International Journal of Applied Power Engineering (IJAPE)
Vol. 14, No. 4, December 2025, pp. 960~969
ISSN: 2252-8792, DOI: 10.11591/ijape.v14.i4.pp960-969

Transmission line fault detection using empirical mode decomposition in presence of wind intermittency

Venkata Krishna Bokka[1,2], E. R. Biju[1], Sai Veerraju Mortha[2], Majahar Hussain Mahammad[3], Shaik Mohammad Irshad[3]
[1]Department of Electrical Engineering, Annamalai University, Chidambaram, India
[2]Department of Electrical and Electronics Engineering, Sagi Ramakrishnamraju Engineering College, Bhimavaram, India
[3]Department of Electrical Engineering, College of Engineering, King Khalid University, Abha, Saudi Arabia

Article Info

Article history:

Received Dec 1, 2024
Revised Aug 14, 2025
Accepted Oct 16, 2025

Keywords:

Empirical mode decomposition
Fault detection
Faults
Protection
Wind

ABSTRACT

The regular fault detection approaches are failed to detect the faults in wind integrated transmission networks due to intermittency nature of the wind energy. More reliable schemes are required to accomplish the detection of faults in presence wind. This article proposed empirical mode decomposition (EMD) based fault detection scheme to detect various faults in wind integrated transmission lines during the normal and stressed conditions of the system. The instantaneous current measurements available at either sending or receiving end are processed through EMD to decompose it into a series of intrinsic mode functions (IMFs) and IMF2 is identified as a dominated IMF with numerous case wise investigations. 1/4th cycle moving window is used to calculate the absolute sum of the IMF2 coefficients to detect the faults with the support of a predefined threshold. The efficacy of the method is tested on different types of faults during the normal condition in presence of wind and later extended to stressed conditions such as power swing. The method is reliable during the typical cases and includes remote end and high resistance faults. All the experiments are carried out in Simulink to generate the measurement data and programs are executed in MATLAB.

Corresponding Author:

Venkata Krishna Bokka
Department of Electrical Engineering, Annamalai University
Chidambaram, Tamil Nadu-608002, India
Email: bvenkatakrishna@gmail.com

1. INTRODUCTION

Integrating wind power into transmission lines is essential since the majority of fossil-based energy resources are decreasing and not meeting the demand of the users. The integration of renewables into power system presents several unique challenges for fault detection and protection. The variability and intermittency of wind power generation make fault detection more challenging, as traditional methods may struggle to adapt to rapidly fluctuating power flows [1]. Moreover, the variable fault current contributions from wind turbines, coupled with the increasing penetration of wind energy, increases the complexity of detecting and isolating faults in transmission lines. Addressing these challenges requires the development of advanced fault detection algorithms [2]. A few research works are available in the literature on protection of wind integrated transmission lines highlighting the need of the advanced schemes in this area. Some of the recent studies are available to explore the status of the protection algorithms adopted for the wind integrated transmission networks [3].

Conventional schemes such as distance and differential protection functions are applied in wind transmission lines with few changes so that those schemes are suitable to detect various faults. The phase current samples indicators at both terminals of the transmission lines are used under differential protection scheme for fault detection in transmission lines connected to wind farms (WF) in the consideration of power [4]. Apart from the modified distance and differential protection algorithms, signal processing techniques are significantly useful to capture the disturbances in the measurements due to events like faults and the methods incorporated with such tools are helpful to enhance the outputs of the protection functions in terms of the performance attributes like dependability, security, and speed. A hybrid method is used which combines wavelet transform (WT) for noise reduction, Clarke transform to find the gradient of the signal component, and decision tree for fault diagnosis [5]. Stockwell transform is another powerful signal processing tool to extract the frequency components from the power system voltage and current measurements suggested in [5] and [6] to detect and discriminate the faults from other events in a wind integrated transmission lines. Furthermore, artificial intelligence techniques like support vector machines and artificial neural networks are also used for detection and classification tasks [7]. A hybrid approach combining signal processing tools and machine learning algorithms for adaptive fault classification in wind energy integrated power transmission line protection systems is proposed in [8]. These hybrid methods utilized a combination of signal processing techniques and machine learning algorithms to adaptively classify faults based on dynamic operating conditions. The study reveals the effectiveness of the hybrid approach in improving fault classification accuracy and adaptability to changing system conditions. The studies available in [6]-[8] falls under such hybrid schemes. Each approach has its strengths and limitations, highlighting the need for further research to develop comprehensive and robust solutions for fault detection and classification in renewable energy integrated power system. Overall, these studies provide the importance of approaches to address the unique challenges raised by wind power generation in power system operation and maintenance. Furthermore, optimization-based schemes are suggested to detect and classify the faults in wind integrated transmission lines [9]. Swarm algorithm assistance is provided to differential protection scheme to set its threshold specifically for wind-integrated transmission systems with the help of particle swarm optimizer (PSO) [10]. Furthermore, the approach proposed in [11] used teaching learning-based optimization (TLBO) to improve fault detection functions in wind farm-integrated power networks. This method can potentially optimize fault detection parameters, improving the accuracy, reliability, and efficiency of fault detection mechanisms in complex power systems. After comparing the TLBO and PSO, the method demonstrates the ability to outperform than PSO [10], particularly in terms of convergence speed, solution quality, and computational efficiency. A detection and classification scheme for transmission lines connecting wind farms, specifically utilizing single-end impedance measurements is proposed [12]. This approach is more accurate for fault identification according to the results available in [12]. All these methods [5]-[12] tested on the power system models integrated with large penetrated WF.

The protection logics further strengthened for the power system models integrated with WF and FACTS. Some of the popular works are available in [13]-[17]. An enhanced detection and location tasks are suggested for transmission lines compensated with thyristor-controlled series capacitors (TCSC) connecting wind farms [13]. Also another method is proposed on wind integrated transmission line with TCSC [14]. The identification of defective phases and ground detection in TCSC-compensated lines integrated with wind farms are the main topics of this work. It likely explores advanced techniques to improve fault identification accuracy and speed. Similar to TCSC, impact of unified power flow controller [15] and static VAR compensator [16] along with wind are studied and intelligent schemes are adopted to design the fault detection and classification tasks. Overall, these articles highlight the diverse range of techniques to enhance fault detection and classification in power systems, especially in the context of integrating renewable energy sources like wind farms. Hybrid approaches, swarm intelligence techniques, optimization algorithms, and advanced signal processing tools play significant roles in improving the reliability and efficiency of power systems [18]-[22]. Another challenge is detection of faults during stressed condition like power swing [23]. Few studies are available to detect symmetrical faults during power swing. For example, synchrophasor-assisted power swing detection, which could be crucial for maintaining stability in power systems. Synchrophasor technology enables real-time monitoring and analysis of power system dynamics, aiding in early detection of power swings and potential faults [17]. More effective schemes are required to detect the faults in wind integrated transmission lines during the normal and stressed conditions of the system [24], [25].

In order to identify transmission line faults in wind integrated power systems under both normal and stressed situations, this work proposes an EMD-based fault detection scheme. In order to identify faults, the approach calculates the absolute total of the dominant IMF coefficients of three phase currents for each 1/4th window. The indices are then compared with a predetermined threshold. The method's effectiveness is evaluated under a range of fault types and operating situations, including fault location, fault initiation, fault resistance, and fault nature. Additionally, the investigations are expanded to include a variety of faults, such as high resistance and remote end faults. To examine the method's performance, it was also validated under power swing conditions. MATLAB-Simulink is used for all of the simulations. The rest of the article is organized as follows: Section 2 provides the methodology details followed by test system and simulation results in section 3. Conclusions are presented in section 4.

2. PROPOSED METHOD

The instantaneous currents of test system either at sending or received end are processed through EMD to extract a series of IMFs. EMD is a powerful signal processing technique with applications across various fields. In biomedical engineering, EMD aids in analyzing electrocardiograms for detecting irregularities or abnormalities in heart rhythms. In finance, it assists in analyzing stock market data to identify trends and patterns for informed decision-making. In geophysics, EMD is used for seismic signal analysis, helping to discern important geological features and potential hazards. Additionally, EMD finds utility in environmental science for analyzing climate data and understanding long-term trends and variability. Its adaptability to non-linear and non-stationary signals, robustness to noise, and ability to extract interpretable components make EMD a valuable tool for signal analysis and interpretation across diverse disciplines. There are few research articles in power system relaying [22], [24] where the EMD is used to discriminate the events. It decomposes the raw data of aforementioned fields of interest into a series of several oscillatory modes called intrinsic mode functions (IMFs) and residual component. Let i(t) is available current data in a particular phase processed through EMD, produce n number of IMFs and one residual component. Mathematically:

$$i(t) = \sum_{i=1}^{n} d_i(t) + r(t) \tag{1}$$

where d_i is the IMF of i^{th} oscillatory mode and r is the residual component. The IMFs are simple modes of oscillations of the signal *i(t)* and final residual component is available in *r(t)*. The upper and lower envelopes are constructed from *i(t)* by using the local maxima and local minima is calculated using the (2).

$$d(t) = \frac{1}{2}\{u(t) + l(t)\} \tag{2}$$

The intermediate signal available after the computation of the mean envelope is expressed as (3).

$$h(t) = i(t) - d(t) \tag{3}$$

The first IMF is extracted using the (3) and the residual component is replacing the original signal to extract further IMFs using the similar procedure until no IMF is generated from the residual component. Among all IMFs, a dominated IMF is identified with the help of few case studies and the fault detection index is designed on the dominated IMF. For suppose $d_i(t)$ is the i^{th} IMF of the original signal *i(t),* then the index computed for the N samples (size of window) is (4).

$$index = \sum_{k=1}^{N} |d_i(k)| \tag{4}$$

When the index value exceeds the predefined threshold, then faults are recorded, and which is expressed using (5).

$$index > \theta \tag{5}$$

The concept is extended for each phase of measurement with separate indices by processing the three phase currents through EMD and extracting the series of IMFs along with the dominated IMF. Instead of single index, three phase indicators are used in the proposed approach to detect various faults in the test system during the normal and stressed conditions. Furthermore, these indicators are helpful to classify the types of faults and faulty phases.

3. TEST SYSTEM AND SIMULATION RESULTS

The wind integrated transmission line system, which connects the grid to massive wind farms, is used to evaluate the suggested approach. Figure 1 displays the test system's single line diagram. The letters "G" and "W" stand for grid-side and wind-side buses, respectively. Between busses G and W is a 300-kilometer transmission line that exports power from the WF to the grid. Bus "G" measures the three phase currents, which are then processed by EMD to break down each phase data into a set of IMFs. In addition to wind farm parameters, the additional test system parameters are accessible in [7].

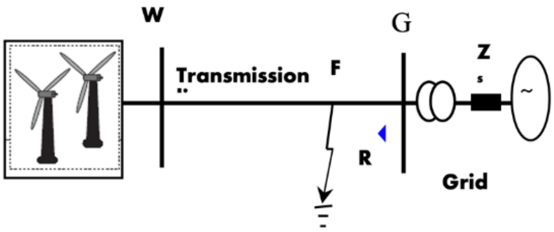

Figure 1. Test system to study the proposed method

3.1. Regular unsymmetrical and symmetrical faults

The current measurements at G for 4 regular unsymmetrical and symmetrical types of faults (LG, LL, LLG, and LLLG) are recorded after test simulations and the signals are plotted in Figure 2. In case of LG fault, AG fault is considered with fault location of 120 km from bus G, inception time of 1.4 s and fault resistance of 20 Ω. Similarly, AB, BCG, and ABCG faults are considered with fault parameters shown in Table 1. The phase current variations are clearly visible in Figures 2(a), 2(b), 2(c), and 2(d) depending on the type of fault initiated in the section between the buses G and W. These currents are processed through EMD to extract the series of IMFs to detect the faults in the system. For example, ABCG fault is started at 1.41 s in the transmission line section and A-phase current is processed through EMD. Figure 3 shows the outputs of EMD in terms of a series of IMFs along with the residual component. The main component is available in IMF 1 and disturbance components are visible from IMF 2 to IMF 5. After extracting all the IMFs, residual components (with less magnitude) is finally retained. The nature of the original signal and IMF1 are similar and therefore it is not suitable for detection purposes. This work suggests that IMF2 is the dominant IMF as it extract the dominant disturbance part of the signal with significant features as shown in Figure 3. Another important issue is the discrimination of faults from other disturbances. It is also possible with IMF2 as shown in Figure 3. Therefore, IMF2 is more suitable to design the fault detection indicator to detect the faults in WF integrated transmission lines. For specific faults, the IMF2 coefficients of the individual phase currents are plotted in Figure 4. In case of AG fault, the IMF2 magnitude rises after inception time of fault in phase A helps to identify the faulty phase to classify the types of faults along with fault detection. A pre-defined threshold of 1 is used to generate the trip for each fault.

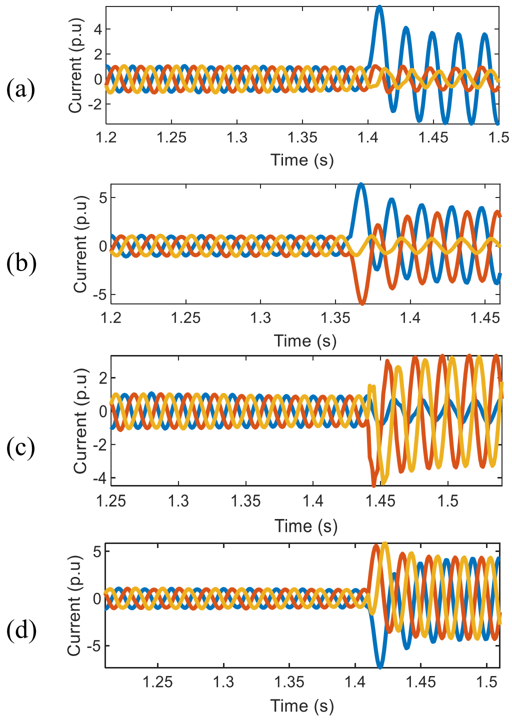

Figure 2. The measured three phase currents at bus G for (a) A-g, (b) A-B, (c) B-C-g, and (d) A-B-C-g faults

Table 1. Fault parameters of various faults

Type of fault	Fault location (km)	Fault time (s)	Fault resistance
AB	80	1.36	5
BCG	220	1.44	10
ABCG	160	1.41	8

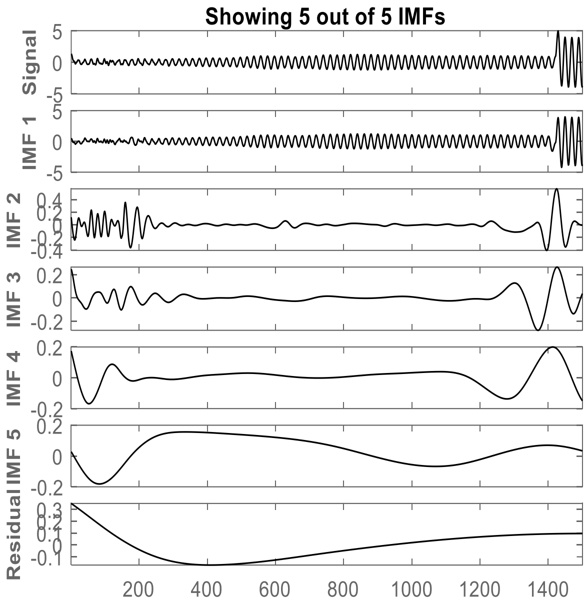

Figure 3. IMFs of the instantaneous current

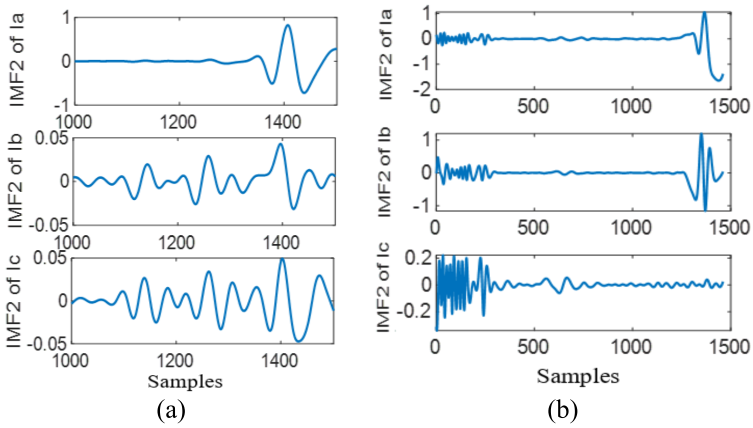

Figure 4. Dominated IMFs of three phase currents for (a) A-g and (b) A-B faults

In case of AB fault, both A and B phase IMFs are responded in terms of the magnitude variation. These IMFs are useful to detect and classify the faults which are presented in Figure 5. The AG, AB, BCG, and ABCG faults are simulated under regular faults and final results of the algorithm are plotted in Figure 5. Each index is computed with IMF 2 magnitude and with initiation of fault, the index exceeds the pre-defined threshold and detected as fault by the proposed algorithm. In Figure 5(a), index 1 exceeds the threshold since the type of fault is AG whereas other 2 indices are below the threshold. Similar results are observed in case of AB, BCG and ABCG faults shown in Figures 5(b), 5(c), and 5(d). Once the fault detection is accomplished from either of indices then faulty phase identification is achieved with the help of the three indices. Furthermore, the involvement of ground is identified by the neural current or zero sequence current. Finally, all the regular types of faults are detected and classified by using the proposed method.

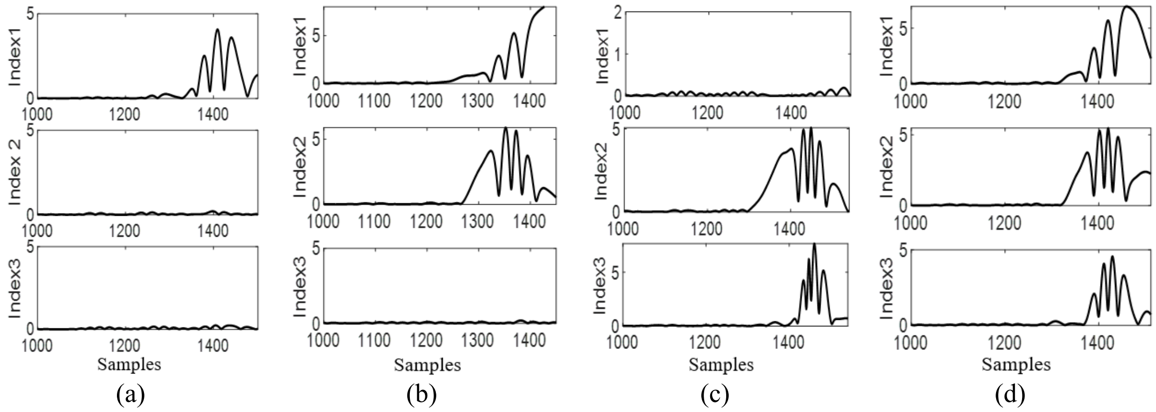

Figure 5. Final fault detection indicators of the three phases of (a) A-g, (b) A-B, (c) B-C-g, and (d) A-B-C-g faults

3.2. Typical faults

Apart from the regular faults, the faults located at remote terminals and faults with high fault resistances are few examples of the typical faults. Detection of such faults is challenging since the fault current is not significantly varied from the normal operating current. The performance of the EMD scheme is tested on both faults. Under remote end fault case, BG fault is considered with fault location of 280 km from the relay point initiated at 1.38 s and fault resistance of 1.38 s. In Figure 6, the 3-phase currents measured at relay point are presented followed by the IMF2 of all phases along with the ground index in Figure 7. These IMFs are used to estimate the indices which are presented in Figure 8. Since the type of fault is BG, the index corresponding to B-phase responded to the fault along with the ground. This detection is possible in first half cycle of the current waveform from the fault inception time. The changes in other nonfaulty phase are below the threshold and therefore the accuracy of the detection and classification of faults by the proposed method is acceptable.

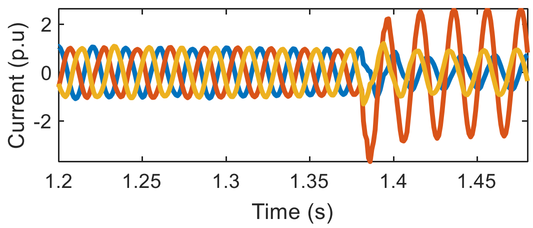

Figure 6. Three phase currents for remote end faults

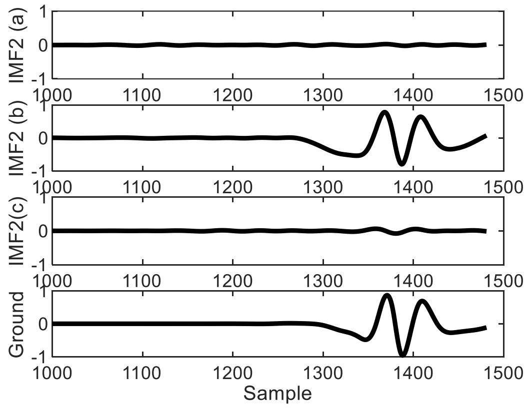

Figure 7. IMF2 coefficients of various phase currents under remote end fault

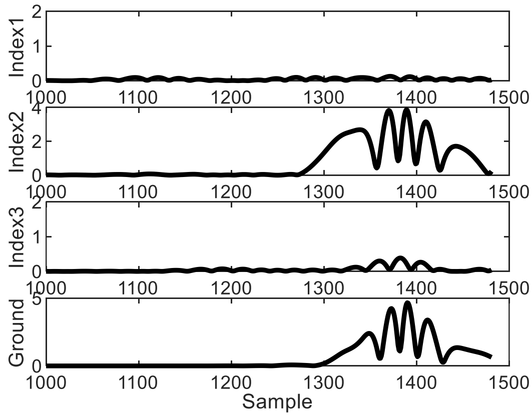

Figure 8. Fault detection outputs of remote end fault

Additionally, to test the effectiveness of the suggested method, a high resistive fault is simulated. This scenario simulates a BG fault that is 65 km from bus G, has a fault resistance of 100 Ω, and has a fault inception time of 1.52 seconds. The reaction of the suggested approach during the high resistance fault is depicted in Figure 9. The detection outputs, as described in section 3.1, can be used to classify regular problems. However, only detection is achieved from the IMF indicators in case of high resistance faults since the type of fault is BG and phase A and phase B indicators exceeds the threshold provide the fault detection decision and failed to get accurate information of the fault classification.

3.3. Faults during the stressed conditions

The performance of the method is further tested during the stressed conditions (power swing) of the test system. In this case, a symmetrical fault is initiated at 1.31 s with a fault resistance of 10 Ω and fault location of 110 km during the swing condition. Figure 10 shows the current measurements at bus G which are processed through EMD to extract the IMFs. The dominated IMFs are used to compute the fault detection indices which are presented in Figure 11. From Figure 11, it is cleared that the proposed method has the ability to detect the typical 3-phase symmetrical faults during the swing condition.

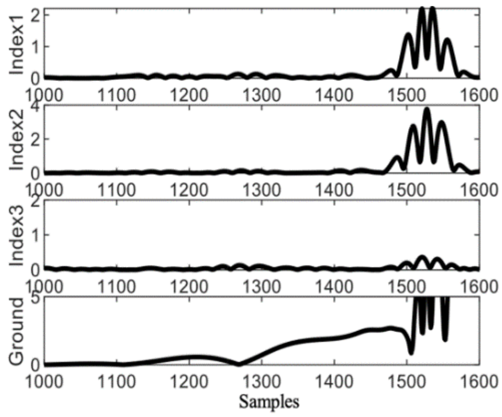

Figure 9. Fault detection outputs of high resistive fault

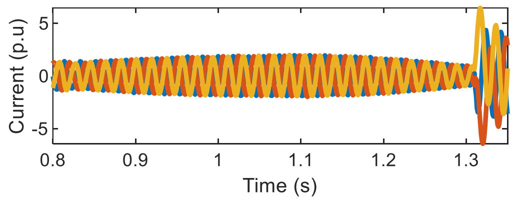

Figure 10. Three phase fault during the swing condition

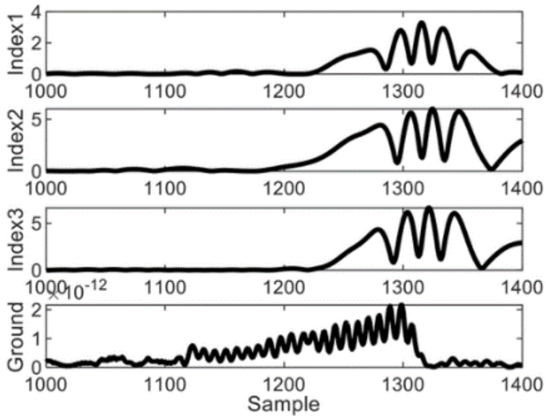

Figure 11. Fault detection outputs for symmetrical fault during the swing condition

4. CONCLUSION

EMD-based fault detection scheme was proposed in this article to detect the faults in the transmission lines connected to wind farms. The scheme is implemented with single end measurements by processing the instantaneous current information into EMD to extract a series of IMFs. The dominated IMF is used to compute the fault detection index to detect and classify the faults occurred in the transmission lines. The proposed algorithm produced high accurate results for regular faults irrespective of the type, location, inception, and resistance of the faults. Furthermore, the technique also provided acceptable results in case of typical faults include remote end and high resistance. The same method is useful to detect the symmetrical faults during the power swing condition is another advantage of the method.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Venkata Krishna Bokka	✓	✓	✓		✓	✓		✓	✓					
E. R. Biju	✓			✓		✓	✓	✓	✓		✓	✓		
Sai Veerraju Mortha		✓	✓	✓			✓			✓		✓	✓	
Majahar Hussain Mahammad		✓			✓	✓			✓		✓			✓
Shaik Mohammad Irshad		✓		✓		✓				✓			✓	✓

C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analysed in this study.

REFERENCES

[1] Y. M. Nsaif, M. S. Hossain Lipu, A. Ayob, Y. Yusof, and A. Hussain, "Fault detection and protection schemes for distributed generation integrated to distribution network: challenges and suggestions," *IEEE Access*, vol. 9, pp. 142693–142717, 2021, doi: 10.1109/ACCESS.2021.3121087.

[2] S. D. Ahmed, F. S. M. Al-Ismail, M. Shafiullah, F. A. Al-Sulaiman, and I. M. El-Amin, "Grid integration challenges of wind energy: a review," *IEEE Access*, vol. 8, pp. 10857–10878, 2020, doi: 10.1109/ACCESS.2020.2964896.

[3] C. D. Prasad, M. Biswal, and P. Ray, "Line protection in presence of high penetration of wind energy: a review on possible solutions," *Electrical Engineering*, vol. 107, no. 7, pp. 8433–8445, 2025, doi: 10.1007/s00202-024-02313-y.

[4] A. Saber, M. F. Shaaban, and H. H. Zeineldin, "A new differential protection algorithm for transmission lines connected to large-scale wind farms," *International Journal of Electrical Power and Energy Systems*, vol. 141, 2022, doi: 10.1016/j.ijepes.2022.108220.

[5] X. D. Wang, X. Gao, Y. M. Liu, and Y. W. Wang, "WRC-SDT based on-line detection method for offshore wind farm transmission line," *IEEE Access*, vol. 8, pp. 53547–53560, 2020, doi: 10.1109/ACCESS.2020.2981294.

[6] S. R. Ola, A. Saraswat, S. K. Goyal, S. K. Jhajharia, and O. P. Mahela, "Detection and analysis of power system faults in the presence of wind power generation using stockwell transform based median," *Lecture Notes in Electrical Engineering*, vol. 607, pp. 319–329, 2020, doi: 10.1007/978-981-15-0214-9_36.

[7] H. Shah, N. Chothani, and J. Chakravorty, "Fault detection and classification in interconnected system with wind generation using ANN and SVM," *Advances in Electrical and Electronic Engineering*, vol. 20, no. 3, pp. 225–239, 2022, doi: 10.15598/aeee.v20i3.4483.

[8] O. Emmanue *et al.*, "Hybrid signal processing and machine learning algorithm for adaptive fault classification of wind farm integrated transmission line protection," *International Journal of Integrated Engineering*, vol. 11, no. 4, pp. 91–100, 2019, doi: 10.30880/ijie.2019.11.04.010.

[9] P. Rajesh, R. Kannan, J. Vishnupriyan, and B. Rajani, "Optimally detecting and classifying the transmission line fault in power system using hybrid technique," *ISA Transactions*, vol. 130, pp. 253–264, 2022, doi: 10.1016/j.isatra.2022.03.017.
[10] C. D. Prasad and M. Biswal, "Swarm intelligence-based differential protection scheme for wind integrated transmission system," *Computers and Electrical Engineering*, vol. 86, 2020, doi: 10.1016/j.compeleceng.2020.106709.
[11] C. D. Prasad, M. Biswal, and P. Ray, "Enhancing fault detection function in wind farm-integrated power network using teaching learning-based optimization technique," *International Transactions on Electrical Energy Systems*, vol. 31, no. 10, 2021, doi: 10.1002/2050-7038.12735.
[12] M. Paul and S. Debnath, "Fault detection and classification scheme for transmission lines connecting windfarm using single end impedance," *IETE Journal of Research*, vol. 69, no. 4, pp. 2057–2069, 2023, doi: 10.1080/03772063.2021.1886601.
[13] B. Sahoo and S. R. Samantaray, "An enhanced fault detection and location estimation method for TCSC compensated line connecting wind farm," *International Journal of Electrical Power and Energy Systems*, vol. 96, pp. 432–441, 2018, doi: 10.1016/j.ijepes.2017.10.022.
[14] S. K. Mohanty, S. B. Santra, and P. Siano, "Faulty phase identification and ground detection in TCSC compensated lines integrated with wind farms," *International Journal of Electrical Power and Energy Systems*, vol. 153, 2023, doi: 10.1016/j.ijepes.2023.109383.
[15] S. Biswas and P. K. Nayak, "A fault detection and classification scheme for unified power flow controller compensated transmission lines connecting wind farms," *IEEE Systems Journal*, vol. 15, no. 1, pp. 297–306, 2021, doi: 10.1109/JSYST.2020.2964421.
[16] S. K. Mishra, "A neuro-wavelet approach for the performance improvement in SVC integrated wind-fed transmission line," *Ain Shams Engineering Journal*, vol. 10, no. 3, pp. 599–611, 2019, doi: 10.1016/j.asej.2018.10.008.
[17] J. T. Rao, B. R. Bhalja, M. V. Andreev, and O. P. Malik, "Synchrophasor assisted power swing detection scheme for wind integrated transmission network," *IEEE Transactions on Power Delivery*, vol. 37, no. 3, pp. 1952–1962, 2022, doi: 10.1109/TPWRD.2021.3101846.
[18] K. Al Kharusi, A. El Haffar, and M. Mesbah, "Fault detection and classification in transmission lines connected to inverter-based generators using machine learning," *Energies*, vol. 15, no. 15, 2022, doi: 10.3390/en15155475.
[19] E. Reyes-Archundia, J. L. Guardado, J. A. Gutiérrez-Gnecchi, E. L. Moreno-Goytia, and N. F. Guerrero-Rodriguez, "Fault analysis in TCSC-compensated lines using wavelets and a PNN," *Neural Computing and Applications*, vol. 30, no. 3, pp. 891–904, 2018, doi: 10.1007/s00521-016-2725-6.
[20] M. Ahanch, M. S. Asasi, and R. McCann, "Transmission lines fault detection, classification and location considering wavelet support vector machine with harris hawks optimization algorithm to improve the SVR training," *2021 8th International Conference on Electrical and Electronics Engineering (ICEEE)*, 2021, pp. 155–160, doi: 10.1109/ICEEE52452.2021.9415887.
[21] S. Mitra, R. Mukhopadhyay, and P. Chattopadhyay, "PSO driven designing of robust and computation efficient 1D-CNN architecture for transmission line fault detection," *Expert Systems with Applications*, vol. 210, 2022, doi: 10.1016/j.eswa.2022.118178.
[22] A. Aggarwal, H. Malik, and R. Sharma, "Feature extraction using EMD and classification through probabilistic neural network for fault diagnosis of transmission line," *2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, 2016, pp. 1–6, doi: 10.1109/ICPEICES.2016.7853709.
[23] B. Patel and P. Bera, "Fast fault detection during power swing on a hybrid transmission line using WPT," *IET Generation, Transmission and Distribution*, vol. 13, no. 10, pp. 1811–1820, 2019, doi: 10.1049/iet-gtd.2018.5233.
[24] A. A. Nazari, F. Razavi, and A. Fakharian, "A new power swing detection method in power systems with large-scale wind farms based on modified empirical-mode decomposition method," *IET Generation, Transmission and Distribution*, vol. 17, no. 6, pp. 1204–1215, 2023, doi: 10.1049/gtd2.12727.
[25] H. Abniki, M. H. Samsi, B. Taheri, and F. Razavi, "Power swing detection in parallel transmission lines connected to wind farms employing del2sg method," *Journal of Electrical Engineering and Technology*, vol. 18, no. 4, pp. 2567–2580, 2023, doi: 10.1007/s42835-022-01348-0.

BIOGRAPHIES OF AUTHORS

Venkata Krishna Bokka received M.Tech. degree in electrical engineering from JNTU Kakinada, in 2013. He is currently pursuing Ph.D. in the Department of Electrical Engineering, Annamalai University, Chidambaram, Tamil Nadu. At present, he is working as assistant professor in the Department of EEE, SRKR Engineering College, Bhimavaram, Andhra Pradesh. His areas of interest include distributed generation. He can be contacted at email: bvenkatakrishna@gmail.com.

E. R. Biju received M.Tech. degree from SASTRA University and Ph.D. from Annamalai University in 2006 and 2016, respectively. He is working as assistant professor in Annamalai University (Depute), Chidambaram, Tamil Nadu. His research area includes power system reliability, distribution system, and power system analysis. He can be contacted at email: kuttanbiju@rediffmail.com.

Sai Veerraju Mortha received an M.E. degree from Anna University and the Ph.D. from JNTU, Hyderabad in 2001 and 2011, respectively. Currently, he is working as professor in SRKR Engineering College, Bhimavaram, Andhra Pradesh, India. His area of research includes power system analysis and stability. He can be contacted at email: saiveerraju@yahoo.co.in.

Majahar Hussain Mahammad received the B.Tech. degree in Electrical and Electronics Engineering from JNTUH in 2004 and M.Tech. degree from JNTUK, Kakinada in 2009, and Ph.D. in electrical engineering from University College of Engineering and Technology, Acharya Nagarjuna University, Guntur, AP-India and working as assistant professor in College of Engineering, King Khalid University, Abha, Kingdom of Saudi Arabia. His research areas of interest are power system operation and control, load frequency control, optimization and application of intelligent control techniques to power systems. He can be contacted at email: mhmohamad@kku.edu.sa.

Shaik Mohammad Irshad is an assistant professor at the Department of Electrical Engineering in the College of Engineering at King Khalid University in Abha, Saudi Arabia. He graduated with a bachelor's degree in electrical and electronics engineering from Jawaharlal Nehru Technological University in Hyderabad, Telangana, India in 2002, and a master's degree in energy systems in the same institution in 2007. In 2022, he obtained his Ph.D. in electrical and electronics engineering from St. Peter's Institute of Higher Education and Research in Chennai. Power quality, integration into power systems, and renewable energy systems are the topics of his research. He can be contacted at email: sirshad@kku.edu.sa.