}$ (Figure 2). The above sequence of segregating the operating cycles for the turbine is pursued using classifier tree learning. A scenario, based on the operative cycles of the electrical turbine in appropriate and accurate time instances is used to predict the faults and to improve the synchronized working of the turbine. The consistent operation and power generation output are achieved using the proposed method and classifier tree learning to identify and segregate the minimum and maximum threshold conditions for accurately predicting failures. The data from, [19], provides a power generator output, verified at 10 min intervals. The active power and theoretical prediction are analyzed based on wind speed (m/s) and direction (°) that impacts the resistance and magnitude of the OP_{cn}. Based on this, the F is estimated as in Figure 3.

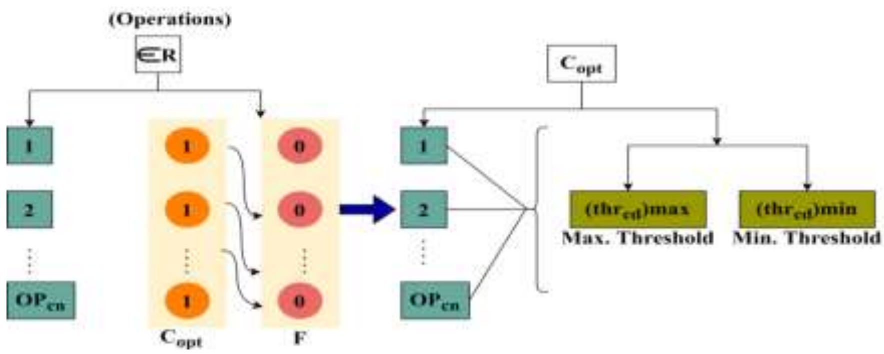

Fig. 2: Classification Learning Illustration

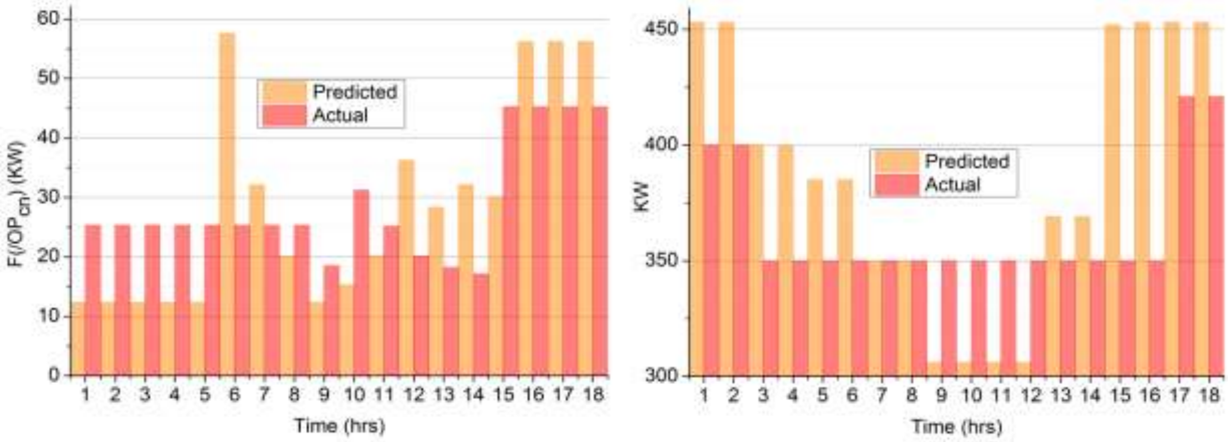

Fig. 3: Power Generated and F Analysis

The predictive process is used by the classifier for segregating min and max for which new cycles are used for regeneration. The intermediate F is prevented by reallocating kW generation from distinct threshold features. The failing feature thresholds are suppressed using multiple $\in R$ meeting the power demands. Therefore the consecutive classification relies on C_{Opt} for new OP_{Cn} across $T_{\exists}$ (Figure 3).

5 Results and Discussion

The metrics of fault prediction, classification rate, prediction time, and altered cycles are used in the comparative analysis. The existing methods IFDPA, [10], and FA-CP-ELM, [15], are incorporated from the related works section along with the proposed method.

6 Fault Prediction

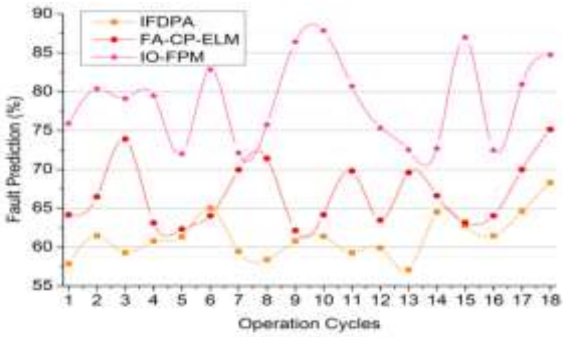

Fig. 4: Fault Prediction

The maximum fault predicted from the electrical turbine based on threshold condition is improved. Using the proposed method, the inferred optimization is performed using classifier tree learning. The proposed method used for rectifying the turbine failures or altered operating cycles in any instance achieves high fault prediction as presented in Figure 4.

7 Classification Rate

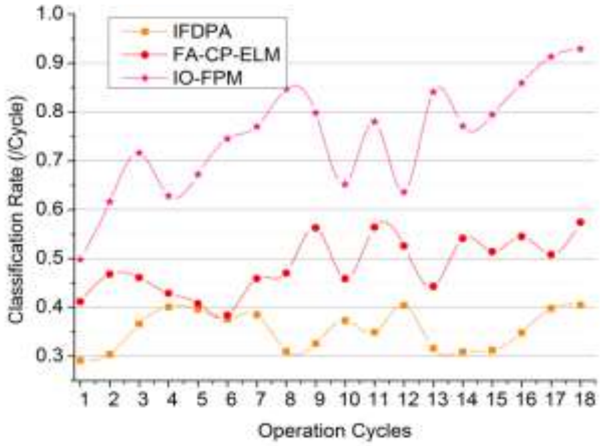

Fig. 5: Classification Rate

In this proposed IO-FPM achieves a high classification rate for computing the resistance and magnitude of the blades in each cycle based on its consistent operation and power generation output, reducing the fault occurrence (Refer to Figure 5). The failure in the electrical turbine is mitigated based on segregating the min/max threshold using a learning process. Therefore, regardless of the consistent operation is maintained for reducing the turbine failures.

8 Prediction Time

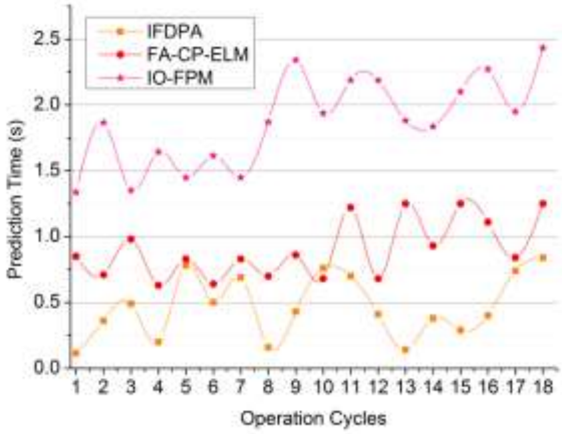

Fig. 6: Prediction Time

This proposed method achieves a high prediction time compared to the other factors as represented in Figure 6. The identification of failures and faults to ensure the support of the electrical turbine prevents failures. Therefore, the proposed method identifies the threshold condition of the operating cycles based on the resistance and magnitude of the blades required to achieve high fault prediction time.

9 Altered Cycles

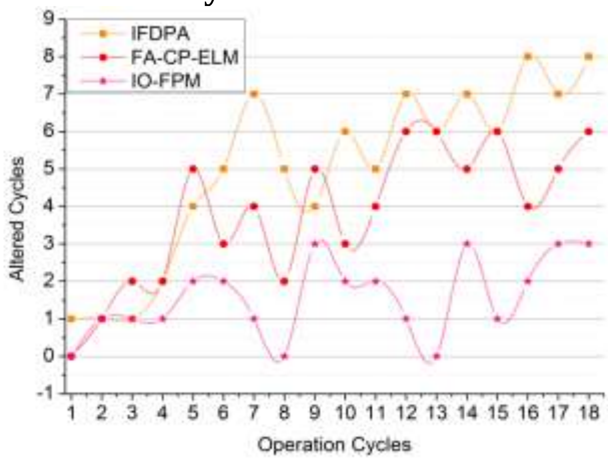

Fig. 7: Altered Cycles

This proposed method used to maintain the consistent operation and power generation output in electrical turbines for segregating the operating cycles achieves fewer failures and computing time is represented in Figure 7. If the failure is high in this process, the particular cycles can be altered. The maximum threshold reduces the turbine failures with less altered cycles.

10 Conclusion

This article introduced the Interference Optimization-based Fault Prediction Method for effective turbine fault detection. Using this method to predict the fault occurrence in an electrical turbine based on minimum and maximum threshold conditions is identified using resistance and magnitude of the blades is addressed for each operation cycle. The minimum and maximum threshold conditions are classified through classifier tree learning. This learning is used to identify power generation interrupts and segregate the operating cycles for the turbine. Based on the high and low thresholds, the failure cycles are identified. The maximum threshold detected cycles are halted and changed using pre-maintenance intervals. The mechanical faults are diagnosed at an early stage using threshold conditions for identifying the turbine failure and operation faults. This proposed fault prediction method uses classifier tree learning for serving smooth operation purposes based on segregating low and high thresholds. From the comparative analysis, it is seen that the proposed method achieves 13.03% high fault prediction and 9.52% less operation cycle alterations.

A common approach for preventing electrical faults in wind turbines is the suggested IO-FPM system. While IO-FPM's classification accuracy in electrical fault prevention is generally good, there are instances of complex problems, including those with prolonged operating times and challenging fault characteristics to identify in wind turbines. A significant field for future research is investigating more techniques that execute better in fault feature extraction and selection for increased classification accuracy and operating speed.

The proposed approach aims to create a defect detection system for wind turbines on multiple dimensions, including crucial component monitoring and overall turbine effectiveness monitoring, which includes the generator. The performance of the statistical technique was tested on a real-world instance involving wind turbines, and it proved effective at recognizing anomalous behaviors before the emergence of flaws. It could be done to improve the proposed approach to include more significant aspects. The advancement of this technique into the prediction of electrical faults is a potential future growth of this strategy. Faults that happened need to be linked to particular patterns on the control charts in the process of defining the anomalous behavior. This helps to determine the cause precisely and sets the stage for later automation of the fault prediction.

References:

[1] Liu, W. X., Yin, R. P., & Zhu, P. Y. (2022). Deep Learning Approach for Sensor Data Prediction and Sensor Fault Diagnosis in Wind Turbine Blade. *IEEE Access*, *10*, 117225-117234.

[2] Li, Y., Hou, L., Tang, M., Sun, Q., Chen, J., Song, W., ... & Cao, L. (2022). Prediction of wind turbine blades icing based on feature Selection and 1D-CNN-SBiGRU. *Multimedia Tools and Applications*, vol.81(3), pp.4365-4385.

[3] Tuerxun, W., Chang, X., Hongyu, G., Zhijie, J., & Huajian, Z. (2021). Fault diagnosis of wind turbines based on a support vector machine optimized by the sparrow search algorithm. *Ieee Access*, vol.9, pp.69307-69315.

[4] Yan, X., & Jia, M. (2022). Bearing fault diagnosis via a parameter-optimized feature mode decomposition. *Measurement*, vol.203, 112016.

[5] Hasanzadeh, N., Payambarpour, S. A., Najafi, A. F., & Magagnato, F. (2021). Investigation of in-pipe drag-based turbine for distributed hydropower harvesting: Modeling and optimization. *Journal of Cleaner Production*, vol.298, 126710.

[6] Ma, L., Xiao, L., Meng, Z., & Huang, X. (2020). Robust adaptive fault reconfiguration for micro-gas turbine based on optimized T–S fuzzy model and nonsingular TSMO. *International Journal of Fuzzy Systems*, vol.22, pp.2204-2222.

[7] Shi, Y., & Zhou, J. (2022). Stability and sensitivity analyses and multi-objective optimization control of the hydro-turbine generator unit. *Nonlinear Dynamics*, vol.107, pp.2245–2273 (2022). https://doi.org/10.1007/s11071-021-07009-7.

[8] Trizoglou, P., Liu, X., & Lin, Z. (2021). Fault detection by an ensemble framework of Extreme Gradient Boosting (XGBoost) in the operation of offshore wind turbines. *Renewable Energy*, vol.179, pp.945-962.

[9] Luo, Z., Liu, C., & Liu, S. (2020). A novel fault prediction method of wind turbine gearbox based on pair-copula construction and BP neural network. *IEEE Access*, vol.8, pp.91924-91939.

[10] Wang, J., Liang, Y., Zheng, Y., Gao, R. X., & Zhang, F. (2020). An integrated fault diagnosis and prognosis approach for predictive maintenance of wind turbine bearing with limited samples. *Renewable Energy*, vol.145, pp.642-650.

[11] Park, Y., Choi, M., Kim, K., Li, X., Jung, C., Na, S., & Choi, G. (2020). Prediction of operating characteristics for industrial gas turbine combustor using an optimized artificial neural network. *Energy*, vol.213, 118769.

[12] Chen, H., Hsu, J. Y., Hsieh, J. Y., Hsu, H. Y., Chang, C. H., & Lin, Y. J. (2021). Predictive maintenance of abnormal wind turbine events by using machine learning based on condition monitoring for anomaly detection. *Journal of Mechanical Science and Technology*, vol.35, pp.5323-5333.

[13] Tahir, M.Z., Nawi, M.N.M., Rajemi, M.F. (2015). Building energy index: A case study of three government office buildings in Malaysia. *Advanced Science Letters,* vol.21(6), pp.1798-1801.

[14] Tahir, M.Z., Jamaludin, R., Nawi, M.N.M., Baluch, N.H., Mohtar, S. (2017). Building energy index (BEI): A study of government office building in Malaysian public university. *Journal of Engineering Science and Technology,* vol.12 (Special Issue 2), pp.192-201.

[15] Yu, W., Huang, S., & Wang, J. (2021). Fault detection based on a combined approach of FA-CP-ELM with application to wind turbine system. *Journal of Electrical Engineering & Technology*, vol.16, pp.547-557.

[16] Wang, X., Yan, X., & He, Y. (2020). Weak fault detection for wind turbine bearing based on ACYCBD and IESB. *Journal of Mechanical Science and Technology*, vol.34, pp.1399-1413.

[17] Wang, A., Pei, Y., Qian, Z., Zareipour, H., Jing, B., & An, J. (2022). A two-stage anomaly decomposition scheme based on multi-variable correlation extraction for wind turbine fault detection and identification. *Applied Energy*, vol.321, 119373.

[18] Ganthia, B. P., Barik, S. K., & Nayak, B. (2022). Genetic Algorithm Optimized and Type-I fuzzy logic controlled power smoothing of mathematical modeled Type-III DFIG based wind turbine system. *Materials Today: Proceedings*, vol.56, 3355-3365.

[19] Erisen, B. (2018). Wind Turbine Scada Dataset. *Kaggle*, [Online]. https://www.kaggle.com/datasets/berkerisen/wind-turbine-scada-dataset (Accessed Date: November 14, 2023).

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)
The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself
No funding was received for conducting this study.

Conflict of Interest
The authors have no conflicts of interest to declare.

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)
This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US