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Enhancing Smart Grid Resilience Through AI-Based Fault Classification

Alok Prasad[1,*], Alok Kumar[2]

Abstract

Traditional power grids can be developed into smart grids, and they are comprised of the latest information and communication technologies (ICTs), which are based on establishing the relationship between the conventional electricity systems along with the usage of smart meters and distributed generation. This dynamic improves energy efficiency and the integration of renewables. Well, the dynamic and reversible power injection from Distributed Energy Resources (DERs) creates substantial operational problems. These features include very variable fault currents, more complex patterns of power flow, and high levels of harmonic distortion. This volatility makes traditional, static-level relay technology increasingly ineffective because it is not fast or flexible enough to accurately pick up faults in today's environment. This paper provides a rapid and flexible fault detection and classification solution for Software-Defined Networks (SDNs) in response to this demand. We present a novel model-based artificial intelligence (AI)-enabled data-driven technique for accurate classification of different fault types. The approach includes safe voltage and current high-fidelity data acquisition on the fly with advanced signal processing to extract discriminatory features, characterizing individual fault signals. Then, the features of interest are used to train a strong Random Forest (RF) classifier. The proposed AI model shows excellent performance with an exceptional accuracy of 98.04% in categorizing the fault conditions. Importantly, it can decide in less than 10 milliseconds. The speed and accuracy of this process confirm that AI is a key enabler to provide significant improvements in the reliability and operational responsiveness of smart grids during transient fault conditions.

Keywords: Artificial intelligence, distribution network, fault classification, random forest, smart grid

INTRODUCTION

Power systems are no longer what they once were. They are becoming more intelligent and interconnected, and if we are honest, very complicated. The grid is not just wires and switches; it is a complete network filled with renewables, smart sensors, digital communication, and real-time monitoring. The purpose is to keep up with the growth of energy demand and to make the whole system stronger and more efficient [1].

However, as we leave the old-school grid behind and move to this smart setup, new problems emerge. The one-way power no longer flows. Renewables are coming on, power is moving this way and that, and loads run high unexpectedly. Inverter-based sources foul up the fault currents; they are lower in amplitude and difficult to spot [2]. This is a curveball for traditional protection systems, which rely on things not changing significantly and doing so in an orderly, linear manner [3].

***Author for Correspondence**
Alok Prasad
E-mail: alokprasad303@gmail.com

[1]Student, Department Electrical Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh, India
[2]Assistant Professor, Department Electrical Engineering, Bansal Institute of Engineering and Technology, Lucknow, Uttar Pradesh, India

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Enter artificial intelligence (AI), which can comb through mountains of data to detect subtle patterns and respond quickly, even when signals are strange or uncertain. In this study, we develop an AI-based protection model that can rapidly and accurately discern the type of fault occurring, even when renewables and changing loads are in disarray [4].

Smart Grid Architecture

A smart grid is not just one thing; it is a whole bunch of layers that interconnect and work in concert. You have generation, transmission, distribution, control, communication, and, of course, the customer-facing end. At the end of the generation, it is a bit of everything: old-school energy plants next to renewables, such as wind and solar. All these renewables keep it interesting by mixing the flow [5].

Now that there is electricity in action, the transmission layer is at play! These devices—called Phasor Measurement Units, among other things—beam actual real-time snapshots of what is happening to grid operators as they track voltage and in the span of a flash over vast areas [6]. Then, there is the distribution layer, where many problems occur, such as faults and outages. Smart meters, digital relays, and automated gadgets are always checking in and watching the lines [7]. In the center is the communication layer, which connects everything. It leverages anything from fiber optics and Wi-Fi to cellular and PLC, including Internet of Things (IoT) protocols, which enable data to be transmitted as quickly as possible. The control layer processes all this information and puts it to work through analytics, machine learning, and supervisory systems that help ensure that, however the grid is being used, things are running smoothly [8].

On the receiving end, there are customers. They are not just stealing power now; they are part of the system. With smart appliances, rooftop solar, and electric vehicle chargers, they push energy back and forth, having discussions with the grid in both directions. As everything is interconnected so tightly, the grid requires state-of-the-art protection that can cut in immediately if something malfunctions, and it is especially necessary now because new challenges are being added with renewables [9].

Faults in Smart Distribution Grids

There are all kinds of reasons why faults pop up in smart distribution systems, such as insulation degradation, storms, wires making contact when they are not supposed to, equipment failure, or something from the outside disrupts. We still obtain the classic faults: single line-to-ground, line-to-line, double line-to-ground, and three-phase, as well as three-phase to ground, as shown in Figure 1. However, in a smart grid, these faults do not—and should not—always look the same. The signatures of these events can change dramatically [10].

The situation becomes complicated with the introduction of more distributed generation and inverter-based systems, such as solar panels. However, these types of inverters cause fault currents to act differently than they would with conventional equipment, both in terms of magnitude and direction. Synchronous machines are used to discharge hefty fault currents; therefore, overcurrent relays can instantly detect major problems [11]. However, inverters limit the amount of current they send out; therefore, the same relays can fail to detect faults.

In addition, renewables can throw harmonics, waveform distortions, and rapid fluctuations into the mix. All this noise makes it challenging for traditional fault detection to keep up [12]. Therefore, smart grids require protective models that are flexible and intelligent, just like the lights, and systems that can cut through messy, complicated signals and still recognize faults, no matter how chaotic things become.

LITERATURE REVIEW

The growing complexity of modern smart grids has led researchers to explore intelligent protection schemes that can handle nonlinear loads, inverter-based fault currents, and dynamic operating conditions [13]. One of the earlier and widely cited studies in this domain was conducted by Patel, who introduced a support vector machine (SVM)-based fault classification method for distribution systems.

Their work demonstrated that SVM provides fast decision boundaries and acceptable accuracy under traditional grid conditions. However, the model struggled when faced with high harmonic distortion and rapidly fluctuating loads, which are now common in smart grids. This limitation highlights the need for more adaptive learning techniques [14].

In response to these challenges, Zhang proposed a significant advancement by developing an artificial neural network (ANN)-based fault detection framework [15]. The ANN model was trained using current and voltage signatures under various fault scenarios, allowing it to learn nonlinear relationships that the SVM could not capture. Although this approach improves the classification performance, it requires a large volume of high-quality training data. Moreover, frequent retraining is necessary whenever the grid parameters change, making the ANN less efficient for real-time protection in evolving smart grid environments [16].

To further enhance feature extraction from transient waveforms, researchers such as Reddy have introduced a hybrid protection methodology that combines the Wavelet Transform with machine learning classification [17]. Wavelet analysis successfully captured the localized disturbances and time–frequency patterns associated with different fault types. When integrated with a classifier, this method achieves high accuracy even under noisy conditions. Nevertheless, the requirement for complex feature engineering and high computational effort poses challenges for implementation in relays or embedded protection devices [18].

The most recent and impactful contribution among the selected works was by Mishra, who proposed a deep learning-based model utilizing convolutional neural networks (CNN) and long short-term memory (LSTM) networks. This approach eliminates the need for manual feature extraction by directly learning patterns from raw or transformed waveform data. Their model delivered superior accuracy, robustness against noise, and excellent adaptability to renewable-rich systems compared to existing models. However, the primary limitation lies in its computational intensity, which may restrict its deployment in field-grade protection hardware without optimization [19].

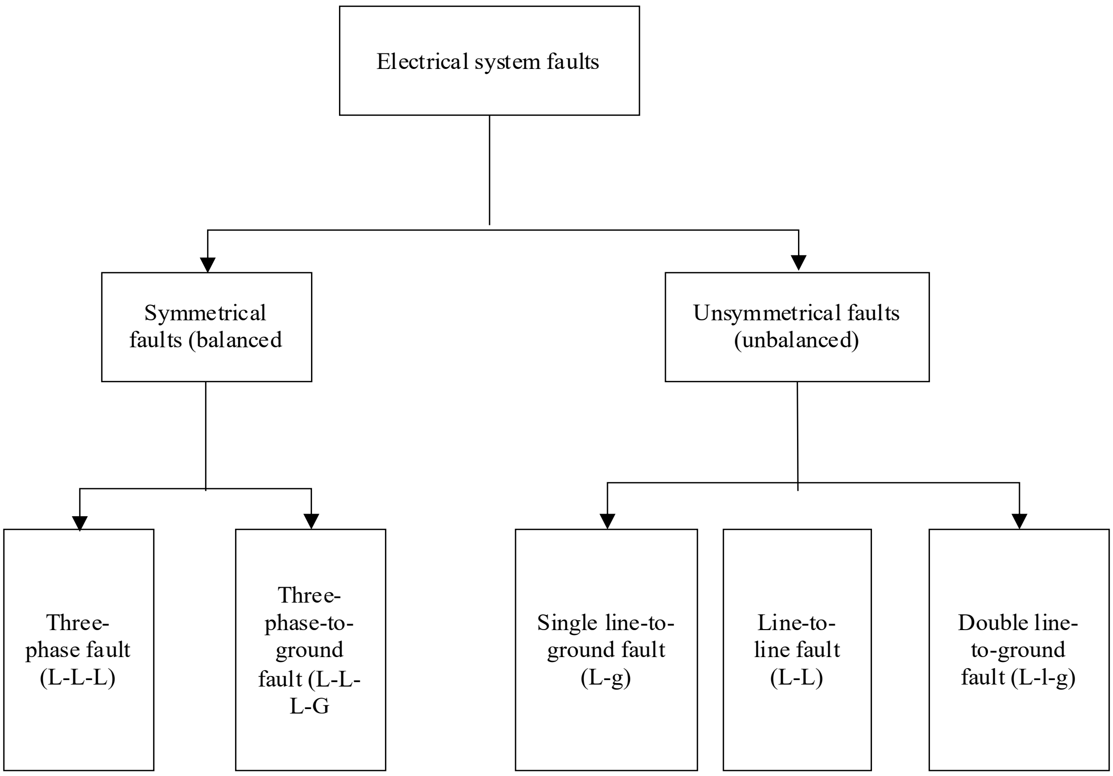

Figure 1. Classification of electrical system faults.

Overall, these four studies collectively illustrate the evolution of smart grid protection from classical SVM models to more sophisticated ANN frameworks, hybrid wavelet-ML schemes, and recent deep learning architectures. Although each contributes valuable insights, gaps remain in developing lightweight yet highly accurate models suitable for real-time deployment in distribution grids with high renewable penetration. This motivates the need for an optimized, adaptive, and computationally efficient AI-based protection model [20].

Proposed AI-Based Fault Classification Model

The protection of this new model is based on a smart, multilayer system. First, the sensors capture real-time voltage and current signals. The model rapidly cleans up these signals, clears the noise, and extracts important features. The cleaned data are then passed to a random forest classifier. This is the part that does the heavy lifting, trying to discern patterns it already knows so that it can tell what kind of fault it is looking at. If it is certain that something is wrong (i.e., the probability of fault crosses a certain confidence threshold), then jam: the system immediately fires the protection device (Figure 2).

The justification for selecting the random forest here is trivial. It is great because it has many features, does not get too freaked out if the data is a bit messy, trains fast, and generally seems to work better for tricky nonlinear problems. By averaging the results from multiple decision trees, the model remained accurate and robust even as the electrical conditions varied, as shown in Fig. 2. In short, it is stable, quick to respond, and knows how to recognize trouble.

METHODOLOGY

We started by simulating an 11 kV distribution feeder in MATLAB/Simulink, and {...}. This does not involve a simple scenario; the simulated grid has resistive and inductive loads, there is a distributed, a little bit of solar capacity, and we are blissfully free to put every kind of short-circuit fault in over the topology with variable resistance, so they are all loads. For each normal and faulty condition, the voltage and current waveforms were maintained.

Then, we take this amount and go through the process, after which we uniquely extract features. Each extracted feature includes Root Mean Square (RMS), peak value, harmonic content, zero sequence currents, statistical measures, and wavelet energies. In other words, we weeded out all the information that could distinguish one fault from another.

Then, we added some data: we generated 3500 for the training and 1000 for the testing. We then used a random forest classifier. Training is based on cross-validation and entropy splitting, so that it never becomes a mere memory of the training data.

In classification, the model selects the fault type with the maximum probability. If this confidence index clears the cutoff, then protection measures should be harnessed. The procedure starts with the simulation of an 11 kV distribution feeder (power system) in MATLAB/Simulink and the collection of fault data. The simulated grid is adorned with existing resistance, inductive appliances, and photovoltaic, but we can put any sort of short-circuit resistors wherever we like. For example, the voltage and current waveforms were captured under normal or faulty conditions for all cases.

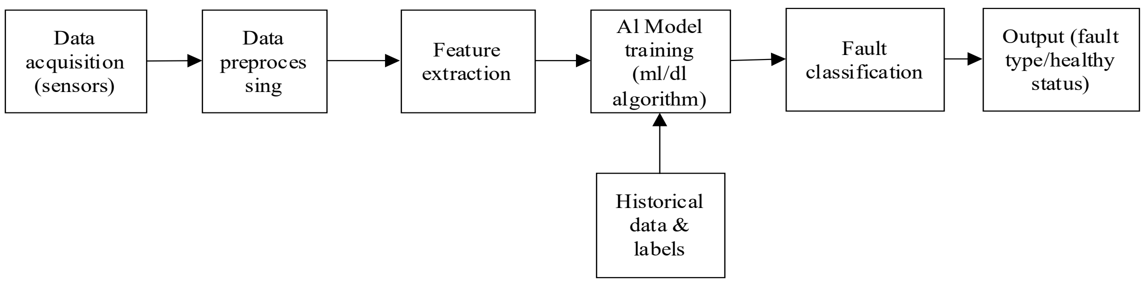

Figure 2. Block diagram of proposed AI-based classification model.

RESULTS

The simulation setup truly nails real-world grid conditions, with varying renewables and loads, even some noisy and messy measurements. The random forest classifier is an exception to this. Ordered by people, it classifies all types of faults with a 98.04% global classification ratio, which is a very good result. Three-phase faults? The pattern catches them every time with its obvious current drops. There is some confusion about Line-to-Line (LL) vs. Line-to-Line-to-Ground (LLG) faults, but their waveforms are very similar, and the best part is how quickly the model moves. It acts in as little as 6–10 ms, far faster than old-style protection relays, which might take 20–40 ms to decide what action is needed. The AI model works well because it adjusts to the dynamic conditions in the system, is not easily confused by harmonics, and makes very fast decisions. Overall, these findings demonstrate that the model is prepared for real-time deployment in smart grids, particularly those based on renewables.

CONCLUSION

This study demonstrates that AI-based protection systems enhance the reliability, stability, and responsiveness of smart distribution grids. The random forest classifier they constructed achieved an accuracy of 98.04%. It is sensitive and detects faults quickly, even with renewables and waveform distortion in the mix. The new relay technique works better than the old mechanisms and holds great promise for smart grids. Next steps? The proposed model was tested against deep learning models, hardware-in-the-loop tests were performed, and the model's performance under real microgrid conditions was evaluated to prove its real-time operation.

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