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Fault Section Identification in Distribution Networks with DFIG and PMSG Using Current Transients

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Abstract— Growing integration of wind - based generators such as Doubly Fed Induction Generators (DFIG) and Permanent Magnet Synchronous Generators (PMSG) into distribution networks has made conventional fault detection approaches increasingly unreliable. This paper proposes a two-stage intelligent Fault Section Identification (FSI) framework that processes phase current signals recorded exclusively at the distribution substation within a compact two-cycle observation window. In the first stage, an Artificial Neural Network (ANN) classifier determines whether a fault resides on the main feeder or a lateral branch. In the second stage, a regression-based ANN estimates the distance from the substation to the fault point. Transient features, namely Energy Per Unit (EPU) and Relative Energy Entropy Per Unit (REEPU), are derived from Discrete Wavelet Transform (DWT) decomposition and fed into the ANN models after applying a regularization index. The IEEE 34-node test feeder, modeled in MATLAB/Simulink, serves as the evaluation platform. Simulations cover a wide range of fault conditions, including variations in fault type, inception angle, resistance, and renewable penetration level. The proposed method achieves a fault identification accuracy of approximately 95% and keeps the fault location error within 5.2%, demonstrating its effectiveness for modern renewable-integrated distribution systems.

Index Terms— Fault Identification(FI); Fault Location(FL); Discrete Wavelet Transform(DWT); Artificial Neural Networks(ANN).

I. INTRODUCTION

Modern distribution networks are undergoing rapid transformation with the growing presence of renewable sources such as wind and solar. Advanced generators, including Doubly Fed Induction Generators (DFIG) and Permanent Magnet Synchronous Generators (PMSG), contribute to sustainability but also introduce complexity in fault studies. Fault Section Identification (FSI) plays a crucial role in isolating defective portions of the grid to ensure uninterrupted supply. In conventional radial systems, faults are typically recognized through current magnitude and directional analysis. However, with high renewable penetration, fault currents become less predictable due to variations in generator technology, control schemes, and operating conditions.

Transient current analysis offers valuable insights into fault behavior. The Discrete Wavelet Transform (DWT) is particularly effective for analyzing non-stationary signals. When combined with Artificial Neural Networks (ANN), it enables reliable identification of fault signatures. The proposed approach introduces a two-stage framework for Fault Identification (FI) and Fault Location (FL), relying solely on substation phase currents within a short two-cycle observation window.

II. LITERATURE SURVEY

Recent researches highlights the different types of strategies for the integration of renewable energy with hybrid storage in EV charging and vehicle systems.

- Solar PV with Hybrid Storage (2023) — A PV based charging station using batteries and supercapacitors with MPPT and stepwise current charging, which gives us the advantage of reduced battery stress and stable operation, even though dependence on solar irradiance and system complexity remains challenging.
- Adaptive Energy Management in Hybrid Microgrids (2025) — An ANFIS based controller optimizes power flow in PV wind storage microgrids. Report shows us that it gains include ~92% efficiency improvement, but dependence on accurate forecasting and scalability issues are noted.
- Review of Hybrid Storage in EVs (2024) —It surveys battery–supercapacitor systems, highlighting the improved efficiency, transient response, and battery life. But is also have a drawbacks of high cost, control complexity, and thermal management.
- Advanced HESS Control for EVs (2024) — Explores PI, MPC, and RBF controllers for battery–supercapacitor systems under varied driving cycles. The results shows us the robust SoC control and responsiveness, but the real world deployment faces cost and complexity barriers.
- Rule Based Battery–Supercapacitor Management (2023) — A simpler dynamic power limiting strategy reduces battery stress and enhances reliability. But due to lack of adaptability limits it's performance under high variable conditions.
- Grid Integrated PV + BESS (2024) — Comparative analysis shows PV + battery storage lowers energy cost and emissions versus grid only charging.
- Improved PSO for EV HESS (2025) — Optimization allocates energy between battery and supercapacitor, achieving ~93% efficiency and reducing battery load.

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But, computational overhead and limited scalability to charging stations are the drawbacks.

- Solar–Hydrogen–Battery Charging (2024) — Bi level optimization coordinates PV, hydrogen, and battery storage across multiple stations. It offers reduced grid reliance, but it have a drawbacks of high infrastructure cost and efficiency losses in hydrogen conversion.
- Autonomous Hybrid Microgrid (2025) — PV wind battery microgrid with Parrot Optimization EMS reduces fossil backup and cost. Also it promises for remote EV charging, transient response and urban deployment still remains as concerns.
- Hybrid Fuzzy–MPC for Fast Charging (2025) — Combines fuzzy logic with predictive control to manage renewable powered fast charging, reducing grid stress and improving thermal management. Complexity and high data requirements are limitations.

III. IMPLEMENTATION

- The process begins with signal acquisition, in which voltage and current data will be collected. This input is then undergoes preprocessing, which consists of filtering, normalization to ensure data quality.
- In the next step, we used a feature extraction is used to derive the meaningful attributes from the signals. These feature represents time-domain, frequency-domain characteristics, which serves as a input for the system.
- Then we go through the classification stage ,in which the system will evaluate whether it is operating normally or showing any faults. Based on this decision, the it proceeds to alert generation and logging which providing visual notifications and record events for future maintenance planning.
- The above process improves the reliability by reducing the human error and system response time, thereby supporting efficient monitoring and fault management.

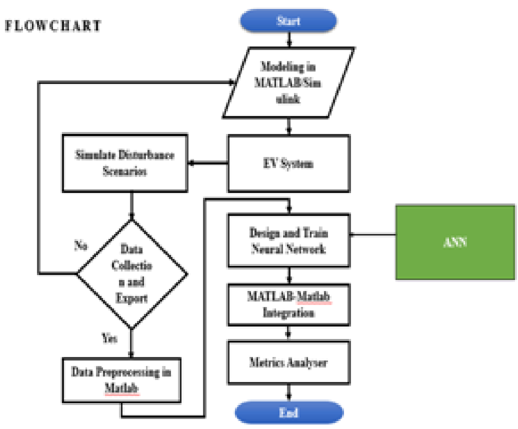

Fig.1 : Flow chart

PMSG – Simulink model :

The below imageshowsamodel of a wind turbine system which uses a Permanent Magnet Synchronous Generator (PMSG). This modeluses boththe mechanical components like pitch angle controller and wind turbine with electrical power conversion steps, which includes a rectifier,DC link, and a three-phase grid-connected inverter. This system helps us to simulate the generated power and its output delivery to a grid-connected load.

Fig.2 : Simulink Model of PMSG-based Wind Energy Conversion System (WECS)

Simulation Results:

The below figure showsus the transient response of the generator's terminal characteristics, such as voltage or power, over a 10-seconds of simulation time. Both plots show a gradually, non-linear increasing from zero before stabilizing, represents the start-up sequence of the wind turbine as it collects the wind energy and accelerates the generator shaft. The steady ramp-up in the graph gives us a controlled approach to achieve a steady-state operation before any faults are introduced into the system.

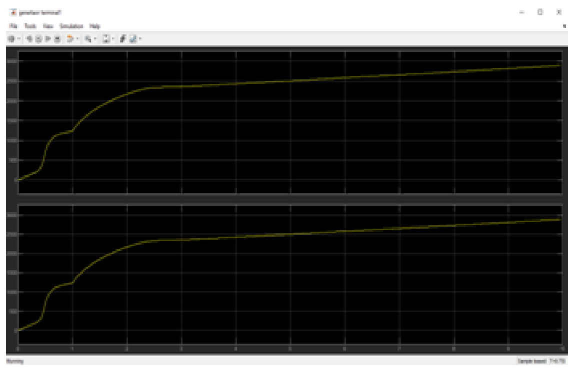

Fig.3 : Time-Domain Scope Output of Generator Terminal Parameters

IV. PROPOSED METHOD

The proposed framework introduces an intelligent two-stage Fault Section Identification (FSI) technique that combines Discrete Wavelet Transform (DWT) with Artificial Neural Networks (ANN). Instead of relying on steady-state impedance, the method analyzes high-frequency current transients measured only at the substation.

A short two-cycle window is used to capture disturbances. From the DWT decomposition, features such as Energy Per Unit (EPU) and Relative Energy Entropy Per Unit (REEPU) are extracted.

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Stage 1: An ANN classifier determines whether the fault lies on the main feeder or a branch.

Stage 2: A regression-based ANN estimates the distance of the fault from the substation.

The system is evaluated under different fault types, resistances, and inception angles. By integrating intelligent learning, it achieves strong accuracy and resilience even in networks with DFIG and PMSG-based wind generation.

Advantages

- High accuracy in fault identification (around 95%).
- Low error in fault location (approximately 5%).
- Requires only substation current measurements.
- Performs effectively with wind generation integration.

Rapid

V. CONCLUSION

- This present project uses an intelligent Fault Section Identification (FSI) framework for the distribution networks by using DFIG and PMSG-based wind generation. By reviewing the transient current signals capturedat the substation and concentrating mainly on a short two-cycle observation screen, the method gives us the limitations of conventional impedance-based approaches. The combination of both DWT and ANN, in which the Discrete Wavelet Transform (DWT) for feature extraction and the Artificial Neural Networks (ANN) for classification and regression gives us the both accurate fault section recognition and accurate fault distance estimation.
- The outcomes of this project confirmed that the proposed two-stage methodology achieved a high accuracy in fault identification and maintains low error in fault location across variety of operating scenarios, including the up and downs in faults, resistance, inception angle, and renewable penetration.This modelgives us the speed, reliability, and adaptabilitymaking thismore suitable for modern distribution systems with renewable energy integration. Lastly, this projectpromotes for a stronger protection schemes and improves overall system reliability.

REFERENCE

[1] S. F. Alwash, V. K. Ramachandaramurthy and N. Mithulananthan, "Fault-Location Scheme for Power Distribution System with Distributed Generation," IEEE Transactions on Power Delivery, 30(3) 1187-1195, 2015, https://doi.org/10.1109/TPWRD.2014.2372045.

[2] Bahmanyar, S. Jamali, A. Estebsari, and E. Bompard, “A comparison framework for distribution system outage and fault location methods,” Electric Power Systems Research, 145, 19-34, 2017, https://doi.org/10.1016/j.epsr.2016.12.018.

[3] Rane, Udaysing V., et al. “Network on Chip(NoC) Mesh Topology FPGA Verification: Real Time Operating System Emulation Framework.” 2024 Fourth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT) [Bhilai, India], 2024, pp. 1–5. DOI.org (Crossref), https://doi.org/10.1109/ICAECT60202.2024.10468944

[4] P. Manditereza and R. Bansal, “Renewable distributed generation: the hidden challenges - a review from the protection perspective,” Renewable and Sustainable Energy Reviews, 58, 1457–1465, 2016, https://doi.org/10.1016/j.rser.2015.12.276.

[5] M. Shih, A. Conde, Z. Leonowicz, and L. Martirano, “An adaptive overcurrent coordination scheme to improve relay sensitivity and overcome drawbacks due to distributed generation in smart grids,” IEEE Transactions on Industry Applications, 53(6), 5217–5228, 2017, https://doi.org/10.1109/TIA.2017.2717880.

[6] Gundu, Srinivasa Rao, et al. “High-Performance Computing-Based Scalable ‘Cloud Forensics-as-a-Service’ Readiness Framework Factors—A Review.” Cyber Security and Network Security, edited by Sabyasachi Pramanik et al., 1st ed., Wiley, 2022, pp. 27–45. DOI.org (Crossref), https://doi.org/10.1002/9781119812555.ch2.

[7] H. Maruf, F. Müller, M. Hossan, and B. Chowdhury, “Locating faults in distribution systems in the presence of distributed generation using machine learning techniques,” 9th IEEE International Symposium on Power Electronics for Distributed Generation Systems (PEDG), NC, USA, 1-6, 2018, https://doi.org/10.1109/PEDG.2018.8447728.

[8] R.H. Salim, K.R. Caino de Oliveira, A.D. Filomena, M. Resener, A.S. Bretas, “Hybrid fault diagnosis scheme implementation for power distribution systems automation”, IEEE Trans. Power Deliv. 23, 1846–1856, 2008,https://doi.org/10.1109/TPWRD.2008.917919.

[9] Abhyankar, Girish G., et al. “Gaussian Vortex Beam Modeling for Multiplexing in Data Communication Using OAM.” Journal of Physics: Conference Series, vol. 1921, no. 1, May 2021, p. 012054. DOI.org (Crossref), https://doi.org/10.1088/1742-6596/1921/1/012054.

[10] Adewole, R. Tzoneva, and S. Behardien, "Distribution network fault section identification and fault location using wavelet entropy and neural networks," Applied Soft Computing, 46, 296-306, 2016, https://doi.org/10.1016/j.asoc.2016.05.013.

[11] M. Kim, J. An, Y. Oh, S. Lim, D. Kwak, and J. Song, "A method for fault section identification of distribution networks based on validation of fault indicators using artificial neural network," Energies, 16, 5397, 2023, https://doi.org/doi:10.3390/en16145397.

[12] Y. Tuna and A. Ali, "Convolutional neural network-assisted fault detection and location using few PMUs," Electric Power Systems Research, 235, 110705, 2024, https://doi.org/10.1016/j.epsr.2024.110705.

[13] Saxena, Shruti, et al. “Blockchain Enhanced Smart Healthcare Management for Chronic Diseases.” Discover Computing, vol. 28, no. 1, June 2025, p. 112. DOI.org (Crossref), https://doi.org/10.1007/s10791-025-09574-6.

[14] L. Acácio, P. Guaracy, T. Diniz, D. Araujo, and L. Araujo, “Evaluation of the impact of different neural network structures and data input on fault detection,”

IEEE PES Innovative Smart Grid Technologies Conference-Latin America (ISGT Latin America), Quito, Ecuador, 1-5, 2017, https://doi.org/10.1109/ISGTLA.2017.8126699.

[15] Gundu, Srinivasa Rao, et al. "Robotic Technology-Based Cloud Computing for Improved Services." SN Computer Science, vol. 1, no. 4, July 2020, p. 190. DOI.org (Crossref), https://doi.org/10.1007/s42979-020-00203-1.

[16] Panem, Charanarur, et al. "Data Reduction and Recovery in Wireless Communication System: An Extensive Experimental Evaluation Using PSK and QAM Modulations." International Journal of Communication Systems, vol. 35, no. 11, July 2022, p. e5198. DOI.org (Crossref), https://doi.org/10.1002/dac.5198.

[17] H. Orozco, J. M. Flórez, and S. P. Londoño, "An impedance relation index to predict the fault locator performance considering different load models," Electric Power Systems Research, 107, 199-205, 2014,https://doi.org/10.1016/j.epsr.2013.10.007.

[18] O. Henao, A. Bretas, A. H. Orozco, R. Ch. Leborgne and D. Schwanz, "Inverter-based DG impact on impedance-based fault location algorithms," 11th IEEE/IAS International Conference on Industry Applications, Brazil, 1-6, 2014,https://doi.org/10.1109/INDUSCON.2014.70594252014.

[19] Charanarur, Panem, et al. "Design Optimization-Based Software-Defined Networking Scheme for Detecting and Preventing Attacks." Multimedia Tools and Applications, vol. 83, no. 28, Feb. 2024, pp. 71151–69. DOI.org (Crossref), https://doi.org/10.1007/s11042-024-18466-8.

[20] F. Mohammadi, G. Nazri, and M. Saif, "A fast fault detection and identification approach in power distribution systems," International Conference on Power Generation Systems and Renewable Energy Technologies (PGSRET), Turkey, 1-4, 2019,https://doi.org/10.1109/PGSRET.2019.8882676.

[21] Gundu, Srinivasa Rao, et al. "Emerging Computational Challenges in Cloud Computing and RTEAH Algorithm Based Solution." Journal of Ambient Intelligence and Humanized Computing, vol. 13, no. 9, Sept. 2022, pp. 4249–63. DOI.org (Crossref), https://doi.org/10.1007/s12652-021-03380-w.

[22] O. Naidu, R. Gore, N. George, and S. Ashok, "A new approach for fault location on modern distribution systems with integrated DER," Biennial International Conference on Power and Energy Systems: Towards Sustainable Energy (PESTSE), India, 1-6, 2016, https://doi.org/10.1109/PESTSE.2016.7516499.

[23] Panem, Charanarur, et al. "Sensor's Data Transmission with BPSK Using LDPC (Min-Sum) Error Corrections over MIMO Channel: Analysis over RMSE and BER." Materials Today: Proceedings, vol. 27, 2020, pp. 571–75. DOI.org (Crossref), https://doi.org/10.1016/j.matpr.2019.12.039.

[24] G. Richard, "Wind farm – DFIG and PMSG detailed model," MathWorks 2024b. Available: https://www.mathworks.com/help/physmod/sps/ug/windfarmdfig-detailed-model.html.