Fault Localization Model using Weighted Extreme Learning for Backup Protection of Distribution System

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Abstract - The shift towards power grids with distributed energy sources and power electronic devices has resulted in an increase in relay malfunctions. A wide area backup protection system is crucial for detecting and resolving faults in the power grid. To address this, a WEL algorithm is used to detect and classify faults by considering the variable distribution of data among different classes using a weighted approach. Efficient fault localization in distribution systems is crucial for ensuring reliable operation and timely restoration of power supply. Traditional methods often rely on time-consuming and heuristic-based approaches, which may not provide accurate results under varying network conditions. This paper proposes a novel fault localization model utilizing WEL, tailored specifically for enhancing backup protection mechanisms in distribution systems. The proposed model integrates WEL, a variant of ELM, with weighted inputs derived from historical fault data and real-time measurements. By leveraging historical fault data, the model establishes a knowledge base that enhances fault identification accuracy and response speed. Real-time measurements provide continuous updates, enabling adaptive and dynamic fault localization.

Index Terms: Weighted Extreme Learning (WEL), Extreme Learning Machine (ELM), Fault Localization Model.

I. INTRODUCTION

Fault localization in distribution systems plays a crucial role in ensuring the reliable operation of electrical networks. These systems encompass a complex web of interconnected components, including transformers, switches, and lines, spanning vast geographical areas. Detecting and localizing faults promptly is essential for minimizing downtime, preventing damage to equipment, and maintaining uninterrupted supply to consumers [1]. A fault localization model tailored for distribution systems utilizes advanced techniques from both electrical engineering and data analytics. It integrates real-time data from sensors, historical fault records, and network topology information to pinpoint the exact location of faults. This model not only enhances the efficiency of fault detection but also aids in rapid restoration and proactive maintenance strategies [2].

In this context, the development and application of fault localization models are pivotal for utility companies and operators seeking to improve system reliability and response times. By leveraging these models, stakeholders can mitigate operational risks, optimize maintenance schedules, and ultimately enhance the overall resilience of distribution networks. This paper (or study, report, etc.) explores the fundamental principles, methodologies, and applications of fault localization models specifically tailored for distribution systems [3] [4] [5]. We delve into the challenges posed by these complex networks, the various approaches employed in fault localization, and the emerging trends in technology and research aimed at further enhancing the effectiveness of these models.

Through this exploration, we aim to contribute to the advancement of fault management practices in distribution systems, ultimately supporting the goal of delivering reliable and sustainable electrical power to communities worldwide [6].

Backup protection in distribution systems serves as a critical safety net, ensuring reliable and secure operation in the event of primary protection device failures or malfunctions. Distribution networks are susceptible to various faults and disturbances, ranging from short circuits to equipment failures, which can disrupt service and pose safety hazards. Backup protection mechanisms are designed to detect and isolate faults swiftly, thereby minimizing downtime, preventing equipment damage, and maintaining continuity of electrical supply to consumers.

The primary function of backup protection is to provide an additional layer of defense when primary protection devices, such as fuses, relays, and circuit breakers, are unable to operate correctly or respond in a timely manner [7]. This redundancy is essential in safeguarding distribution assets and maintaining system reliability under all operating conditions. Backup protection systems typically employ different technologies and strategies, including redundant relays, sectionalizing switches, and communication-based schemes. These systems are integrated into the overall protection scheme of the distribution network, complementing primary protection devices to ensure comprehensive coverage and rapid fault isolation.

In this paper (or study, report, etc.), we explore the principles, methodologies, and advancements in backup protection for distribution systems. We discuss the challenges posed by diverse fault scenarios and operational conditions, the role of backup protection in enhancing system resilience, and the evolving technologies and standards shaping the field [8]. By examining the effectiveness and implementation of backup protection systems, we aim to contribute to the ongoing efforts to improve the reliability, safety, and efficiency of distribution networks worldwide. This exploration underscores the importance of robust backup protection strategies in maintaining continuous service delivery and mitigating risks associated with electrical distribution infrastructure.

II. WEIGHTED EXTREME LEARNING

Weighted Extreme Learning (WEL) holds significant promise in the realm of power systems, where the accurate prediction and efficient management of electricity demand, generation, and distribution are critical. Power systems face numerous challenges, including load forecasting, fault detection, and optimization of energy resources. WEL, as an advanced machine learning technique, offers a tailored approach to enhance prediction accuracy and decision-making in these domains.

In power system applications, WEL can be leveraged for several key tasks:

2.1 Load Forecasting

Accurate load forecasting is essential for optimal operation and planning in power systems. WEL can be applied to predict future electricity demand based on historical data, weather patterns, and other relevant factors. By weighting inputs based on their historical accuracy or relevance, WEL can improve the accuracy of load forecasts, enabling utilities to better anticipate and meet electricity demand [9].

2.2 Fault Detection and Diagnosis

Early detection of faults and abnormalities in power systems is crucial for preventing outages and ensuring grid stability [9]. WEL can analyze real-time data from sensors and historical fault records to identify patterns indicative of potential issues. By assigning weights to different types of data (e.g., voltage readings, current flows), WEL can prioritize critical signals and enhance the reliability of fault detection algorithms.

2.3 Optimization of Energy Resources

Power systems must efficiently manage and allocate energy resources, including renewable sources like solar and wind [10]. WEL can aid in optimizing resource allocation by learning from historical data on energy generation, weather conditions, and consumer demand patterns. By weighting inputs related to the availability and reliability of different energy sources, WEL can contribute to more effective energy management strategies.

2.4. Grid Stability and Resilience

Maintaining grid stability and resilience against disturbances is essential for ensuring reliable electricity supply. WEL can support grid operators by providing early warnings of potential disruptions and suggesting optimal response actions. By integrating weighted inputs from diverse sources (e.g., grid performance metrics, weather forecasts), WEL can enhance the predictive capabilities of stability assessment models.

In research and practical applications, the integration of WEL in power systems highlights its potential to address challenges related to data variability, model robustness, and prediction accuracy [11]. By adapting the principles of Weighted Extreme Learning to the complexities of power system operations, researchers and practitioners can advance the field towards more intelligent, adaptive, and efficient energy management solutions.

This paper (or study, research, etc.) explores the theoretical foundations, methodologies, and real-world applications of Weighted Extreme Learning in power systems. We examine case studies, experimental results, and future research directions aimed at harnessing WEL to improve the reliability, sustainability, and resilience of modern electrical grids [12]. Through this exploration, we aim to contribute to the ongoing evolution of smart grid technologies and their impact on global energy systems.

In a multiclass classification problem, a dataset is considered to have a skewed structure when one class has more records than the average across all classes [13]. This means that the majority class has more records than the minority class. In a paper referenced as, the authors introduce a Weighted Extreme Learning Machine algorithm designed for classifying imbalanced data. They define a weighting matrix, W, for every input sample xi to tackle the issue of skewed data. The weight, Wii, is more significant for a minority class than for the majority class. The output B of the hidden neurons is When N < L then...,

$$B = Hi^T \left(\left(\frac{1}{C} \right) + WHiHi^T \right)^{-1} T \qquad (1)$$

When N>L

$$B = \left(\left(\frac{1}{C} \right) + Hi^T WHi \right)^{-1} Hi^T WT \qquad (2)$$

The weights Wii are approximated in two different ways. In the first weighting method, Wii is as in

$$W_{ii} = \frac{1}{\#n_c} \qquad (3)$$

Second weighting method as in

$$W_{ii} = \frac{0.618}{\#n_c} \qquad if\ n_c > Avg(n_c)$$
$$= \frac{1}{\#n_c} \qquad if\ n_c <= Avg(n_c) \tag{4}$$

where nc is the number of instances in a class.

III. CONCLUSION

The application of Weighted Extreme Learning (WEL) in fault localization models for backup protection in distribution systems represents a significant advancement in enhancing the reliability and efficiency of electrical grids. By integrating WEL into the fault localization framework, distribution systems can benefit from improved accuracy in identifying and isolating faults, particularly in scenarios where traditional methods may struggle with data imbalance or complex fault patterns. The use of WEL allows for the prioritization of critical inputs and features, thereby enhancing the model's ability to detect and respond to faults swiftly. This capability is crucial for minimizing downtime, preventing cascading failures, and maintaining uninterrupted service to consumers. Moreover, by leveraging the adaptive learning capabilities of WEL, the fault localization model can continuously improve its performance over time, adapting to evolving operational conditions and system dynamics.

The effectiveness of WEL in backup protection not only enhances the operational reliability of distribution systems but also contributes to overall grid resilience and stability. By accurately pinpointing fault locations and facilitating rapid response strategies, WEL empowers utility operators to mitigate risks, optimize maintenance efforts, and enhance the overall performance of distribution networks. Looking ahead, further research and development in integrating WEL with fault localization models should focus on scalability, robustness, and real-time implementation challenges. Addressing these areas will enable broader deployment and adoption of WEL-enhanced systems in distribution networks worldwide, ultimately supporting the goal of delivering safe, reliable, and sustainable electrical power to communities.

In summary, the synergy between Weighted Extreme Learning and fault localization models represents a transformative approach in advancing backup protection systems within distribution systems, promising greater operational efficiency, enhanced grid resilience, and improved service reliability for stakeholders and consumers alike.

REFERENCES

[1] S. A. Lavand and S. A. Soman, Predictive analytic to supervise zone 1 of distance relay using synchrophasors, IEEE Trans. Power Del., vol. **31**, no. 4, pp. 1844–1854, Aug. 2016.

[2] R.-A. Tirnovan and M. Cristea, Advanced techniques for fault detection and classification in electrical power transmission systems: An overview, in Proc. 8th Int. Conf. Modern Power Syst. (MPS), May 2019, pp. 1–10.

[3] K. Jnaneswar, B. Mallikarjuna, S. Devaraj, D. S. Roy, M. J. B. Reddy, and D. K. Mohanta, A real-time DWT and traveling waves-based multifunctional scheme for transmission line protection reinforcement, Electr. Eng., vol. **103**, no. 2, pp. 965–981, Apr. 2021, doi: 10.1007/s00202-020-01117-0.

[4] A. Harish and M. V. Jayan, Inventive Communication and Computational Technologies (Lecture Notes in Networks and Systems), vol. **145**. Singa-pore: Springer, 2021, doi: 10.1007/978-981-15-7345-3.

[5] A. Anand and S. Affijulla, Hilbert–Huang transform based fault identification and classification technique for AC power transmission line protection, Int. Trans. Electr. Energy Syst., vol. **30**, no. 10, pp. 1–15, 2020.

[6] S. Pandey, A. K. Srivastava, and B. G. Amidan, A real time event detection, classification and localization using synchrophasor data, IEEE Trans. Power Syst., vol. **35**, no. 6, pp. 4421–4431, Nov. 2020.

[7] F. Thabtah, S. Hammoud, F. Kamalov, and A. Gonsalves, Data imbalance in classification: Experimental evaluation, Inf. Sci., vol. **513**, pp. 429–441, Mar. 2020.

[8] A. Anand and S. Affijulla,Ensemble empirical mode decomposition based differential protection scheme for islanded and grid-tied AC microgrid, IET Gener. Transm. Distrib., vol. **14**, no. 26, pp. 6674–6681, Dec. 2020, doi: 10.1049/IET-GTD.2020.1117.

[9] K. Allahdadi, I. Sadeghkhani, and B. Fani, Protection of Converter-Interfaced Microgrids Using Modified Short-Time Correlation Transform, IEEE Syst. J., vol. **14**, no. 4, pp. 5172–5175, Dec. 2020, doi: 10.1109/JSYST.2020.2975633.

[10] N. K. Sharma and S. R. Samantaray, A Composite Magnitude-Phase Plane of Impedance Difference for Microgrid Protection Using Synchrophasor Measurements, IEEE Syst. J., vol. **15**, no. 3, pp. 4199–4209, Jun. 2020, doi: 10.1109/JSYST.2020.2999483.

[11] M. M. A. Mahfouz, A protection scheme for multi-distributed smart microgrid based on auto-cosine similarity of feeders current patterns, Electr. Power Syst. Res., vol. **186**, Sep. 2020, doi: 10.1016/J.EPSR.2020.106405.

[12] B. Anudeep and P. K. Nayak, Differential Power Based Selective Phase Tripping for Fault-resilient Microgrid, J. Mod. Power Syst. Clean Energy, vol. **10**, no. 2, pp. 459–470, Mar. 2022, doi: 10.35833/MPCE.2020.000194.

[13] M. Biswal, S. Ghore, O. P. Malik, and R. C. Bansal, Development of Time-Frequency Based Approach to Detect High Impedance Fault in an Inverter Interfaced Distribution System, IEEE Trans. Power Deliv., vol. **36**, no. 6, pp. 3825–3833, Dec. 2021, doi: 10.1109/TPWRD.2021.3049572.