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Multiple faults detection in doubly-fed induction generator wind turbine using artificial neural network

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ABSTRACT

The development of fault detection methods in wind turbine (WT), especially for single fault detection, is continuously increasing. However, the rapid growth of fault detection in WT leads to another challenge where multiple faults can occur. The single fault detection method in WT is no longer reliable, especially when multiple faults occur simultaneously. Therefore, multiple faults detection in doubly-fed induction generators (DFIG) WT was proposed using an artificial neural networks (ANN) model. These multiple faults include internal and external stator faults happening simultaneously. Internal stator faults cover inter-turn short circuit faults and open circuit faults, while external stator faults cover loss of excitation and external short circuit faults. The performance of the developed multiple faults detection model was measured using accuracy and the root mean square error (RMSE) value. The results show that the developed model performs well with high accuracy and a low RMSE value. Thus, the developed model can accurately detect the coexistence of multiple faults in DFIG WT.

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1. INTRODUCTION

In recent years, the wind turbine (WT) has emerged as a viable alternative for electrical power generation, owing to its environmental and economic benefits. Plus, the global wind power energy council (GWEC) expects onshore wind installations to surpass the 100 GW mark annually, while offshore wind is projected to exceed 25 GW in a single year for the first time in 2025 [1]. Consequently, current research has focused on WTs, particularly in fault detection, as it plays a crucial role in improving operational reliability and safety. Faults in WTs encompass both electrical and mechanical issues. A WT's production capacity, uptime, performance, and reliability are negatively impacted by electrical and mechanical faults. Over a longer length of time, mechanical breakdowns are less common but nonetheless harmful to WTs. Meanwhile, electrical failures are expensive and the most common failures in WTs. In general, the main electrical machine defects in WTs include stator winding faults, fractured rotor bars, cracked rotor end rings, air-gap eccentricity, bent shafts, rotor winding short-circuits, and bearing and gearbox failures.

A critical breakdown in the WT system often stems from generator failures, particularly in the stator and rotor. Swana and Doorsamy [2] investigates a short-circuit fault involving the inter-turn windings of both the stator and rotor. Additional studies on stator faults are presented in [3], [4], while rotor fault research is documented in studies [5], [6]. The majority of fault detection techniques utilize machine learning methods, including wavelet analysis [5], [7], [8], fast Fourier transform (FFT) [9], current signature analysis [4], [10],

[11], and artificial neural networks (ANN) [2], [12], [13]. In previous work, Abadi *et al.* [9] conducted research on inter-turn fault detection in doubly-fed induction generators (DFIG) for wind turbine applications using FFT. Moreover, Gong and Qiao [10] conducted an imbalance fault detection study of direct-drive wind turbines using generator current signals. Azamfar *et al.* [11] proposed fault diagnosis for the gearbox using current signature analysis. At the same time, Liu *et al.* [12] researched fault detection for wind turbine systems using neural networks.

However, previous studies have primarily focused on fault detection for single faults. In such situations, it is assumed that only one fault exists in the system at any given time [14]. Early fault detection is crucial to reduce maintenance costs and extend the life expectancy of WTs. Yet, it is equally important to consider other factors when multiple faults occur. Addressing the multiple fault problem is crucial because solely focusing on single faults can lead to inaccurate or unsuccessful diagnoses when multiple faults are present [14], [15]. The study [16] presents a new algorithm for generating test patterns to detect multiple faults in a combinational logic network, while Dorantes *et al.* [17] proposed a novel methodology for multiple-fault detection and identification. This approach is supported by a feature-level fusion strategy and a hierarchical structure of self-organizing maps (SOM). The study [17] introduces a novel way to diagnose multiple defects in a kinematic chain driven by an induction motor at various operating frequencies. In study [18], induction motor bearings and gearbox bearings on the kinematic chain are analyzed using a multiple-fault detection approach based on vibration and current analysis. Donate *et al.* [19] develops a universal wavelet-based methodology for multiple fault identification in induction motors during the startup vibration transient. This work provides a quantitative general technique for online induction motor monitoring and automatic defect identification. Additionally, a hardware processing unit is introduced for real-time applications. The suggested methodology is tested in three distinct cases: a motor with broken rotor bars, a shaft that is not balanced, and a motor with a load that is not properly aligned.

Several methods for multiple defect detection have been developed, but they often provide qualitative results, necessitating expert technicians to estimate the state and risking potential observation mistakes. The presence of multiple faults in WT and the overlapping effects of these faults in the physical magnitudes currently present a significant challenge in achieving accurate diagnosis results. Additionally, the interactions among fault effects can obscure fault signatures, making the identification of multiple faults difficult [14]. Thus, this paper addresses the issue of multiple faults detection in WT generators using an ANN model to mitigate the risk of incorrect diagnosis when multiple faults occur. Notably, there is a lack of related research in multiple faults detection specifically focusing on WT generators, although multiple faults in induction motors are commonly observed, as documented in studies such as [20]–[22]. For instance, Messaoudi and Sbita [20] conducted experiments to detect multiple faults simultaneously in induction motors using current signature analysis. This suggests the possibility of multiple faults occurring in WT generators. As a result, this study assumes the occurrence of internal and external faults simultaneously for the purpose of developing a multiple faults detection method.

2. METHOD

The proposed method for this study involves obtaining data from MATLAB Simulink, building and testing an ANN model, and conducting an evaluation. This study involves a systematic process with distinct steps aimed at fault detection in a DFIG WT system. The methodology unfolds as follows:

a. Apply multiple faults of internal and external stator faults in the DFIG WT system using MATLAB Simulink
b. Obtain the current and voltage of the stator and rotor based on the direct-quadrate (*dq*) axis for training and testing data.
c. Construct a two-layer backpropagation neural network and conduct supervised training for fault detection.
d. Test the performance of the trained network.
e. Check the performance of the retrained network to ensure the new network shows improved performance. If not, repeat steps (c) and (d) until better performance is obtained.
f. Measure the performance of the output response of the ANN fault detection model.
g. Identify the condition of the DFIG WT based on the output response of the ANN model.

The internal and external stator faults were applied to the DFIG WT system under four conditions; inter-turn short circuit fault and loss of excitation (LOE) fault, inter-turn short circuit fault and external short circuit (ESC) fault, open circuit fault and LOE fault, and open circuit fault and ESC fault. Inter-turn short circuit fault and open circuit fault were applied based on the stator resistance and stator inductance values [23], [24]. Meanwhile, LOE and ESC faults were applied based on Figures 1 and 2. Figure 1 depicts a Simulink model for a WT with LOE fault, while Figure 2 illustrates a Simulink model for a WT with ESC fault. In LOE fault detection, the DFIG is connected to two parallel lines (30 km) through a step-up transformer, as shown in Figure 1. A three-phase fault was applied in the DFIG WT model for ESC fault detection.

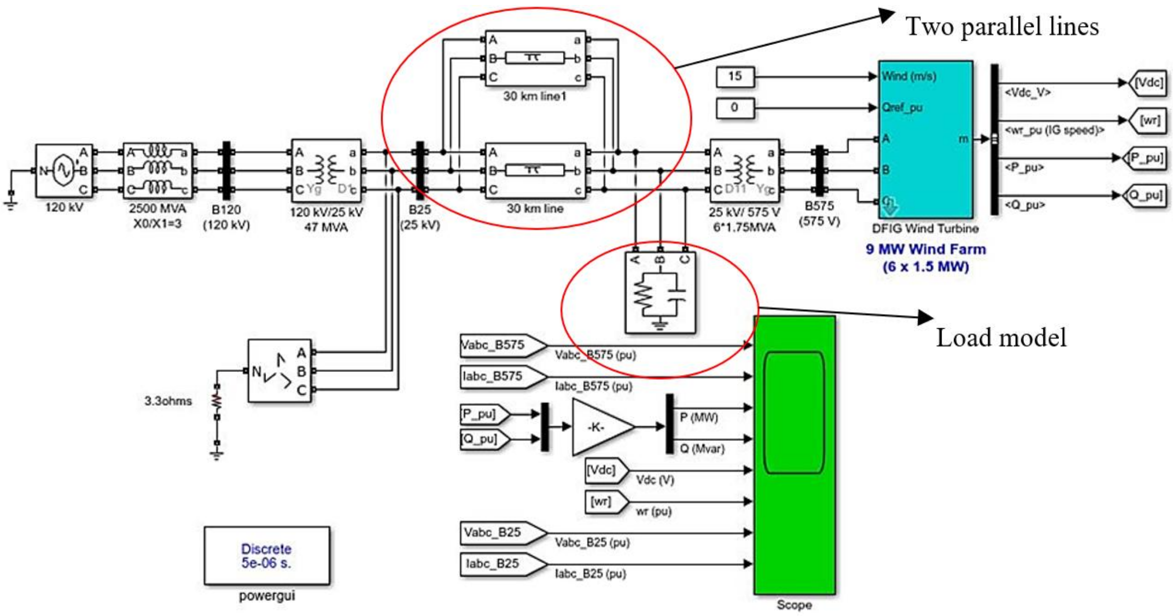

Figure 1. Simulink model for WT with LOE fault

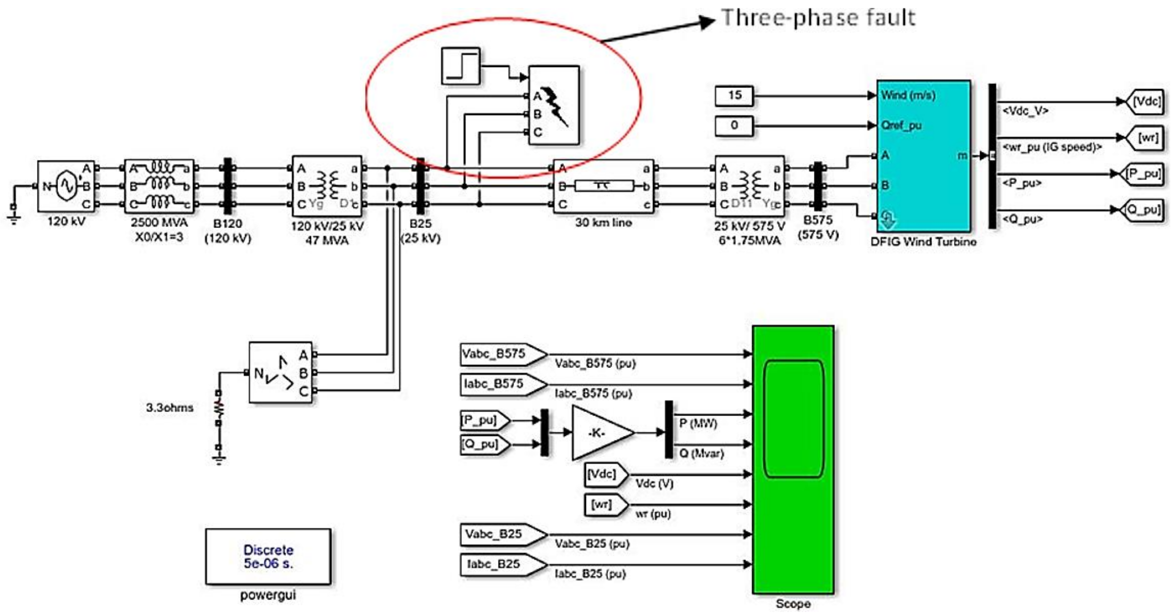

Figure 2. Simulink model for WT with ESC fault

All simulated responses were utilized for both training and testing data. Subsequently, the process involved constructing a two-layer backpropagation neural network and conducting supervised training for fault detection. In this paper, the utilization of ANN is highlighted, given its successful application across diverse problem domains and its proven superiority over traditional methods, especially in handling data characterized by noise or incompleteness [25]. Additionally, ANNs exhibit the capacity to preprocess input patterns, generating more straightforward patterns with reduced components [25]. The parameters of nodes, activation function, epoch, and batch size for the ANN model are outlined in Table 1.

Table 1. The parameters for the ANN model

Parameters	Value
Nodes at layer 1	350
Nodes at layer 2	350
Activation function in layer 1	ReLU
Activation function in layer 2	ReLU
Activation function in the output layer	Double sigmoid
Epoch	1,000
Batch size	500

The ANN fault detection model was developed using voltage and current inputs of the stator and rotor based on the dq axis (V_{qs}, V_{ds}, V_{qr}, V_{dr}, I_{qs}, I_{ds}, I_{qr}, and I_{dr}) with outputs including stator resistance (R_s), stator inductance (L_s), stator flux (φ_s), and negative sequence current (I^-). The condition of the DFIG WT is determined based on the output response of the ANN model. The output parameters of the machine learning model used to distinguish the condition of the WT generator are presented in Table 2.

Table 2. Output parameters value for multiple faults case [23], [24], [26]

Conditions	R_s (pu)	L_s (pu)	φ_s (pu)	I^- (pu)
Inter-turn short circuit and LOE	0.0023	0.308	<1	<0.05
Inter-turn short circuit and ESC	0.0023	0.308	<1	>0.05
Open circuit and LOE	0.23	30.8	<1	<0.05
Open circuit and ESC	0.23	30.8	>1	>0.05

The ANN model was tested to assess the performance of the trained network. The retrained network's performance was evaluated to ensure that it outperforms the original network. If not, the model will be rebuilt and tested again until better results are obtained. The performance of the ANN model was measured by calculating the accuracy and the root mean square error (RMSE) value of the output response.

3. RESULTS AND DISCUSSION

The results were presented based on accuracy and RMSE value, showcasing the output response comparison between the actual and ANN models, along with fault classification for the DFIG WT model in a random input test. The outputs (R_s, L_s, φ_s and I^-) of the ANN model were displayed in Table 3 along with their accuracy and RMSE value. The accuracy and RMSE values were determined based on the difference between the real values from MATLAB Simulink and the output values derived from the ANN model. According to the results, the accuracy for every output was more than 80.6%, and the RMSE values were very low, almost near to zero in all conditions.

Table 3. The accuracy and the RMSE value

Conditions	Accuracy (%)				RMSE			
	R_s	L_s	φ_s	I^-	R_s	L_s	φ_s	I^-
Inter-turn short circuit and LOE	98.00	99.84	99.72	85.75	0.00006	0.00060	0.00154	0.00015
Inter-turn short circuit and ESC	95.79	99.29	99.40	99.28	0.00013	0.01780	0.00574	0.01478
Open circuit and LOE	99.60	100.00	99.02	80.60	0.00111	0.00001	0.00819	0.00021
Open circuit and ESC	99.01	100.00	90.30	82.64	0.00621	0.00001	0.15243	0.02400

Figures 3 to 5 show the output response between the actual and ANN output response in different conditions. The ANN outputs response is represented by the dashed red line, while the actual response from MATLAB Simulink is represented by the solid blue line. Figure 3 shows the output response for stator resistance in the presence of multiple faults, including inter-turn short circuit faults and LOE faults. The ANN output response was consistent with the actual response, which was 0.0023 pu, as shown in Figure 3.

Figure 4 shows the output response for stator inductance in the presence of multiple faults, including inter-turn short circuit and ESC. Meanwhile, Figure 5 illustrates the output response for negative sequence current in the presence of multiple faults, including open circuit and LOE. Both figures demonstrate that the ANN output response can accurately capture the real response, and the output response follows the parameter values listed in Table 2 to distinguish between the conditions of the DFIG WT model.

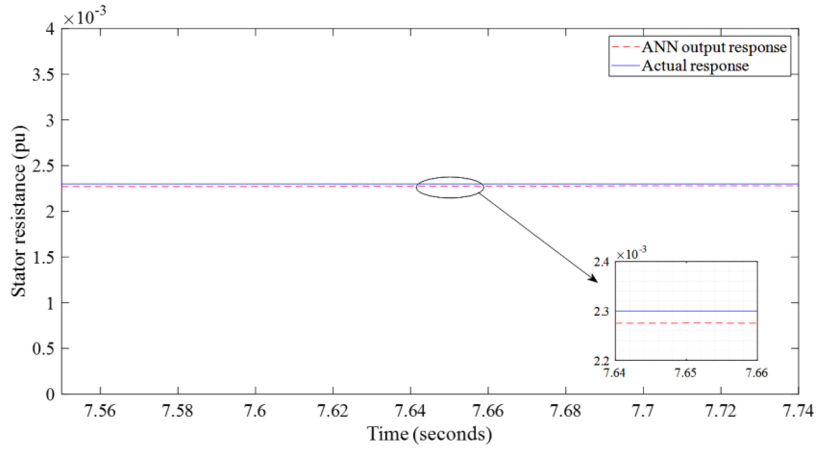

Figure 3. Stator resistance in multiple faults of inter-turn short circuit and LOE

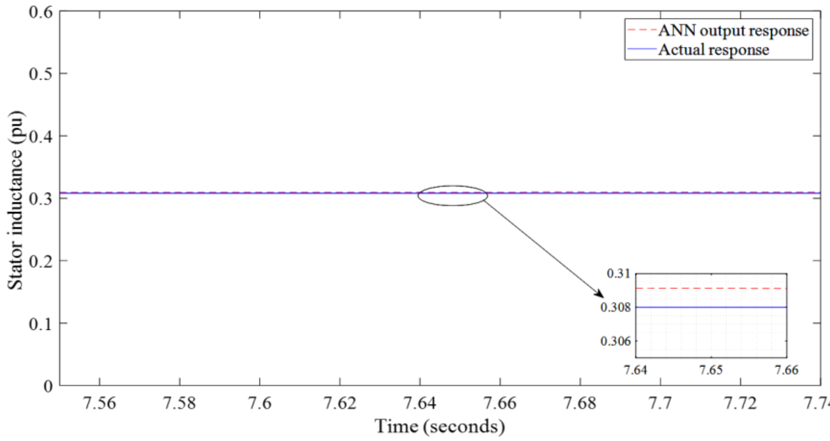

Figure 4. Stator inductance in multiple faults of inter-turn short circuit and ESC

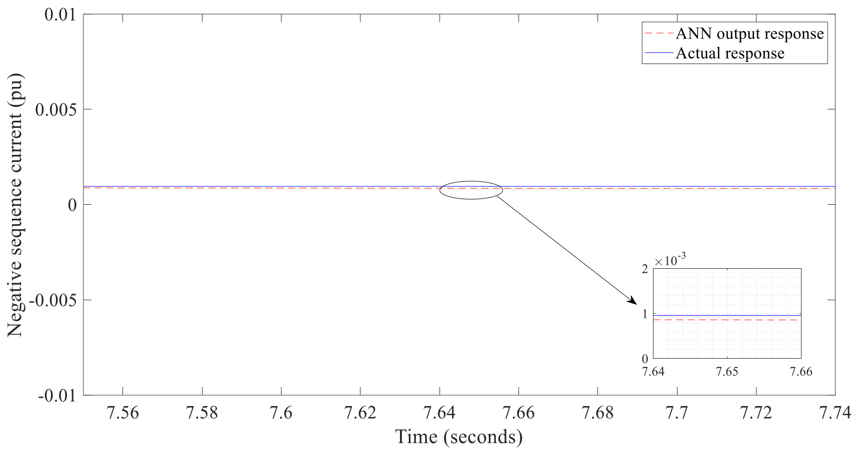

Figure 5. Negative sequence current in multiple faults of open circuit and LOE

Table 4 shows the classification of faults based on 16 different tests under 4 different conditions, each utilizing a different random input vector. There were 8 input vectors (V_{qs}, V_{ds}, V_{qr}, V_{dr}, I_{qs}, I_{ds}, I_{qr}, I_{dr}) and four output vectors (R_s, L_s, φ_s and I^-) in the ANN model. The ANN model classifies the vectors based on four conditions: inter-turn short circuit fault and LOE fault, inter-turn short circuit fault and ESC fault, open circuit fault and LOE fault, and open circuit fault and ESC fault. These conditions are determined by the parameters for the output values of the ANN model, as listed in Table 2. From the results, the ANN successfully detects the output vectors and classifies them into their respective conditions, as indicated in Table 2.

Table 4. The accuracy and the RMSE value

No	Input $[V_{qs} : V_{ds} : V_{qr} : V_{dr}: I_{qs} : I_{ds} : I_{qr} : I_{dr}]$	ANN Output $[R_s : L_s : \varphi_s : I^-]$	Conditions
1	[0.452515; -0.230351; -0.000035; 0.000017; -0.053860; 1.819449; 0.822892; -0.409892]	[0.00227;0.3074;0.493; 0.000570]	Inter-turn short circuit and LOE
2	[0.452486; -0.230342; -0.000035; 0.000017; -0.054977; 1.819903; 0.823556; -0.410157]	[0.00227; 0.3074; 0.493; 0.000573]	
3	[0.452387; -0.230284; -0.000035; 0.000017; -0.056095; 1.820353; 0.824221; -0.410420]	[0.00227; 0.3074; 0.493; 0.000576]	
4	[0.452221; -0.230180; -0.000035; 0.000017; -0.057214; 1.820801; 0.824888; -0.410681]	[0.00226; 0.30742; 0.493; 0.000579]	
5	[-0.140199; 0.443238; -0.000002; -0.000034; -1.578006; -0.816630; 0.055685; 0.800788]	[0.00226; 0.309; 0.471; 0.352]	Inter-turn short circuit and ESC
6	[-0.139799; 0.442710; -0.000002; -0.000034; -1.579758; -0.818456; 0.056811; 0.801910]	[0.00226; 0.309; 0.471; 0.352]	
7	[-0.139371; 0.442149; -0.000003; -0.000034; -1.581500; -0.820293; 0.057929; 0.803041]	[0.00226; 0.309; 0.472; 0.352]	
8	[-0.138914; 0.441558; -0.000003; -0.000034; -1.583230; -0.822143; 0.059041; 0.804179]	[0.00226; 0.309; 0.472; 0.352]	
9	[-0.283594; 0.383753; 0.238799; -0.413567; 0.817311; -0.485023; -0.884790; 0.499063]	[0.229; 30.79; 0.6649; 0.000851]	Open circuit and LOE
10	[-0.283079; 0.383190; 0.238861; -0.413675; 0.817146; -0.484696; -0.884609; 0.498710]	[0.229; 30.79; 0.6649; 0.000851]	
11	[-0.282522; 0.382559; 0.238923; -0.413782; 0.816981; -0.484369; -0.884428; 0.498358]	[0.229; 30.79; 0.6649; 0.0008524]	
12	[-0.281914; 0.381843; -0.238862; -0.413808; 0.816817; -0.484043; -0.884249; 0.498006]	[0.229; 30.79; 0.66494; 0.0008529]	
13	[-0.243348; 1.001583; -0.468843; -0.000034; 0.219948; -0.739104; -0.274761; 0.786227]	[0.23; 30.8; 1.1338; 0.0734]	Open circuit and ESC
14	[-0.243420; 1.000075; -0.468804; -0.000034; 0.220069; -0.739314; -0.274911; 0.786435]	[0.23; 30.8; 1.13401; 0.0734]	
15	[-0.243465; 0.998438; -0.468764; -0.000034; 0.220190; -0.739526; -0.275062; 0.786645]	[0.23; 30.8; 1.13418; 0.0734]	
16	[-0.243479; 0.996677; -0.468725; -0.000034; 0.220312; -0.739741; -0.275213; 0.786858]	[0.23; 30.8; 1.1343; 0.0734]	

4. CONCLUSION

The goal of this study is to develop a multiple faults detection system for DFIG WT by using ANN. The performance of the ANN model is evaluated by assessing accuracy and the RMSE values, indicating the difference between the actual and ANN output values. The highest accuracy value and the RMSE value closest to zero value indicate the highest model performance. Thus, the ANN model's effectiveness is determined by both accuracy and RMSE. Results show that the accuracy exceeded 80.6% for all conditions, and the RMSE values were close to zero for nearly all scenarios. Additionally, the ANN output response accurately mirrors the actual response in all cases. The obtained outcomes demonstrate the effectiveness of the ANN model in capturing actual response patterns. Various failure scenarios were employed to assess the ANN fault classifier and validate the developed ANN model. The results of the ANN fault classifier indicate that, under all circumstances, the output parameters were consistently followed by the ANN fault classifier. This demonstrated the effectiveness of the ANN model for multiple faults detection. Conclusively, the multiple faults detection system for DFIG WT employing ANN was successfully established and demonstrated its effectiveness.

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REFERENCES

[1] M. Hutchinson and F. Zhao, “Global wind report 2023,” *GWEC Global Wind Energy Council*, 2023. Accessed: Feb. 20, 2024. [Online]. Available: https://gwec.net/wp-content/uploads/2023/04/GWEC-2023_interactive.pdf

[2] E. F. Swana and W. Doorsamy, “Investigation of combined electrical modalities for fault diagnosis on a wound-rotor induction generator,” *IEEE Access*, vol. 7, pp. 32333–32342, 2019, doi: 10.1109/ACCESS.2019.2904238.

[3] I. Kuiler, M. Adonis, and A. Raji, “Preventive maintenance and fault detection for wind turbine generators using a statistical model,” in *Fault Detection and Diagnosis*, InTech, 2018.

[4] R. K. Ibrahim and S. Watson, “Stator winding fault diagnosis in synchronous generators for wind turbine applications,” in *5th IET International Conference on Renewable Power Generation (RPG) 2016*, London, UK, 2016, pp. 1-6, doi: 10.1049/cp.2016.0550.

[5] Himani and R. Dahiya, “Condition monitoring of wind turbine for rotor fault detection under non stationary conditions,” *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 2441–2452, Dec. 2018, doi: 10.1016/j.asej.2017.04.002.

[6] H. Sabir, M. Ouassaid, and N. Ngote, “Diagnosis of rotor winding inter-turn short circuit fault in wind turbine based on DFIG using hybrid TSA/DWT approach,” in *2018 6th International Renewable and Sustainable Energy Conference (IRSEC)*, Dec. 2018, pp. 1–6, doi: 10.1109/IRSEC.2018.8703006.

[7] P. Liang, C. Deng, J. Wu, and Z. Yang, “Intelligent fault diagnosis of rotating machinery via wavelet transform, generative adversarial nets and convolutional neural network,” *Measurement*, vol. 159, Jul. 2020, doi: 10.1016/j.measurement.2020.107768.

[8] M. Jalayer, C. Orsenigo, and C. Vercellis, “Fault detection and diagnosis for rotating machinery: a model based on convolutional LSTM, Fast Fourier and continuous wavelet transforms,” *Computers in Industry*, vol. 125, Feb. 2021, doi: 10.1016/j.compind.2020.103378.

[9] F. Silva, M. B. Abadi, S. M. A. Cruz, A. P. Gonçalves, A. M. S. Mendes, and A. Ribeiro, “Inter-turn fault detection in doubly-fed induction generators for wind turbine applications using the stator reactive power analysis,” in *3rd Renewable Power Generation Conference (RPG 2014),* Naples, 2014, pp. 1-6, doi: 10.1049/cp.2014.0914.

[10] X. Gong and W. Qiao, “Imbalance fault detection of direct-drive wind turbines using generator current signals,” *IEEE Transactions on Energy Conversion*, vol. 27, no. 2, pp. 468–476, Jun. 2012, doi: 10.1109/TEC.2012.2189008.

[11] M. Azamfar, J. Singh, I. Bravo-Imaz, and J. Lee, “Multisensor data fusion for gearbox fault diagnosis using 2-D convolutional neural network and motor current signature analysis,” *Mechanical Systems and Signal Processing*, vol. 144, Oct. 2020, doi: 10.1016/j.ymssp.2020.106861.

[12] Z. Liu, C. Xiao, T. Zhang, and X. Zhang, “Research on fault detection for three types of wind turbine subsystems using machine learning,” *Energies*, vol. 13, no. 2, Jan. 2020, doi: 10.3390/en13020460.

[13] S. Toma, L. Capocchi, and G.-A. Capolino, “Wound-rotor induction generator interturn short-circuits diagnosis using a new digital neural network,” *IEEE Transactions on Industrial Electronics*, vol. 60, no. 9, pp. 4043–4052, Sep. 2013, doi: 10.1109/TIE.2012.2229675.

[14] H. Yin, S. Yang, X. Zhu, S. Jin, and X. Wang, “Satellite fault diagnosis using support vector machines based on a hybrid voting mechanism,” *The Scientific World Journal*, vol. 2014, pp. 1–11, 2014, doi: 10.1155/2014/582042.

[15] M. Daigle, X. Koutsoukos, and G. Biswas, “Multiple fault diagnosis in complex physical systems,” in *Proceeding 17th International Workshop Principles of Diagnosis*, pp. 69–76, 2006.

[16] D. C. Bossen and Se June Hong, “Cause-effect analysis for multiple fault detection in combinational networks,” *IEEE Transactions on Computers*, vol. C–20, no. 11, pp. 1252–1257, Nov. 1971, doi: 10.1109/T-C.1971.223124.

[17] J. J. Saucedo-Dorantes, M. Delgado-Prieto, R. D. J. Romero-Troncoso, and R. A. Osornio-Rios, “Multiple-fault detection and identification scheme based on hierarchical self-organizing maps applied to an electric machine,” *Applied Soft Computing*, vol. 81, Aug. 2019, doi: 10.1016/j.asoc.2019.105497.

[18] J. J. Saucedo-Dorantes, M. Delgado-Prieto, J. A. Ortega-Redondo, R. A. Osornio-Rios, and R. de J. Romero-Troncoso, “Multiple-fault detection methodology based on vibration and current analysis applied to bearings in induction motors and gearboxes on the kinematic chain,” *Shock and Vibration*, vol. 2016, pp. 1–13, 2016, doi: 10.1155/2016/5467643.

[19] C. Rodriguez-Donate, R. J. Romero-Troncoso, E. Cabal-Yepez, A. Garcia-Perez, and R. A. Osornio-Rios, “Wavelet-based general methodology for multiple fault detection on induction motors at the startup vibration transient,” *Journal of Vibration and Control*, vol. 17, no. 9, pp. 1299–1309, Aug. 2011, doi: 10.1177/1077546310379141.

[20] M. Messaoudi and L. Sbita, “Multiple faults diagnosis in induction motor using the MCSA method,” *International Journal of Signal & Image Processing*, vol. 1, no. 3, 2010.

[21] A. L. Martinez-Herrera, E. R. Ferrucho-Alvarez, L. M. Ledesma-Carrillo, R. I. Mata-Chavez, M. Lopez-Ramirez, and E. Cabal-Yepez, “Multiple fault detection in induction motors through Homogeneity and Kurtosis computation,” *Energies*, vol. 15, no. 4, Feb. 2022, doi: 10.3390/en15041541.

[22] R. K. Sharma, “Multiple fault detection in induction motor,” *Journal of Emerging Technologies and Innovative Research (JETIR)*, vol. 6, no. 2, pp. 151–157, 2019.

[23] W. Yang, P. J. Tavner, and R. Court, “An online technique for condition monitoring the induction generators used in wind and marine turbines,” *Mechanical Systems and Signal Processing*, vol. 38, no. 1, pp. 103–112, Jul. 2013, doi: 10.1016/j.ymssp.2012.03.002.

[24] H. Zhao, W. Hao, H. Wu, Z. Yang, and X. Shi, “Modeling and simulation of aircraft main generator stator winding faults,” *Journal of Computational Methods in Sciences and Engineering*, vol. 17, no. 4, pp. 691–704, Nov. 2017, doi: 10.3233/JCM-170753.

[25] C. Srinivasa Rao, “Design of artificial intelligent controller for automatic generation control of two area hydrothermal system,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 2, no. 2, pp. 183–190, Mar. 2011, doi: 10.11591/ijece.v2i2.111.

[26] H. Yaghobi and H. Mortazavi, “A novel method to prevent incorrect operation of synchronous generator loss of excitation relay during and after different external faults,” *International Transactions on Electrical Energy Systems*, vol. 25, no. 9, pp. 1717–1735, Sep. 2015, doi: 10.1002/etep.1922.

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