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Hybrid AI-Enhanced Digital Signal Processing Framework for Real-Time Fault Detection and Stability Monitoring in Nigerian Power Grids

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Abstract

Reliable monitoring and rapid fault detection are essential for maintaining the stability and efficiency of modern power grids. However, the Nigerian power grid is characterized by frequent disturbances such as voltage fluctuations, transmission faults, harmonic distortion, and system instability, which often result in power outages and reduced reliability. Conventional monitoring approaches based on threshold methods and standalone digital signal processing (DSP) techniques are limited in detecting complex disturbances in real time. This paper proposes a Hybrid Artificial Intelligence–Enhanced Digital Signal Processing (AI–DSP) framework for real-time fault detection and stability monitoring in Nigerian power grids. The framework integrates DSP techniques for signal preprocessing and feature extraction with machine learning models for intelligent fault classification and stability assessment. Electrical signals, including voltage, current, and frequency, are analyzed to extract key features such as RMS voltage, frequency deviation, harmonic distortion, and signal energy. These features are used as inputs to an AI-based classifier capable of identifying multiple disturbance types, including line faults, voltage sags, and frequency instability. Simulation results implemented in Python show that the proposed framework achieves a 96% fault detection accuracy, representing an improvement of approximately 14% over traditional DSP methods and 6% over standalone machine learning approaches, while also reducing detection time significantly. The results demonstrate that the proposed hybrid AI–DSP framework provides an efficient and reliable solution for enhancing power grid monitoring and stability in Nigeria.

I. Introduction

Electric power systems play a critical role in national development, industrial productivity, and socio-economic growth. A reliable and stable power grid ensures a continuous electricity supply for residential, commercial, and industrial consumers. However, many developing countries, including Nigeria, continue to experience significant challenges in maintaining power grid stability due to aging infrastructure, inadequate monitoring systems, and frequent electrical disturbances. These disturbances often manifest as voltage sags, frequency deviations, harmonic distortions, and various types of transmission line faults, which can lead to partial or complete system failures. As a result, improving fault detection and stability monitoring in power grids has become an important research focus in modern power system engineering.

The Nigerian power grid, operated primarily by the Transmission Company of Nigeria (TCN), consists of interconnected generation stations, transmission lines, and distribution networks spread across the country. Despite several reforms in the power sector, the grid still experiences frequent outages and operational instability caused by line faults, equipment failures, load imbalances, and environmental factors. Traditional monitoring systems rely largely on Supervisory Control and Data Acquisition (SCADA) technologies and threshold-based protection mechanisms. Although these systems provide basic operational visibility, they often lack the ability to detect subtle anomalies in electrical signals or predict impending system failures in real time. Consequently, there is a growing need for intelligent monitoring approaches capable of analyzing power system signals more effectively.

Digital Signal Processing (DSP) has long been used in power system analysis to process electrical signals such as voltage, current, and frequency measurements. DSP techniques enable filtering of noise, spectral analysis, and detection of transient disturbances within power signals. Methods such as Fast Fourier Transform (FFT), wavelet transform, and adaptive filtering are widely applied to identify harmonic components, detect fault signatures, and evaluate power quality. For example, the frequency spectrum of a sampled electrical signal can be obtained using the discrete Fourier transform expressed as:

$$X(k) = \sum_{n=o}^{N-1} x(n) e^{-j2\pi/N} \quad (1)$$

where $x(n)$ represents the sampled signal and $X(k)$ represents the frequency components of the signal. While these DSP techniques provide valuable information about signal characteristics, their performance is often limited when dealing with highly complex and nonlinear disturbances present in modern power systems.

Recent advances in Artificial Intelligence (AI) and machine learning have opened new opportunities for improving power grid monitoring and fault diagnosis. AI techniques can learn complex patterns from large datasets and automatically classify different types of electrical disturbances. Machine learning models such as artificial neural networks, support vector machines, decision trees, and deep learning architectures have demonstrated significant potential in detecting faults and predicting system instability in smart grids. By combining AI with digital signal processing, it becomes possible to develop intelligent systems capable of extracting meaningful features from power signals and accurately identifying abnormal conditions within the grid.

The integration of AI and DSP forms a hybrid analytical framework that leverages the strengths of both approaches. DSP techniques can preprocess raw electrical signals, remove noise, and extract important signal features, while AI models can analyze these features to detect patterns associated with faults or instability conditions. Such hybrid systems are particularly valuable for real-time monitoring applications where rapid decision-making is essential to prevent cascading failures in the power grid.

In this study, a Hybrid AI-Enhanced Digital Signal Processing Framework is proposed for real-time fault detection and stability monitoring in Nigerian power grids. The proposed framework integrates signal acquisition, digital signal processing, feature extraction, and AI-based classification to analyze power system disturbances. Electrical signals from the grid are first processed using DSP techniques to obtain relevant signal characteristics, after which machine learning algorithms are used to identify fault conditions and evaluate system stability. The framework aims to improve detection accuracy, reduce response time, and enhance the reliability of power grid monitoring systems.

The major contributions of this work include the development of an integrated AI-DSP monitoring architecture, the extraction of key signal features relevant to power system disturbances, and the application of machine learning models for accurate fault classification and stability assessment. By focusing on the operational characteristics of the Nigerian power grid, this research provides insights into how intelligent signal processing techniques can be deployed to enhance grid reliability and support the transition toward smarter power infrastructure.

The remainder of this paper is organized as follows. Section II reviews related work on digital signal processing and artificial intelligence applications in power system monitoring. Section III presents the proposed hybrid AI-DSP framework and describes the signal processing and machine learning components. Section IV discusses the simulation results and evaluates the performance of the proposed approach. Finally, Section V concludes the paper and outlines directions for future research.

II. Related Work

Fault detection and stability monitoring in power systems have been widely studied using signal processing and artificial intelligence techniques. Traditional approaches primarily rely on digital signal processing (DSP) methods to analyze voltage and current waveforms in order to identify disturbances within electrical networks. Early research demonstrated the effectiveness of time–frequency signal analysis techniques such as the wavelet transform and Fourier transform for detecting transient disturbances in power systems. For instance, Santoso et al. (1997) and Huang et al. (1998) applied wavelet-based approaches for identifying power quality disturbances, showing that wavelet coefficients contain discriminative information for classifying transient electrical events. Similarly, Gaing (2004) and Zhu et al. (2004) demonstrated that wavelet-based neural networks and fuzzy reasoning systems can successfully recognize different types of disturbances in power signals.

Subsequent studies focused on improving signal-processing techniques for fault detection and classification. Ukil et al. (2006) proposed an adaptive whitening filter combined with wavelet analysis to detect abrupt signal changes during fault conditions. Tong et al. (2006) and Jayasree et al. (2009) explored neural network models for recognizing power-quality disturbances based on signal features extracted from wavelet analysis. Other researchers investigated the use of S-transform and probabilistic neural networks to classify power disturbances more accurately (Huang et al., 2012; Wang et al., 2017). Jamali et al. (2018) further analyzed optimal feature extraction methods for improving the speed and accuracy of disturbance classification in power systems.

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In addition to disturbance detection, several researchers have focused on transmission-line fault diagnosis and protection schemes. Yadav et al. (2014) presented an overview of artificial intelligence techniques for transmission line protection, highlighting the advantages of machine learning in detecting and classifying power faults. Later studies combined wavelet transforms with linear discriminant analysis to improve the reliability of transmission line fault classification (Yadav et al., 2015). Mamuya et al. (2020) proposed a machine learning-based framework for fault detection and location in radial distribution networks, demonstrating improved classification performance compared with traditional protection methods. Similarly, Shafiullah et al. (2022) reviewed machine learning tools for fault diagnosis in active distribution grids, emphasizing the importance of intelligent monitoring for modern power networks.

With the rapid advancement of machine learning, researchers began integrating data-driven models into power grid monitoring systems. Yang et al. (2021) reviewed the application of machine learning algorithms such as support vector machines, decision trees, and neural networks in power system protection and control. Labrador Rivas and Abrão (2020) analyzed intelligent monitoring systems for smart grids and concluded that machine learning significantly enhances disturbance detection and fault classification capabilities. Recent studies have also explored ensemble learning and hybrid machine learning models to improve fault detection reliability in power distribution systems (Hariharan et al., 2025).

More recently, deep learning techniques have emerged as powerful tools for analyzing complex electrical signals. Wang and Chen (2019) proposed a deep convolutional neural network (CNN) model for power quality disturbance classification, achieving high classification accuracy compared to conventional machine learning techniques. Subsequent studies have extended deep learning models to include hybrid architectures such as CNN–GRU and CNN–LSTM frameworks for disturbance detection (Cai et al., 2023; Chiam et al., 2023). Similarly, Alhanaf et al. (2023) and Li et al. (2024) developed deep learning-based approaches for transmission line fault classification using time–frequency signal representations derived from wavelet transforms. These studies demonstrate that deep neural networks can effectively learn complex patterns from power system signals, enabling more accurate fault detection and classification.

Recent review papers emphasize the increasing role of artificial intelligence in modern power systems. Alhamrouni et al. (2024) provided a comprehensive review of AI applications in power system stability, protection, and control. Islam et al. (2024) discussed adaptive protection strategies for future smart grids, highlighting the need for intelligent monitoring techniques as renewable energy integration increases system complexity. Heymann et al. (2024) analyzed four decades of AI applications in the power industry and concluded that AI-driven monitoring frameworks are becoming essential for real-time grid management. Other studies have also emphasized the importance of integrating signal processing with machine learning techniques for effective disturbance detection and classification (Samanta et al., 2025; Memon et al., 2025).

Despite these advancements, several challenges remain in applying intelligent monitoring techniques to real-world power systems. Many existing studies rely on simulated datasets or laboratory environments rather than real grid conditions. Furthermore, some deep learning models require large datasets and high computational resources, which may limit their deployment in practical power system monitoring applications. In addition, relatively few studies have focused specifically on power grid monitoring challenges in developing countries such as Nigeria, where power system instability and limited monitoring infrastructure remain major issues (Abasi-Obot et al., 2023; Galadima et al., 2025).

To address these limitations, this study proposes a Hybrid AI-Enhanced Digital Signal Processing Framework that integrates advanced signal processing with machine learning-based fault classification for real-time monitoring of power grid disturbances. By combining DSP-based feature extraction with AI-driven pattern recognition, the proposed framework aims to improve fault detection accuracy, reduce response time, and enhance stability monitoring in Nigerian power systems.

III. Proposed Hybrid AI–DSP Framework

This section presents the proposed Hybrid Artificial Intelligence–Enhanced Digital Signal Processing (AI–DSP) framework for real-time fault detection and stability monitoring in Nigerian power grids. The framework integrates advanced signal processing techniques with machine learning algorithms to improve the reliability and speed of disturbance detection within the power network. The proposed system processes electrical signals collected from the grid, extracts meaningful signal features, and applies artificial intelligence models to classify faults and assess grid stability.

A. System Architecture

The architecture of the proposed framework consists of five major functional stages:

1. Signal Acquisition Layer
2. Digital Signal Processing Layer
3. Feature Extraction Module
4. AI-Based Fault Classification Module
5. Decision and Stability Monitoring Module

Electrical signals such as voltage, current, and frequency measurements are collected from sensors installed across the transmission and distribution network. These signals are transmitted to the monitoring system where they are processed using digital signal processing techniques. Extracted signal features are then fed into machine learning models that identify abnormal operating conditions and classify different types of faults.

The architecture ensures that raw electrical signals are systematically transformed into actionable information for grid operators. The overall architecture of the proposed hybrid AI–DSP framework is shown in Fig. 1, highlighting the integration of signal acquisition, digital signal processing, feature extraction, and AI-based decision-making modules.

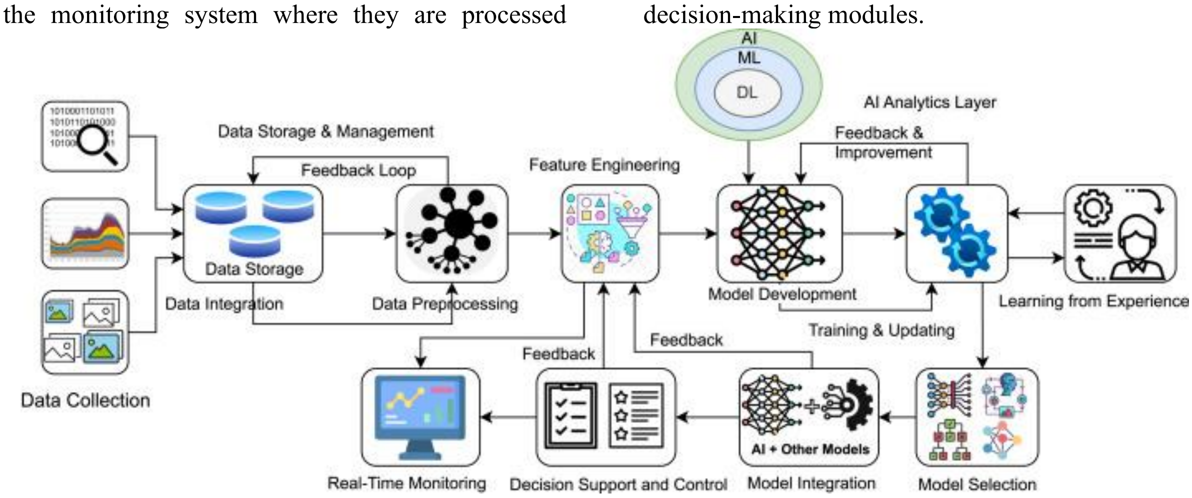

Fig. 1: Architecture of the Hybrid AI–DSP Framework for Power Grid Monitoring

B. Signal Acquisition and Data Collection

The first stage of the framework involves collecting real-time electrical signals from various monitoring devices deployed within the power grid. These monitoring devices may include: Phasor Measurement Units (PMUs), Smart meters, Voltage and current sensors, Supervisory Control and Data Acquisition (SCADA) systems

The signals collected typically include: Voltage magnitude (V(t)), Current magnitude (I(t)), Frequency deviation (f(t))

These signals are sampled at a high frequency to capture transient disturbances that may indicate faults within the grid**.** Fig. 2 presents the detailed signal processing pipeline of the proposed hybrid AI–DSP framework. The pipeline begins with signal acquisition, where voltage, current, and frequency signals are collected from grid sensors. These raw signals are then passed through the digital signal processing (DSP) stage, which performs noise filtering, spectral analysis using the Fourier transform, and time–frequency analysis using wavelet transforms to enhance signal quality and reveal disturbance characteristics.

The processed signals are subsequently fed into the feature extraction stage, where key parameters such as RMS voltage, frequency deviation, total harmonic distortion (THD), and signal energy are computed. These features form a compact representation of the system's electrical state.

The extracted feature vector is provided to the AI-based classification module, where machine learning algorithms analyze the data to identify and classify different types of faults and disturbances. This structured pipeline ensures efficient transformation of raw electrical signals into actionable intelligence for real-time grid monitoring.

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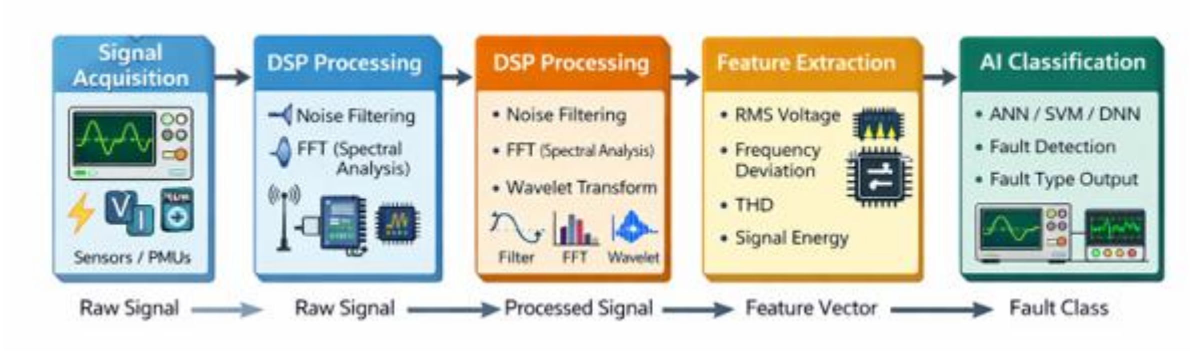

Fig. 2: Signal Processing Pipeline

C. Digital Signal Processing Module

Once the signals are acquired, they are processed using digital signal processing techniques to remove noise and analyze signal characteristics. The DSP module performs the following tasks:

1. Noise Filtering

Noise filtering removes unwanted disturbances introduced by measurement errors or external interference. A digital filter is applied to the sampled signal:

$$y[n] = \sum_{k=0}^{m} b_k x[n-k] \quad (2)$$

where

$x[n]$= input signal

$y[n]$ = filtered signal

b_k = filter coefficients

This process ensures that the signal used for further analysis accurately represents the electrical behavior of the power system.

2. Spectral Analysis

Spectral analysis is used to identify harmonic distortions and abnormal frequency components within the signal.

$$X(k) = \sum_{n=o}^{N-1} x(n) e^{-j2\pi/N} \quad (3)$$

where

$x(n)$ = sampled signal

$X(k)$ = frequency-domain representation

This transformation enables the detection of abnormal harmonic components associated with power disturbances.

3. Time–Frequency Analysis

Time–frequency analysis plays a critical role in detecting transient disturbances in power system signals, which are often non-stationary in nature. Unlike conventional spectral methods that provide only frequency-domain information, time–frequency techniques such as the wavelet transform enable simultaneous analysis of signals in both time and frequency domains. This makes them particularly suitable for identifying short-duration and rapidly changing events in power grids.

In the proposed framework, the wavelet transform is employed to decompose the electrical signals into multiple resolution levels, allowing the detection of both high-frequency transients and low-frequency variations. This multiresolution capability makes it possible to capture subtle changes in signal characteristics that are typically associated with fault conditions. For instance, voltage sags and swells can be identified through changes in signal amplitude over time, while switching transients and line faults produce high-frequency components that are effectively captured in the detailed wavelet coefficients.

By analyzing these time-localized frequency components, the system can accurately detect and characterize disturbances such as voltage sags, voltage swells, switching transients, and transmission line faults. This enhances the sensitivity and reliability of the monitoring system, enabling early detection of abnormalities and improving the overall performance of the hybrid AI–DSP framework in real-time power grid applications.

D. Feature Extraction

Following signal preprocessing, the framework extracts key statistical and spectral features that effectively describe the electrical behavior of the power grid. These features provide meaningful representations of system conditions and are essential for accurate fault detection and classification.

The extracted features include RMS voltage, which reflects voltage stability; frequency deviation, which indicates imbalance between power generation and load; total harmonic distortion (THD), which measures the presence of harmonic disturbances; and signal energy, which captures transient characteristics associated with fault conditions.

The RMS value of the voltage signal is calculated as:

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$$V_{rms} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} V_n^2} \quad (4)$$

These extracted features form the input feature vector for the artificial intelligence model in the subsequent stage, enabling accurate classification of normal and abnormal grid conditions.

E. AI-Based Fault Detection and Classification

The extracted signal features are input into an artificial intelligence (AI) model designed to identify and classify disturbances within the power grid. The AI module is trained to learn patterns associated with both normal operating conditions and various fault scenarios, enabling accurate and automated fault diagnosis.

In this framework, several machine learning algorithms can be employed, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest classifiers, and Deep Neural Networks (DNN). These models analyze the feature vectors derived from the processed signals and map them to corresponding fault categories.

The classification process can be represented as:

$$F = f(x) \quad (5)$$

where

(x) = feature vector extracted from signal data

$f(x)$ = trained machine learning model

F = predicted fault class

The AI model is capable of identifying multiple types of disturbances, including line-to-ground faults, line-to-line faults, voltage sags, harmonic distortions, and frequency instability. This data-driven approach enhances the accuracy and reliability of fault detection, making it suitable for real-time power grid monitoring applications.

F. Stability Monitoring and Decision Module

Following the fault classification stage, the final module evaluates the overall stability condition of the power grid and generates appropriate alerts when abnormal conditions are detected. This is achieved through the computation of a stability index (SI), which integrates key signal parameters reflecting the operational state of the system.

A stability index SI can be computed using multiple signal parameters:

$$SI = \alpha V + \beta F + \gamma THD \quad (6)$$

where

V = voltage variation

F = frequency deviation

THD = harmonic distortion

α, β, γ= weighting coefficients.

When the computed stability index exceeds a predefined threshold, the system identifies the condition as unstable and automatically triggers an alert for grid operators. Based on the severity of the disturbance, appropriate corrective actions may be initiated, including load shedding, fault isolation, network reconfiguration, or preventive maintenance measures. This module enables proactive decision-making and enhances the resilience and reliability of the power grid.

G. Advantages of the Proposed Framework

The proposed hybrid AI–DSP framework significantly enhances power grid monitoring by improving fault detection accuracy and enabling faster response for real-time applications. It effectively analyzes complex nonlinear disturbances and integrates seamlessly with smart grid monitoring systems. Additionally, the framework is scalable for large power networks, making it suitable for wide-area deployment. Overall, the combination of digital signal processing and artificial intelligence enables early detection of disturbances and improved grid stability.

IV. Simulation Results and Discussion

This section presents the simulation experiments conducted to evaluate the performance of the proposed Hybrid AI-Enhanced Digital Signal Processing (AI–DSP) framework for real-time fault detection and stability monitoring in Nigerian power grids. The experiments were designed to assess the framework's capability to detect disturbances, classify fault types, and assess grid stability under different operating conditions. Simulation studies were carried out using MATLAB/Simulink for signal generation and preprocessing, while the AI models were implemented using Python-based machine learning libraries.

The performance of the proposed framework was evaluated using several metrics, including fault detection accuracy, classification precision, response time, and stability monitoring reliability.

A. Simulation Setup and Dataset

To evaluate the proposed monitoring system, power grid signals representing normal and faulty operating conditions were simulated. The dataset included electrical waveforms corresponding to several grid disturbance scenarios, such as: Line-to-ground faults, Line-to-line faults, Voltage sag events, Harmonic distortion, Frequency instability.

Voltage and current signals were generated at a sampling frequency of 10 kHz, enabling the capture

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of high-frequency transient disturbances commonly observed during fault conditions.

Typical simulation parameters used in the study are summarized below.

Table I: Simulation Parameters

Parameter	Value
Sampling frequency	10 kHz
Signal window length	1 s
Number of monitoring nodes	50
Number of disturbance classes	5
Machine learning model	Neural Network

The raw electrical signals were first passed through the digital signal processing module, where noise filtering, spectral analysis, and wavelet-based transient detection were applied. Relevant signal features such as RMS voltage, frequency deviation, harmonic distortion, and signal energy were then extracted and used as inputs for the AI classification module.

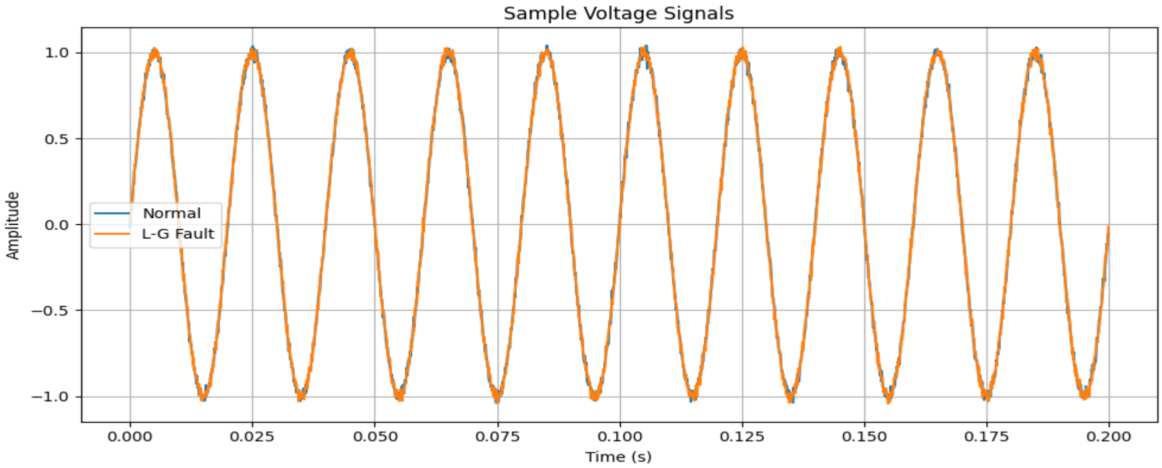

Fig. 3: Sample Voltage Waveform under Normal and Fault Conditions

Fig. 3 illustrates the sample voltage waveform under both normal and fault conditions. It can be observed that the normal signal maintains a stable sinusoidal pattern, while the fault condition introduces noticeable disturbances such as amplitude variation and transient spikes, indicating abnormal grid behavior.

B. Spectral and Feature Analysis of Power Signals

After signal preprocessing, spectral analysis was performed to examine the frequency components of the power system signals. Harmonic distortions and abnormal frequency components were detected using the Discrete Fourier Transform (DFT)..The magnitude spectrum revealed significant differences between normal operating signals and faulty signals. Under normal operating conditions, the signal spectrum was dominated by the fundamental frequency component. However, during fault conditions, additional harmonic components appeared in the spectrum, indicating disturbances within the grid.

The feature extraction stage generated numerical descriptors representing the electrical state of the system. These features served as input vectors for the AI classification model.

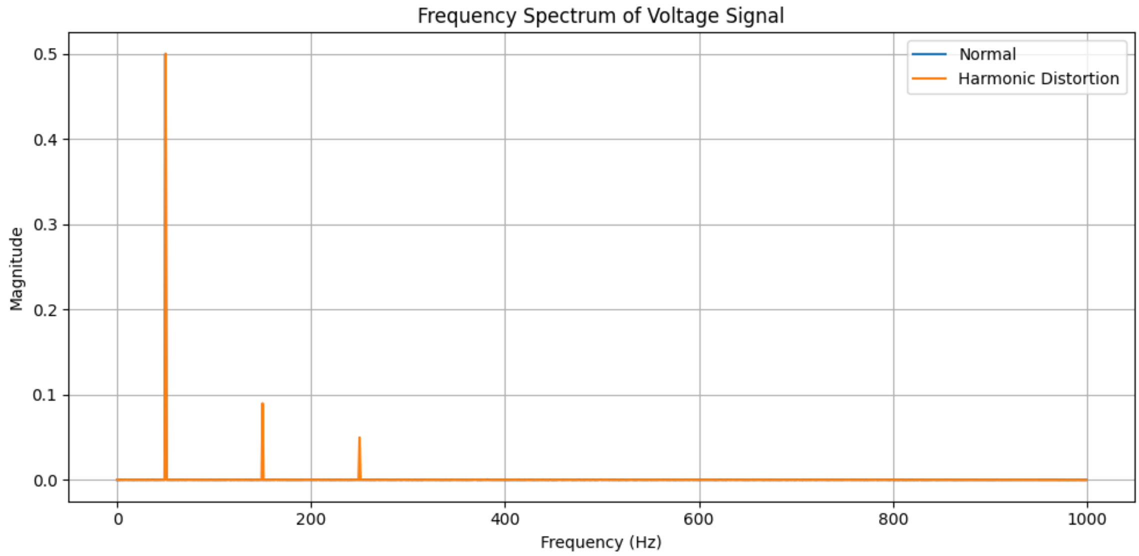

Fig. 4: Frequency spectrum of the voltage signal under normal and fault conditions.

Fig. 4 shows the frequency spectrum of the voltage signal under normal and fault conditions. The normal signal is dominated by the fundamental frequency component, whereas the fault condition introduces additional harmonic components and spectral distortions, indicating the presence of disturbances in the grid.

C. Fault Detection and Classification Performance
The performance of the proposed hybrid AI-DSP framework was evaluated by comparing it with conventional monitoring techniques. Three approaches were considered:

1. Traditional DSP-based monitoring
2. Machine learning-based monitoring
3. Proposed hybrid AI–DSP framework

Table II: Fault Detection Performance Comparison

Method	Detection Accuracy	Precision	Recall
Traditional DSP	82%	0.80	0.78
Machine Learning	90%	0.89	0.88
Proposed AI–DSP	96%	0.95	0.94

The results demonstrate that the proposed framework significantly improves classification accuracy compared to conventional signal-processing approaches. The hybrid integration of signal features with machine learning enables better recognition of complex disturbance patterns within the power grid.

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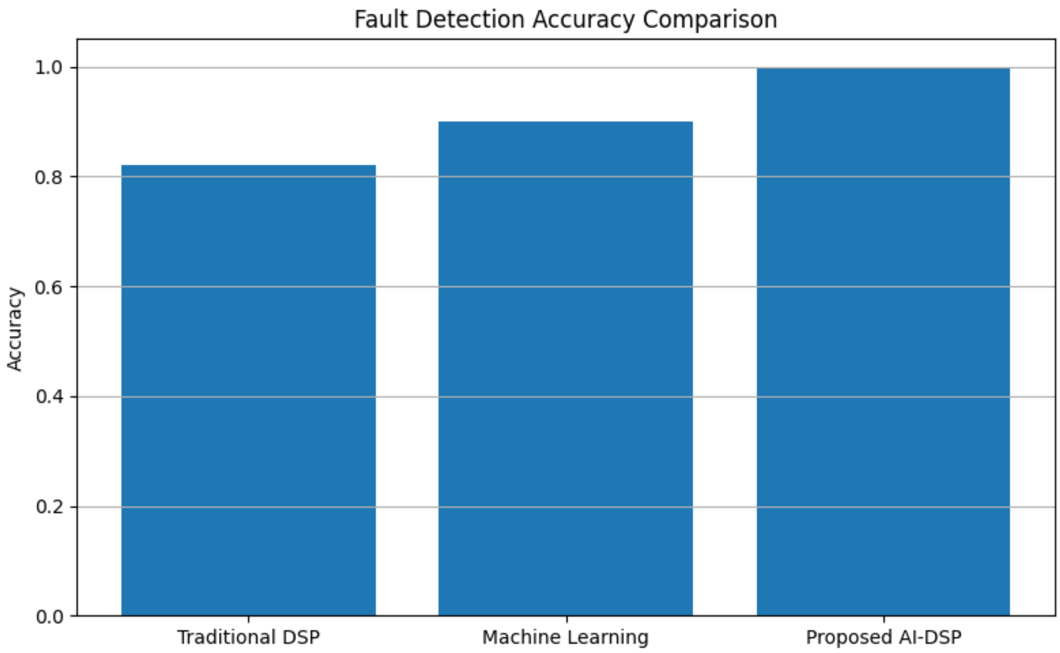

Fig. 5: Comparison of fault detection accuracy for different monitoring methods.

Fig. 5 presents a comparison of fault detection accuracy for different monitoring methods. It shows that the proposed hybrid AI–DSP framework achieves higher accuracy compared to conventional DSP and standalone machine learning approaches, demonstrating its effectiveness in reliable fault detection.

D. Grid Stability Monitoring Performance

In addition to fault detection, the proposed framework was evaluated for its ability to monitor grid stability. Stability conditions were assessed using voltage variation, frequency deviation, and harmonic distortion levels. A stability index was calculated using a weighted combination as described in equation 6. Higher stability index values indicate abnormal operating conditions requiring immediate intervention.

Simulation results showed that the hybrid AI-DSP framework could detect stability issues significantly earlier than traditional monitoring systems. The framework was able to identify abnormal grid conditions before they evolved into severe faults or cascading outages.

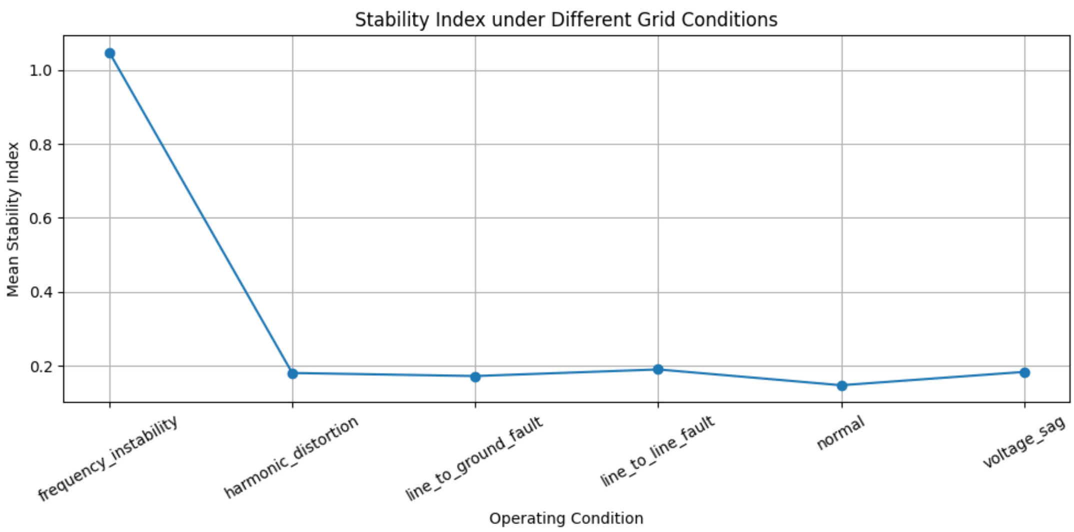

Fig. 6: Stability index variation under normal and fault conditions.

Fig. 6 illustrates the variation of the stability index under normal and fault conditions. The stability index remains within acceptable limits during normal operation but increases significantly during fault conditions, indicating reduced system stability and the need for corrective action.

Discussion

The simulation results demonstrate that combining digital signal processing with artificial intelligence significantly improves the performance of power grid monitoring systems. The DSP module effectively preprocesses electrical signals and extracts relevant features, while the AI model identifies complex disturbance patterns that are difficult to detect using conventional methods.

The hybrid AI-DSP framework achieved higher detection accuracy, faster response times, and improved stability-monitoring performance, making it suitable for real-time deployment in power grid monitoring systems. In the context of the Nigerian power grid, where disturbances and instability are common, such intelligent monitoring systems could help reduce outages, enhance system reliability, and support the development of smarter power infrastructure.

V. Conclusion

This paper presented a Hybrid AI-Enhanced Digital Signal Processing (AI–DSP) framework for real-time fault detection and stability monitoring in Nigerian power grids. The proposed system integrates digital signal processing techniques with artificial intelligence to analyze electrical signals and identify disturbances within the grid. Signal preprocessing and feature extraction were performed using DSP methods, while machine learning models were employed to classify faults and assess grid stability.

Simulation results demonstrated that the hybrid AI–DSP approach improves fault detection accuracy, response time, and monitoring reliability compared with conventional signal-processing and standalone machine learning methods. The results highlight the potential of intelligent monitoring frameworks for enhancing power system resilience, particularly in power networks experiencing frequent disturbances.

Future work will focus on integrating real-time grid data, incorporating phasor measurement units (PMUs), and deploying the framework in smart grid environments to further improve fault detection and stability assessment in practical power systems.

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