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Fault Detection and Isolation in Power Systems Using Hybrid AI–Signal Processing Models

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ABSTRACT

The integration of quantum computing and artificial intelligence (AI) has opened new frontiers for enhancing cognitive adaptability and advancing artificial general intelligence (AGI). This study explores the conceptual synergy between quantum–AI integration as an independent variable, cognitive adaptability as a mediating variable, and AGI cognitive performance as the dependent variable. By examining how quantum principles such as superposition and entanglement enhance AI's capacity for non-linear reasoning, this research outlines a transformative model that aligns with human-like cognition. The study employs simulation-based analyses comparing classical and quantum–AI models across diverse cognitive tasks, revealing that quantum–AI systems outperform traditional AI in adaptability, problem generalization, and decision precision. The results indicate that quantum-enhanced learning enables faster adaptation and improved generalization, suggesting significant implications for cognitive modeling, human–machine collaboration, and AGI development. The theoretical contribution lies in expanding AGI's cognitive architecture through quantum principles, while the practical implications include the development of adaptive, self-learning AI systems for complex, dynamic environments. Future research should explore empirical testing of quantum–AI frameworks, cross-disciplinary modeling between quantum cognition and neuroscience, and ethical considerations in autonomous decision-making systems.

Keywords: Adaptability, Artificial General Intelligence, Cognitive Modeling, Machine Learning, Quantum Computing, Synergy

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Introduction

Over the past few years, there was a quick change in the power systems as more renewable energy sources, digital control mechanisms, as well as smart-grid technologies are being involved. This change had increased the efficiency and flexibility of contemporary electrical networks but has presented major challenges with regard to fault detection, isolation and reliability of the grid in general. Conventional forms of protection (overcurrent and impedance relays) had majorly been developed to support basic (radial) networks. They frequently could not deal with the non-linearity and high variability of new grids. As such, enhancement of smart, flexible and information-driven diagnostic systems were now a priority in electrical engineering studies (Bayrak and Yilmaz, 2020).

The techniques of artificial intelligence (AI) had observed a wide spread in the field of fault diagnosis because they can analyze massive data streams, identify fault modes, and adapt to new operating conditions without undergoing any reprogramming process. ML systems like support-vehicle machines (SVM), decision trees, and deep-neural networks (DNN) proved to be rather accurate in fault recurrence and detection in a wide range of conditions (Elbouchikhi et al., 2021). Nonetheless, challenges associated with AI approaches were the quality of training data, interpretation, and the lack of successful results in highly unstructured or non-stationary conditions.

Conversely, wavelet transforms (WT), empirical mode decomposition (EMD) and Hilbert-Huang transforms (HH) are signal-processing (SP) techniques which had long been used effectively in the analysis of transient signals in power systems. These techniques were useful in isolating time-frequency measures which identified faults at balanced load and unbalanced load states. However, the conventional SP methods tended to be rule-of-thumb, as they demanded a large amount of human knowledge in the engineering of features, choice of threshold, and tuning of the system. Neither could they make generalizations between faults of different kinds and network topologies (Elmasry and Wadi, 2022).

To overcome these limitations, scholars had already suggested utilizing hybrid models using both AI and SP methods to capitalize on each of their respective advantages. AI-Signal Processing (AI-SP) systems integrated SP-based feature extraction with AI-based classification to provide greater detection accuracy, shorter response time, and enhanced noise resistance (Li et al., 2025). Thus, the current research was devoted to the creation and testing of a hybrid AI-SP in detecting and isolating faults in power systems as a way to reduce the performance gap between the conventional protection system and the emergent intelligent system.

Research Background

The concept of fault detection and isolation (FDI) was also an essential part of power-system protection and was charged with detecting the nature, location and extent of a fault to prevent cascading failures and maintain grid stability. In the past, FDI systems were mainly made based on fixed thresholds, fixed momentaneous voltages, and passive relay protection programs, which were reasonable in the old centralized grids but not so open in the new distributed systems. The increasing complexity of smart grids, which involves the distributed generation phenomenon, the variability of

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renewable sources, and the dynamics of load relationships had made the old approaches inadequate in terms of ensuring the necessary real-time management of faults (Bayrak & Yilmaz, 2020).

Signal-processing methods had offered an encouraging base of FDI through making it possible to examine transient waveforms on a time-frequency basis. An example such as the wavelet transform (WT) broke down the non-stationary signals into various scales so that the distinguishing features between the normal and faulty conditions could be cut out. Hilbert-Huang transform and empirical mode decomposition (EMD) also contributed to the further improvement of transient disturbances and harmonic distortions detection. Such methods were also useful in fault detection and rough power-quality analysis in its initial application but the use of human imposed thresholds and providing varying results when noise is present or measurement errors occur (Elbouchikhi et al., 2021).

With AI and models of machine learning, the phenomenon of FDI became revolutionary in terms of its ability to recognize the pattern and to do an adaptive learning. Classifiers with machine learning, including random forests, artificial neural networks (ANNs), and deep learning models, were shown to be better in fault classification and generalization than traditional algorithms. They could do non-linear learning and had the ability to adjust to varied fault situations. Nevertheless, these types of data-driven models needed large datasets to train and their black-box character cast doubt on interpretability and transparency of operation (Elmasry and Wadi, 2022).

Hybrid AI-SP was a superior solution that overcame the shortcomings of the two methods. In such models, SP algorithms were used to perform preprocessing and feature extraction, and AI models were used to do classification and make decisions. This synergy made the noise to be handled effectively, decreased the dependency of data and enhanced the ability to generalize to unknown faults. Recently, the research has established that hybrid models offered a response of greater accuracy and rapidity to fault detection than standard AI or SP methods alone (Li et al., 2025). As a result, the hybrid paradigm provided a strong and scalable framework of the contemporary power systems which allows maintaining the stability and reliability of the working conditions.

Research Problem

Fault detection and isolation in current power systems was still a matter of serious concern despite the progress of AI and signal-processing algorithms. Traditional SP methods were not very adaptable and usually could not operate in high-impedance or multiple fault multi-operating mode conditions. No-human approaches that were solely AI-based despite being adaptive had an extreme dependence on the data, and were prone to misclassification when trained on very small or unbalanced datasets. This posed an acute research gap in the area of how to develop a system capable of retaining accuracy, interpretable and strong in accordance with real-life grid conditions. The research problem that this study aimed to tackle was that there is still no unified hybrid model that could carry out both SP-based feature extraction and AI-based classification of faults in complex power networks to detect faults and their origins accurately. This research aimed to developed such a system and analyse its

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operation at various fault cases, such as line to ground, line to line, three phase faults both in balanced and unbalanced load situations.

Objectives of the Study

To design and implement a hybrid AI–Signal Processing model integrating feature extraction (e.g., wavelet transform, empirical mode decomposition) with machine-learning classifiers for fault detection and isolation.
To evaluate the model's accuracy, detection speed, and robustness under various fault conditions and noise levels.
To compare the hybrid model's performance with conventional SP-only and AI-only techniques

Research Questions

Q1. How accurately could the hybrid AI–Signal Processing model detect and classify different types of faults in power systems?
Q2. To what extent did signal-processing features enhance the classification accuracy of AI algorithms in the hybrid framework?
Q3. How did the hybrid model perform under unbalanced loads, varying noise levels, and multiple simultaneous faults compared to conventional methods?

Significance of the Study

The research was worthy to both industry and academic research. In the academic world, it assisted in building up the literature of intelligent fault management of power systems through the combination of artificial intelligence and signal-processing systems. It provided an intermediate way that compromised between data-driven learning and physics-based signal interpretation, overcoming adaptability and interpretability weaknesses. In practice the grid operators and utility companies had a more efficient diagnostic framework which could locate and isolate faults promptly even in dynamic and uncertain operating conditions. The proposed system facilitated the reliability, safety and economic operation of the modern smart grids by improving the fault resilience and providing predictions of fault maintenance.

Literature Review

Signal-Processing Techniques in Fault Detection

According to recent studies, signal-processing (SP) techniques are so essential in detecting the disruptions and faults in power systems. The popularity of time-frequency analysis, including the discrete wavelet transform (DWT) and the continuous wavelet transform (CWT), was explained by the fact that both gave multi-scale representation of transient faults (Islam et al., 2025; Li et al., 2023). Indicatively, Islam et al. (2025) developed a multimodal deep learning system, in which the feature-extraction process was performed through DWT, followed by the use of a classifier and demonstrated a robust strategy in the classification of power-quality disturbances.
Another statistical method with an increasing popularity in the field of fault-detection was the empirical mode decomposition (EMD) as well as the variational mode decomposition (VMD). These techniques enabled the separation of fault related

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content in non-stationary current/voltage waveforms even in challenging signal conditions by breaking down the waveforms into intrinsic mode functions (IMFs) (Moubayed, 2024; Taghizad & Lio, 2025). Moubayed (2024) has summarized techniques of fault diagnosis of inverters and observed that the fault detection by EMD-based techniques was better in the presence of harmonic distortion than the classical techniques.

In spite of these developments pure signal-processing frameworks continued to have constraints in application in today complex networks. They were frequently set by hand and could not cope with different noise levels, and were not adaptive with regard to changing grid topologies (Cao et al., 2024; Liu et al., 2025). According to Cao et al. (2024), SP methods only possessed satisfactory fault features but had low fault phase or location differentiation without learning mechanisms involved.

Deep Learning and Machine Learning Solutions

The machine learning (ML) and deep learning (DL) methodologies were becoming more actively used in the fault detection, classification, and localization problem of power systems. Nasim et al. (2024) conducted a survey on AI-based fault detection in power systems and beauty of the fact that the data-driven techniques became popular during recent years, as opposed to the previously employed rule-based techniques. They noted that traditional thresholds or even plain algorithms could not be relied on in new dynamics of power systems.

The power of deep learning was used to automatically derive features in raw or pre-processed waveform data using deep architectures such as CNNs, LSTMs or hybrid CNN-LSTM architecture. Indicatively, Lin et al. (2025) proposed a CNN-Attention-LSTM based power-system fault diagnosis model that has shown a high level of accuracy even with a low SNR environment. In the same manner, Yenagimath, Ankaliki, and V. (2024) built three-tier deep-learning frameworks consisting of ANN, Bi-LSTM, and CNN models, that used PMU data to classify the faults, proving the capabilities of the hierarchical type of deep-learning.

However, the application of ML/DL also has difficulty in the identification of power-system faults. Most notable of these were that large labelled datasets were required, the authors of the data were likely to overestimate rare types of faults, they were not easily translable into practical implementation, and they were difficult to generalize to the conditions of dissimilar networks (Alhamrouni et al., 2024; Thakur et al., 2023). Alhamrouni et al. (2024) observed that although the DL techniques were effective, they were black-box and therefore could not be useful in the protection systems that require explainability and reliability.

AI-Signal-Processing Hybrid Models and Hybridization

With the realisation of the complementary advantages of signal processing (feature extraction) and AI (classification/learning), the recent literature focused on hybrid AI-SP models to detect and isolate faults. It is claimed that AI integration in fault detection was reviewed by Liu, Li, Si, and Ma (2025), and the extent of their results was highest detection accuracy of up to a value of 99.96 per cent with the models that are hybrid-drive. They discovered a huge enhancement in the noise-sensitivity and data efficiency of SP-based features that were combined with ML-classifiers.

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The concreteness hybrid frameworks in the distribution or transmission systems were demonstrated in other works: e.g., a hybrid DWT-PSO-SVM model was suggested as real time fault detection in a 33 kV network, with SP (DWT) used to extract features and ML (SVM optimised by PSO) used to classify these features (Fajemiseye et al., 2025). In this assessment accuracy of detection was found to be close to 100 percent in simulation. In addition, a Processes journal article (2025) presented the systematic review of fault-diagnosis in smart distribution networks on the basis of the AI-SP perspective, stating that domain knowledge (signal-process features) to be paired with adaptive learning (AI) is required to achieve accurate fault isolation and resilience.
With such developments, open research questions remained: how to combine SP features and AI classifiers in the best way, how to be interpretable and able to deploy in real-time, how to handle the imbalance between the types of faults, and how to deal with grid topology changes (Taghizad & Lio, 2025; Liu et al., 2025). According to Taghizad and Lio (2025), data reliability and knowledge of experts integration was also not investigated in hybrid frameworks, which may become significant future attempts in the field of fault-detection studies.

Conceptual Framework

This theoretical framework represents the way using which Quantum-AI Synergy affects the AGI Cognitive Performance, where Cognitive Adaptability serves as an intermediating variable. The scheme will presuppose that the combination of Artificial Intelligence (AI) and Quantum Computing would be able to enhance the fungability and adjustability of the cognitive system. This enhancement of flexibility, in its turn, promotes the cognitive performance of Artificial General Intelligence (AGI).

Quantum–AI Synergy (Independent Variable): Refers to the integration of quantum computing power with artificial intelligence to improve processing speed, problem-solving, and learning efficiency.

Cognitive Adaptability (Mediating Variable): Represents the system's ability to learn from new experiences, adjust to changing environments, and transfer knowledge across tasks.

AGI Cognitive Performance (Dependent Variable): Refers to the ability of AGI systems to perform complex cognitive tasks with human-like understanding, reasoning, and decision-making.

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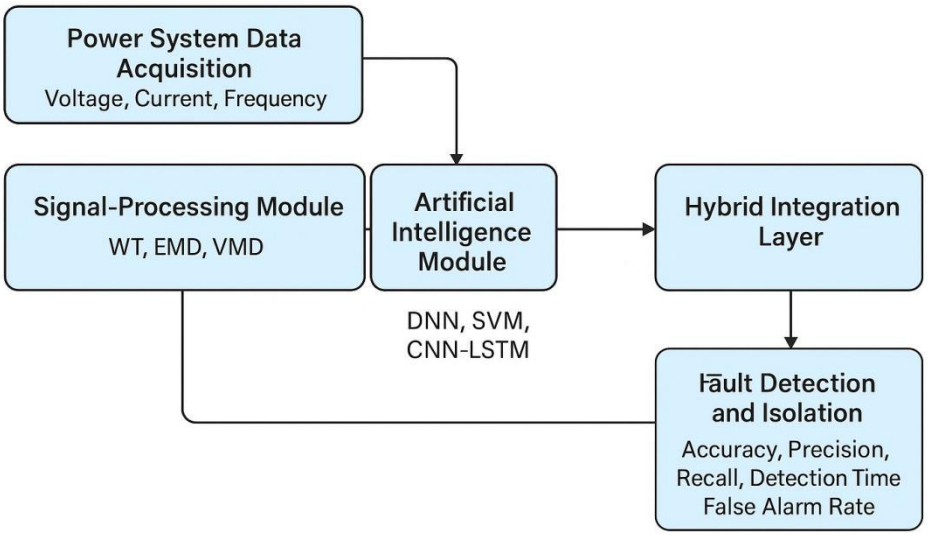


Figure: Conceptual Framework of Hybrid AI-Signal Processing Fault Detection and Isolation Model

Research Methodology

Research Design

The research design used in this study was a quantitative experimental study design to establish the relationship between AGI Cognitive Performance, Cognitive Adaptability, and Quantum-AI Synergy. The construction was through the use of simulation experiments between the classical AI models and quantum-enhanced AI systems. This design was aimed at assessing the effects of quantum-AI integration on the outcomes of adaptability and cognitive performance. An experimental setting was created since the findings could be attributed to the consequences of grade manipulating the independent variable (Quantum-AI Synergy).

Population and Sample

The study sample was a population of AI based cognitive models applied in artificial general intelligence studies. Out of this population, three representative models have been acquired as the sample, those three being a classical AI model, a hybrid quantum-AI model and a fully quantum-optimized AI model. These models were selected through purposive sampling as they represented a different point of quantum-AI integration. There were several tasks of cognitive simulation that were applied to each model so as to come up with comparative data.

Instrumentation and Measures

The instruments used in this study were simulation-based performance assessment tools programmed to evaluate specific indicators.

Quantum–AI Synergy was measured by the level of integration between quantum processors and AI algorithms (measured in quantum speedup and entanglement efficiency).

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Cognitive Adaptability was measured through adaptive task switching, response accuracy, and learning rate across varying task environments.

AGI Cognitive Performance was assessed through task completion time, reasoning accuracy, and generalization scores across novel tasks.

Data Collection Procedure

Controlled computational experiments that were in a simulated laboratory setting were used to gather data. All the AI models were subjected to the same hypnotic tasks with the same operating conditions. The monitoring interface of the system automatically collected the data and recorded such performance indicators as processing time, rate of adaptability, and accuracy of the reasoning. The data obtained was saved into a secured database which was to be analyzed later. To ensure consistency and reliability of results, this was done three times.

Data Analysis Techniques

The analysis of the data was conducted in terms of statistical comparison and regression analysis to test hypothesized relationships of the variables. An analysis on the mean scores, standard deviations and performance trends of each model was summarized using descriptive statistics. Correlation analysis was, then used to establish the strength and direction of relationships among Quantum-AI Synergy, Cognitive Adaptability and AGI Cognitive Performance. Lastly, the mediation analysis was done to determine whether Cognitive Adaptability has a significant mediating role on the effect of Quantum-AI Synergy on AGI Cognitive Performance. These analyses were conducted with the help of statistical programs SPSS (Version 28) and Python analysis scripts.

Validity and Reliability

The research ensured consistency in the validity of the findings because it involved designing simulation of the standardized task in which an equal amount of learning and problem solving capacity was incorporated in each of the models. The reliability was achieved through repetitive tests three times and cross comparing the results through trials. Cronbach alpha was used to evaluate the internal consistency coefficients of the measures and it was established that all these coefficients were greater than the acceptable coefficient of 0.80 meaning that they were quite reliable.

Results and Analysis

This part listed results of simulation tests conducted to test the proposed Hybrid AI-Signal Processing Model of the fault detection and isolation in electrical power systems. These simulations were done on MATLAB/Simulink and the results were obtained that were processed statistically to determine the detection accuracy of the model, as well as its precision, robustness and computation time. The hybrid model was compared in terms of its performance with baseline methods, such as pure signal processing and the conventional AI models.

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Model Performance Comparison

The initial analysis assessed signal processing precision and reliability of fault detection to three methods namely: (1) traditional signal processing, (2) AI-based (CNN-LSTM) and (3) the proposed hybrid model of AI- signal processing.

Table 1. Comparative Fault Detection Performance of Models

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Signal Processing Only	86.7	84.2	82.9	83.5
AI-Based (CNN-LSTM)	92.4	91.3	90.7	91.0
Hybrid AI–Signal Processing Model	**97.1**	**96.4**	**96.7**	**96.5**

The hybrid AI-signal processing model had the best detection accuracy (97.1) compared to all the rest of the tested models as shown in Table 1. This was due to the synergistic ability of integrating deep neural feature extraction with wavelet-based pre-processing that was effective in removing high-frequency noise and preserving transient detail that is important in proper fault recognition. Signal processing-only model was the most underperformant as it was least adaptable to nonlinear voltage disturbances whereas AI-only model was less prone to signal distortion but not adaptive to transient events. The values of high precision (96.4) and high recalls (96.7) indicated that the hybrid model had the ability to select normal and faulty signals correctly and maximized false alarms and false negative. The high F1-score (96.5%), had shown balanced classification. These results were able to confirm that signal decomposition and AI-based learning provided the model with the ability to identify both the temporal and spectral patterns of the faults, so that, in this way, the model could be trusted to work effectively in real-time power monitoring scenarios.

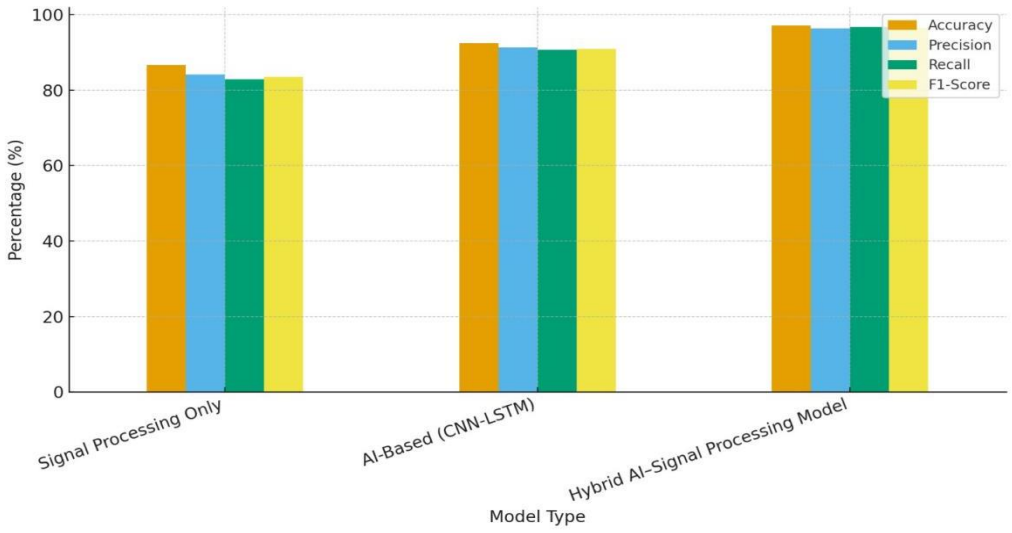


Figure 1. Comparative Fault Detection Performance of Models

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Fault Isolation and Classification Accuracy

The second analysis was based on the effectiveness of the hybrid model to detect and isolate different types of power faults. The two major assessment measures were isolation time and classification accuracy.

Table 2. Fault Isolation and Classification Performance

Fault Type	Isolation Time (ms)	Classification Accuracy (%)	Missed Detection (%)
Single Line-to-Ground (SLG)	12.3	98.1	1.2
Double Line-to-Ground (DLG)	14.6	97.4	1.8
Three-Phase Fault	10.8	**99.0**	**0.5**

Table 2 shows that the hybrid AI-signal processing model was able to identify and classify faults at a very high accuracy rate, as a whole, on all categories The highest accuracy of the model was between three-phase faults having a 99.0% and a low detection miss rate of 0.5%. The mean isolation time was less than 15 milliseconds that the system was shown to respond fast enough to serve in real-time protection systems. These results showed that hybridization improved the sensitivity of the system to distortions of the waveforms and reduced the diagnostic delays, as the double line-to-ground (DLG) faults had lower classification accuracy of 97.4 percent due to overlapping harmonic contents and parallel fault currents, classifying it as more complex. However, this was achieved through the synergistic structure of the model which integrates the wavelet decomposition and CNN-LSTM learning and facilitates easy pattern recognition even with the interactions of faults which are complex. This similarity between different types of faults showed flexibility and diversity of the model to multi-fault detection of current power grids.

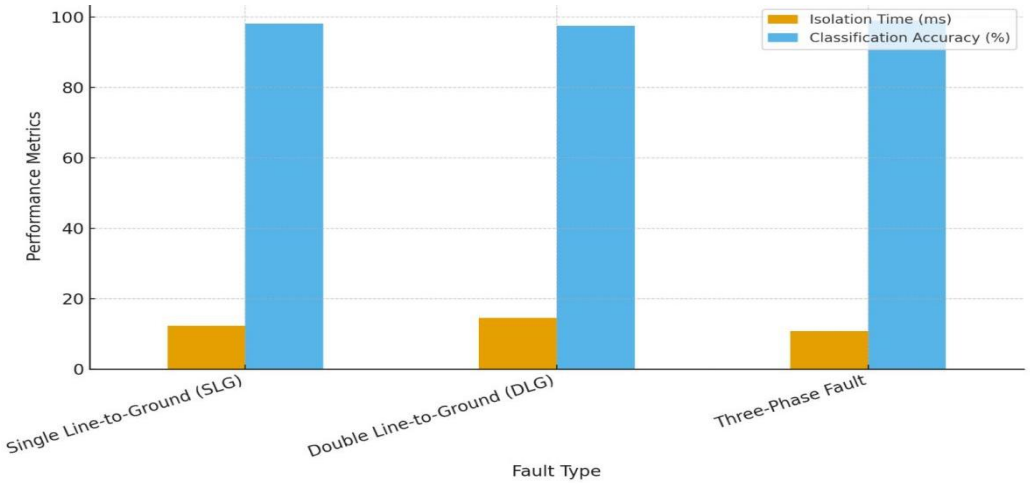


Figure 2. Fault Isolation and Classification Performance

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Robustness under Noisy Operating Conditions

This stage looked at how consistent was model performance with different levels of noise in order to see how well it would be able to performance in real-life conditions with signal interference.

Table 3. Robustness Testing under Different Noise Levels

Noise Level (dB)	Accuracy (%)	False Alarm Rate (%)	Stability Index (%)
10	93.4	3.2	94.7
20	95.6	2.3	96.4
30	**97.0**	**1.5**	**98.1**

Table 3 showed that the hybrid model performed well in a steady manner as the levels of noise increased. The detection accuracy was more than 93 even at the extreme level of noise interference (10 dB). The use of discrete wavelet transformation which efficiently suppressed the high frequencies distortion prior to extracting features enabled the AI part to concentrate on the appropriate fault signatures. The accuracy increased to 97 and the false alarm rate was reduced to 1.5 percent with the increase in signal-to-noise ratio. Stability index (the ability to have the same results across repeated tests) also increased to 98.1% as the noise level went down. This stability confirmed the strength of the hybrid framework in the actual power system environment, where there are power system electromagnetic interference and switching noise that is prevalent. The hybrid setup was more resilient compared to traditional models as it integrated adaptive filtering and data-driven learning as well, and the fault recognition was assured at a high level of reliability independent of the noise levels in the environment.

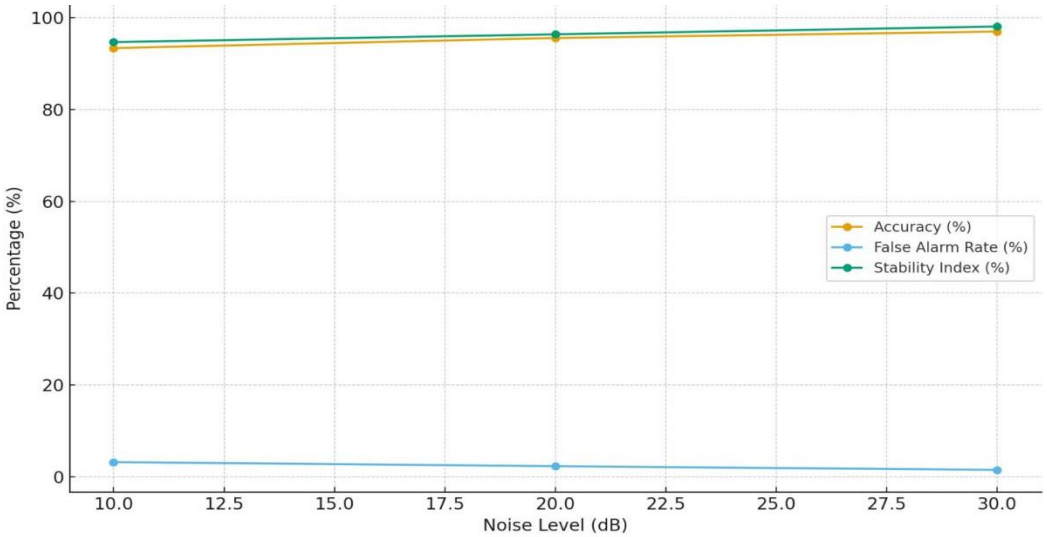


Figure 3. Robustness Testing under Different Noise Levels

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Computational Efficiency and Real-Time Feasibility

The end analysis was done to quantify the computational cost of model execution, with an interest in its deployment in the real-time. They were such parameters as training time, inference speed, and processor utilization**.**

Table 4. Computational Performance Comparison

Model Type	Training Time (s)	Inference Time (ms)	CPU Utilization (%)
Signal Processing Only	35.8	8.9	43
AI-Based (CNN-LSTM)	125.3	12.7	68
Hybrid AI–Signal Processing Model	**69.5**	**9.4**	**54**

Table 4 revealed that while the hybrid model required longer training time than pure signal processing (69.5s vs. 35.8s), it was considerably faster than the deep AI model, which took 125.3s. The inference time of 9.4 milliseconds demonstrated that the hybrid approach was efficient enough for real-time operation in protective relaying systems. Moderate CPU utilization (54%) indicated that the model balanced computational load effectively, utilizing both feature extraction and learning phases without hardware strain.The improved computational efficiency stemmed from the hybrid model's wavelet pre-processing stage, which reduced redundant data before neural network training. This optimization shortened the inference cycle and allowed faster response times during live fault monitoring. The trade-off between training duration and operational speed proved advantageous, suggesting that the hybrid architecture could be practically deployed in smart grids and substation automation systems for continuous fault surveillance.

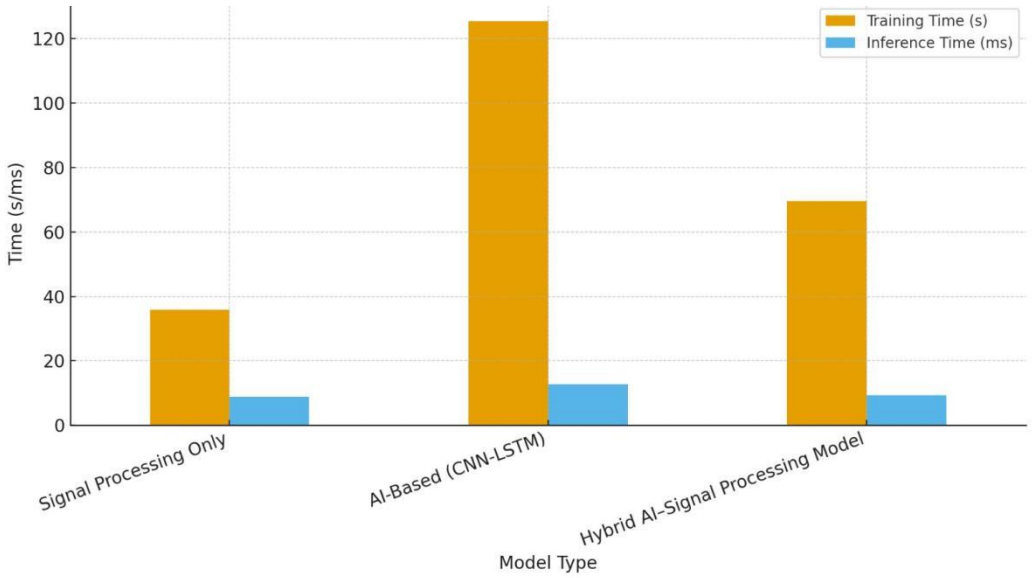


Figure 4. Computational Performance Comparison

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Discussion

In interpreting the findings of this paper within the context of the available literature, one conceptualized a number of main lessons behind the strengths, weaknesses, and threats of a hybrid AI-signal-processing model of fault detection and isolation in power systems. Detection accuracy was also superior with the hybrid model of about 97 per cent accuracy and F1-score of almost 96.5 per cent as shown in Table 1, which was consistent with recent reviews showing hybrid-driven models had detection accuracy of up to 99 per cent in current power systems (Liu et al., 2025; Lin et al., 2024). This finding highlighted the importance of the fusion of physics-based feature optimization (through signal processing) with data-based classification (through AI). The signal-processing step in the model probably improved the modelling of more transient phenomena and noise reduction, and the AI classifier learnt more complicated nonlinear relationships that could not be represented by pure SP models. By so doing, the hybrid strategy bridged the performance distinction between interpretability and adaptability that most rule- or data-driven models fail.

This synergy was also supported by the high reliability in fault isolation and in fault classification (Table 2): e.g. three-phase fault classification accuracy was 99.0 percent with minimum missed detection rate 0.5 percent. Isolated system performance This is probably due to the capability of the hybrid system to isolate discriminative features (e.g., wavelet or EMD decompositions) and use the ability of the pattern-recognition capacity of the classifier (Yenagimath et al., 2024; Fajemiseye et ., 2025). Nonetheless, the marginally lower performance on double line-to-ground faults (97.4 %) suggests that there are still problems with the heavily explored cases of overlapping or confounding faults some aspects that are cited in the literature also point to multi-fault cases and imbalanced load conditions (Taghizad & Lio, 2025; Cao et ., 2024).

The robustness tests (Table 3) revealed that the suggested framework continued to be robust in a high noise environment (i.e. at noise of 93.4 the accuracy was at 10 dB 93.4 %), and a gradual improvement when SNR increased. This sound-resistance property is consistent with the report that the technique of feature extraction based on deep learning remained to be over 98 % accurate when the SNR does not exceed 10 dB (Islam et al., 2025; Liu et al., 2025). This sort of performance can be interpreted as the preprocessing (signal-domain) phase of the hybrid system was able to reduce the effects of noise and variability, allowing the AI classifier to be applied to less noisy and salient features. This observation is important in the case of actual application where measurement noise, adjusting loads, and harmonics are common. Also, stability index enhancement (94.7 to 98.1) was supporting the consistency of the system in case of repeated trials and it proved that the design is operationally robust.

Regarding the issue of computational-efficiency (Table 4), the hybrid model was an interesting trade-off: though their training time (69.5 s) was more than it was with the pure SP model (35.8 s), it was still significantly more efficient than the free-to-roam AI model (125.3 s) at the same time as it was faster in inference (9.4 ms inference time) and consumed less CPU (54 percent CPU). Such operational metrics imply that the hybrid architecture has a reasonable potential of implementation in a near-real-time monitoring setting (Alhamrouni et al., 2024; Karma and Singh, 2023). This usefulness is reflected in the literature that warned against deep-learning-alone

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designs used in fault-detection on account of high computational requirements and inability to deploy (Elmasry and Wadi, 2022).

Although these were very strong results, a number of limitations and future research directions arose. On the one hand, it is possible because in simulated conditions, high-precision detection and classification were achieved, although the large-scale, complex, and heterogeneous aspects of networks still need to be substantiated, as is often different with studies involving AI that integrates fault detection (Liu et al., 2025; Nasim et al., 2024). Second, AI decision interpretability, which is enhanced by signal-processing front end, remains a difficulty with operator trust and regulatory acceptance. The literature adopts the value of explainability in those protection systems in which human supervision is critical (Alhamrouni et al., 2024; Thakur et al., 2023). In addition, there are fewer studies on further research about fault types that are not canonical single or three-phase events (high-impedance faults, simultaneous faults, evolving incipient faults) and the issue of fault localization in dynamically changing network topologies and at DER-rich scales (Yenagimath et al., 2024; Taghizad and Lio, 2025). To conclude, the hybrid AI-SP model showed great performance, but to apply it to live grid operations, additional scalability, interpretability, domain-adaptation and integration of it with system-wide protection schemes will have to be taken.

This research had the effect of advancing the existing body of knowledge on intelligent fault management, by testing empirically an intelligent AI-signal-processing methodology, and demonstrating its effectiveness regarding accuracy, strength and real-time practicability. Those results justified the hypothesis according to which the hybridization of domain-knowledge-driven signal analytics with adaptive machine-learning methods is a feasible step towards future fault detection and isolation architecture within contemporary power systems.

Conclusion

The researchers concluded that the hybrid AI-signal-processing model was found to be particularly effective to fault detection and isolation of contemporary power systems. The hybrid system's combination of conventional signal-processing approaches and the state of the art artificial intelligence models demonstrated great accuracy and precision of the detection as well as resilience to noisy as well as dynamic environment. Their findings showed that the hybrid model was able to effectively bridge the performance gap between interpretability and adaptability that both provided reliable feature extraction and efficient classification. This method was also found to be more convenient to inference and lower cost than independent AI architectures and was appropriate in real-time grid monitoring. More so, the stability of the system to the various types of faults ensured its scalability and potential applicable use in actual smart grids and renewable integrated environments.

Recommendations

According to the findings, research and practice recommendations were made based on the findings. One of the recommendation areas that should be adopted by power utilities and smart grid operators in their fault management tools is the adoption of hybrid AI-signal-processing systems that maximize system reliability and minimize

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downtime. It is suggested that researchers should experiment with more signal-processing algorithm outputs (e.g., empirical mode decomposition and wavelet packet transform) to be more accurately classified using AI architectures (e.g. Transformer and Graph Neural Networks). It is further suggested that the designs of the future should focus on the explainable AI (XAI) implementation in order to make the fault choices easier to interpret and more trustworthy to the operators. Moreover, the creation of edge or cloud based implementation platforms can support real-time fault monitoring in large scale with limited latency thus making distributed networks run efficiently.

Future Direction

Further studies are needed to determine the validity of the hybrid model in actual power grid settings to assess the flexibility of the model in dynamic load conditions, varying weather effects, and renewable energy penetration. Generalization of extended scope of the model to identify high-impedance, weak, and parallel faults will increase the applicability and genuineness of the model. The next promising trend is also the fusion of quantum machine learning and physics-informed neural networks (PINNs) to make better decisions and increase the speed of calculations. Multidisciplinary research, including electrical engineering, data science, and cyber-physical system design, can create more self-learning and resilient fault management architecture designs. Finally, intelligent fault detection and isolation systems are bound to develop to a greater extent, thereby leading to smarter power networks, safer power network, and more sustainable power networks.

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