Extended Abstract

PERFORMANCE ASSESSMENT OF MACHINE LEARNING MODELS FOR TRANSMISSION NETWORK FAULT DIAGNOSIS AMIDST ONGOING RENEWABLE ENERGY SOURCE INTEGRATIONS

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ABSTRACT

The detection, classification, and localization of faults in power systems are imperative to prevent prolonged interruptions in power supply and mitigate cascading failures, and blackouts. Prompt fault localization facilitates swift maintenance actions by utility operators, thereby restoring normal operation quickly. Despite advancements in measuring instruments aiding fault detection, pinpointing the exact fault location remains challenging. Model-based techniques like impedance-based and traveling wave methods have been utilized for fault localization, each presenting limitations such as computational complexity and reliance on expensive equipment.

With the advent of sophisticated measuring instruments, there has been an increasing interest in process history-based fault diagnosis techniques, particularly Machine Learning (ML) models. These models offer automated and rapid fault diagnosis capabilities, thus addressing the shortcomings of conventional methods. However, an up-to-date comprehensive review of ML-driven fault diagnosis in power systems is absent in the literature, necessitating the need to bridge this research gap. This dissertation addresses this gap by presenting a systematic ML-based power system fault diagnosis review. The review incorporates discussion supported with tabulated facts for fault detection, classification, location identification, and exact localization works with techniques used, different simulation tools used, and their application system. Further, the advantages and disadvantages of all the fault diagnosis techniques, the status of research and research trends, and perspectives for needed research have been highlighted.

The increasing integration of renewable energy sources (RES) and distributed generations (DGs) into existing transmission and distribution networks significantly alters power system topology and fault characteristics, depending upon the size of RES integration. Large fluctuations in RES-generated power induce substantial deviations in fault currents. Thereby increasing misclassification rates of ML based fault classification and introducing significant errors in fault location estimation. Moreover, the existing literature on ML-based fault diagnosis in RES-integrated power systems assumes diverse fault data availability. However, in real-world scenarios, integrating a new RES into the power network poses challenges to ML-based fault diagnosis due to the scarcity of diverse fault data of the changed topology shortly after integration. Despite this,

there is a notable absence of studies examining the performance of ML models for transmission line fault diagnosis under increasing RES integrations.

The longer a RES plant stays out of service due to faults, the heavier the financial losses incurred by the associated power transmission company (TRANSCOM). Hence, timely fault localization becomes more crucial for power systems with RES integration. TRANSCOMs not only lose revenue from unsupplied power but also incur expenses by compensating for the shortfall in energy to essential loads. Additionally, TRANSCOMs may face penalties for their inability to transmit power generated by RES plants during outage periods. Therefore, efficient fault localization is imperative for TRANSCOMs. Thus, there arises a need to assess the impact of these changes on fault diagnostic schemes.

Therefore, the performance evaluation of various ML models, examining their efficacy in conventional transmission line fault classification and localization, analyzing the impact of RES integration on ML-based fault diagnosis, assessing the adaptability of ML models to the gradual availability of fault data from RES-integrated power systems, evaluating their suitability for increasing RES penetration levels, and scrutinizing the learning capabilities of ML models as fault data gradually becomes available with increasing RES penetration levels has been explored. The proposed study has been carried out by optimally integrating different sizes of RES into 'IEEE 9-Bus System'. The integrated solar-based RES has been modeled incorporating standard temperature and irradiance variations. A diverse fault database was generated for the IEEE 9 Bus System and RES integrated IEEE 9 Bus system, considering actual field variations of fault attributes.

The research employs a variety of ML classifiers and regression models, assessing their efficacy in fault classification and localization on the standard IEEE 9-bus system. The ongoing integration of RES into the existing transmission networks changes the system topology and fault signatures depending on the size of the newly added RES. However, no study in the literature has analyzed the impact of new RES integration on the fault diagnosis performances of ML models. Therefore, to assess the fault classification and localization performance of potential ML models, two practical scenarios arising from new RES integration have been considered: 1) Impact analysis, when fault data is unavailable for the changed system, and 2) Adaptability analysis: when the changed system fault data is available over time. Impact analysis revealed significant degradation in the fault diagnosis performances of all tested models post RES integrations. The adaptability testing was performed by extensive analysis of the learning trends of ML models with gradual fault data availability. The proposed Bayesian ridge regression has emerged as the fastest learning model for locating transmission line faults. In contrast, XGBoost, Extra Tree, and Random Forest classifiers gave comparable results for fault classification.

Moreover, an investigation of ML models' adaptability and learning competence in classifying and localizing transmission line faults under increasing RES penetration, facilitating model selection amidst minimal fault data availability over time, has also been performed. The increase in the penetration level of existing RES changes the fault current level of the system, introducing significant errors in fault location estimation; hence, such an investigation is notably essential. The investigation considers two practical prospects: 1) Adaptability investigation: when fault data of current penetration level is unavailable, and 2) Learning competence investigation: when fault data of current penetration is available over time. The findings revealed that among the ML classifiers and regression models tested, XGBoost demonstrated superior performance compared to other models examined in the study. In summary, contributions to advancing power systems fault diagnosis techniques have been made by comprehensively reviewing ML-based approaches and evaluating their efficacy in adapting to evolving system configurations and increasing RES integration levels.