Applications of Digital Signal Processing Techniques in Power Quality Detection and Improvement

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Abstract. The integration of digital signal processing (DSP) techniques into smart grids has greatly improved power quality detection, fault diagnosis, and system stability. This paper examines the use of DSP methods such as digital low-pass filters, adaptive filters, Kalman filtering, wavelet transform, sparse signal processing, and deep learning in addressing key power system challenges. Digital low-pass filters enhance zero-crossing detection accuracy by compensating for time delays, while adaptive filters, like the Least Mean Squares (LMS) algorithm, improve noise reduction and harmonic suppression in fault diagnosis. Kalman filtering methods, including the Distributed Quaternion Kalman Filter (DQKF), offer precise frequency estimation under unbalanced grid conditions. Wavelet transform techniques, such as Discrete Wavelet Transform (DWT) and Multi-Resolution Analysis (MRA), effectively detect and mitigate voltage sags and swells. Sparse signal processing methods, like Compressed Sensing (CS), enable efficient data compression and recovery, reducing transmission and storage demands. Deep learning models, including MLPs and LSTMs, provide high accuracy in load forecasting and renewable energy generation prediction, addressing energy supply variability. Results show that DSP techniques, especially when integrated with deep learning, outperform traditional methods in accuracy, adaptability, and computational efficiency, offering robust solutions for smart grid challenges.

Keywords: Digital Signal Processing (DSP), Smart Grids, Fault Diagnosis, Deep Learning.

1 Introduction

The rapid evolution of smart grids has introduced complex challenges in power quality management, fault diagnosis, and system stability. As global energy demands continue to rise and renewable energy sources become increasingly integrated into power systems, the dynamic and non-linear nature of modern grids poses significant challenges for traditional methods. These conventional approaches often struggle to address issues such as voltage sags, swells, harmonics, and frequency deviations, which can lead to equipment instability, energy losses, and even severe grid failures. In this context, digital signal processing (DSP) techniques have emerged as powerful tools to

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enhance the accuracy, adaptability, and computational efficiency of power quality detection and system performance improvement.

The research background of this study is rooted in the growing need for advanced solutions to manage the complexities of smart grids. With the proliferation of distributed energy resources (DERs), such as solar and wind power, the grid's operational environment has become more unpredictable. These renewable sources introduce variability and intermittency, further complicating power quality monitoring and control. Additionally, the massive data generated by Phasor Measurement Units (PMUs), smart meters, and IoT devices demands efficient processing and analysis techniques to ensure real-time decision-making and system reliability. Traditional signal processing methods, while useful, often fall short in handling these high-dimensional, noisy, and non-stationary data streams.

Currently, the application of DSP techniques in smart grids has gained significant traction. Methods such as digital low-pass filters, adaptive filters, Kalman filtering, wavelet transforms, and sparse signal processing are being widely adopted to address specific challenges. For instance, digital low-pass filters improve zero-crossing detection accuracy, while adaptive filters like the Least Mean Squares (LMS) algorithm enhance noise reduction and harmonic suppression. Kalman filtering, particularly the Distributed Quaternion Kalman Filter (DQKF), offers precise frequency estimation under unbalanced grid conditions. Wavelet transform techniques, such as Discrete Wavelet Transform (DWT), enable effective detection and mitigation of voltage sags and swells [1]. Furthermore, sparse signal processing methods like Compressed Sensing (CS) reduce the bandwidth and storage demands of power big data. Despite these advancements, the integration of DSP with emerging technologies such as deep learning remains an area of active research, offering promising avenues for further improving grid performance.

The theme of this paper revolves around the comprehensive exploration of DSP techniques and their integration with advanced technologies like deep learning to address critical challenges in smart grids. By leveraging these methods, power systems can achieve more accurate fault diagnosis, robust frequency estimation, efficient voltage regulation, and scalable data management [2]. This study aims to provide a detailed overview of the latest advancements in DSP applications for smart grids, highlighting their potential to enhance system reliability, efficiency, and adaptability. The findings will contribute to the ongoing efforts to optimize smart grid operations and pave the way for future innovations in real-time monitoring, edge computing, and secure data transmission. Advanced Signal Processing Techniques for Power Quality Monitoring and SystemStability Enhancement.

2 Advanced Signal Processing Techniques for Power Quality Monitoring and System Stability Enhancement

2.1 Application of Digital Low-Pass Filters in Power Quality Detection

Power quality is a critical parameter for the stable operation of power grids, influencing not only the reliability of power systems but also the lifespan of electrical equipment and energy losses. In power quality analysis, the zero-crossing detection method is commonly used for estimating signal frequency. However, to enhance the accuracy of zero-crossing detection, a low-pass filter (LPF) is typically employed to eliminate high-frequency noise. Digital low-pass filters improve the precision of measurement timestamps by detecting zero-crossing points and compensating for their inherent delays [3].

In practical applications, low-pass filters introduce time delays, which affect the accuracy of measurement timestamps. In practical applications, the time delays introduced by low-pass filters can lead to errors in measurement timestamps, affecting overall accuracy. To address this issue, reference [3] proposes the use of an eighth-order Butterworth digital IIR low-pass filter, composed of four biquad sections, to enhance numerical stability. The average group delay of the filter is measured through pulse testing, and this time is forward-corrected during zero-crossing detection. This improvement is evident in simulation results, which demonstrate that the compensated error remains below 0.2% under ideal, noisy, harmonic, and transient signal conditions. This method is characterized by low cost, high precision, strong adaptability, and robust anti-interference capabilities, making it suitable for various power quality detection scenarios.

2.2 Application of Adaptive Filters in Power System Fault Diagnosis

Adaptive filters dynamically adjust their parameters and are widely used in digital signal processing, especially in environments with varying input statistics. Adaptive filters can effectively enhance signals contaminated by noise and reduce the impact of uncertain noise [4]. In smart grids (SG), adaptive filters serve as system identifiers, echo cancellers, and noise cancellers, significantly improving system performance and suppressing harmonics in power systems [5].

Among various adaptive filtering algorithms, the Least Mean Squares (LMS) algorithm is considered the optimal choice due to its stability and fast convergence. The primary task of the LMS algorithm is to achieve minimum mean square error with high convergence speed. In contrast, the Recursive Least Squares (RLS) algorithm, although offering lower steady-state error, suffers from higher computational complexity and potential instability if not properly designed [5]. To further enhance the performance of adaptive filters, researchers have proposed hybrid algorithms that exhibit smaller steady-state errors, stronger tracking capabilities, lower computational complexity, and higher stability, making them suitable for complex power system fault diagnosis scenarios.

2.3 Application of Kalman Filtering in System Frequency Estimation

Power systems in smart grids typically operate with three-phase alternating current, and accurate estimation of system frequency is crucial for the stable operation of electrical equipment. Frequency deviations can lead to instability in electrical equipment and even cause severe accidents. Traditional frequency estimation methods, such as the Clarke transform, have limitations when processing three-phase voltage signals, especially under unbalanced conditions (e.g., sudden changes in voltage amplitude or phase in one phase), where traditional complex-domain processing methods may fail [6].

Kalman filtering, as an efficient recursive estimation algorithm, processes three-phase voltage signals more effectively, especially under unbalanced system conditions, compared to traditional methods. By sharing information between nodes and averaging local estimates, Kalman filtering significantly reduces frequency estimation errors, providing a new solution for frequency monitoring and control in smart grids [6]. In the frequency estimation of smart grids, the Distributed Quaternion Kalman Filter (DQKF) significantly reduces the steady-state variance. Simulation results demonstrate that its steady-state error is approximately 4dB lower than that of the Local Quaternion Kalman Filter (Local-QKF), as shown in Fig. 1. Moreover, DQKF is capable of rapidly tracking frequency changes when the system frequency undergoes step variations. Under unbalanced conditions in three-phase power systems, DQKF maintains accurate frequency estimation, whereas traditional complex-domain filtering methods (such as LCKF and WLCKF) exhibit significant performance degradation. In collaborative target tracking, DQKF performs exceptionally well in three-dimensional target tracking tasks, with the steady-state Mean Square Error (MSE) aligning closely with theoretical analysis. Furthermore, in bearing-only target tracking tasks, DQKF achieves high-precision localization through information diffusion among nodes. Overall, the performance of DQKF in distributed networks approaches that of centralized filters (CQKF), while requiring lower computational and communication overhead, demonstrating its robustness and adaptability in complex environments [6].

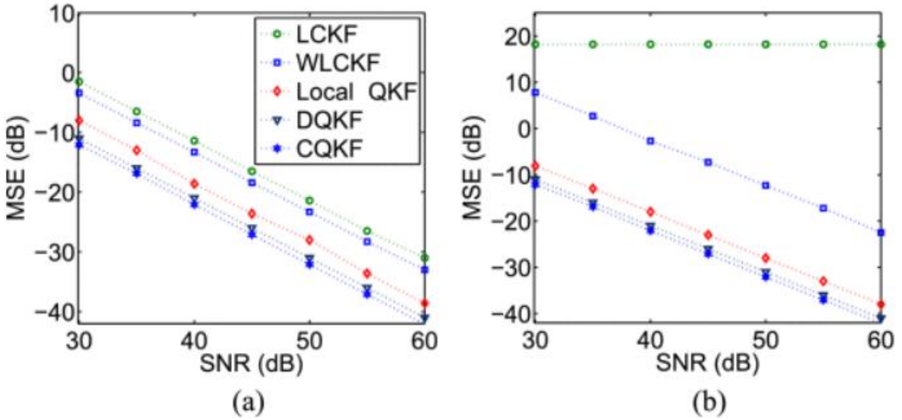

Fig. 1. Simulation result [6].

2.4 Application of Wavelet Transform in Power Quality Improvement

With increasing electricity demand and the rapid development of smart grids, power quality issues have become more prominent. These include voltage sags, swells, harmonics, and interruptions. Among these, voltage sags and swells are the most common power quality problems, particularly affecting sensitive electronic equipment [7]. Wavelet transform, as a mathematical tool, is widely used in signal processing, data compression, and fault detection, especially in applications requiring time-frequency analysis. Through Discrete Wavelet Transform (DWT) and Multi-Resolution Analysis (MRA) techniques, grid voltage signals can be decomposed into multiple levels, extracting approximation and detail coefficients to accurately detect the start and end points of voltage sags and swells [7].

In power quality improvement, wavelet transform selects appropriate mother waveletsto extract signal features and uses microcontrollers to generate PWM signals, controlling MOSFET switches and injection transformers to compensate the required voltage into the grid, ultimately restoring normal voltage levels. As shown in Fig. 2. The wavelet transform-based method significantly enhances the detection and restoration performance of voltage sag and swell in smart grids. Simulation results demonstrate that using the Db4 wavelet for Discrete Wavelet Transform (DWT) and Multi-Resolution Analysis (MRA) accurately identifies the start and end points of voltage events. The system can restore voltage to 220V by injecting 1V-30V during voltage sags (219V-190V) and swells (221V-250V). When the voltage sag falls below 190V or the swell exceeds 250V, the system triggers a protection circuit. The duty cycle of the PWM signal is proportional to the magnitude of the voltage sag or swell. For instance, in cases of 12V and 20V voltage sags, the PWM signal width increases by 12V and 20V, respectively, achieving precise voltage restoration [7].

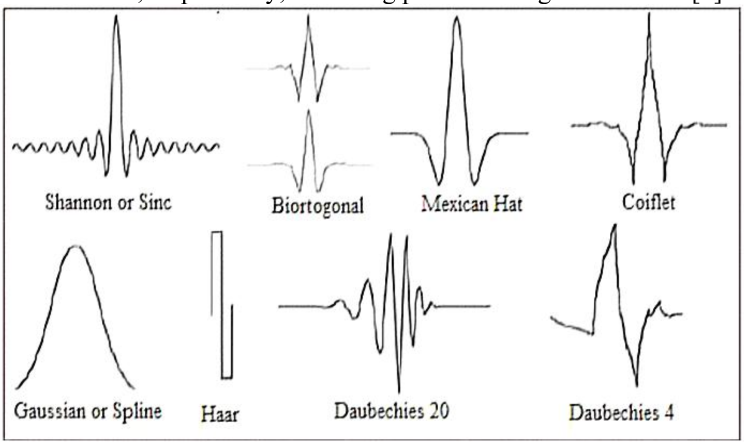

Fig. 2. Types of wavelets [7].

3 Innovative Data Processing and Analysis Techniques for Smart Grid Optimization

3.1 Application of Sparse Signal Processing in Power Big Data Compression and Recovery

Phasor Measurement Units (PMUs) provide high-precision grid state data, including voltage phasors, current phasors, and frequency, at sampling rates of up to 30-120 Hz. However, the massive data generated by PMUs pose significant bandwidth and storage challenges during transmission and storage. To address this issue, sparse signal processing techniques are widely applied in the compression and recovery of power big data. Compressed Sensing (CS) technology allows the reconstruction of original signals from significantly fewer samples than traditional sampling methods require. This approach greatly reduces sampling and transmission costs. Through Fourier transform, wavelet transform, or adaptive sparse dictionary learning, power data can be mapped to a sparse domain, and random projections or greedy algorithms (e.g., Orthogonal Matching Pursuit (OMP), Regularized Orthogonal Matching Pursuit (ROMP)) can be used to capture and store only a small number of key coefficients, achieving data compression ratios of over 10 times [8]. For example, smart meter data can be reduced by more than 90% after sparse encoding. In the data recovery phase, convex optimization reconstruction, non-convex optimization, or distributed compressed sensing methods can be employed to accurately recover the original signal from compressed data [8].Sparse signal processing alleviates the pressure of data transmission and storage. It also supports smart grid monitoring, power market analysis, and edge computing optimization. By combining mathematical optimization methods with the physical characteristics of power systems, sparse signal processing lays a solid foundation for the resource optimization and intelligent development of power systems in the big data era. In the future, this technology will evolve towards real-time grid monitoring, secure data transmission, and intelligent fault prediction, providing stronger technical support for the digital transformation of power systems.

3.2 Application of Deep Learning Combined with Digital Filters in Smart Grid Data Analysis

The transition to smart grids (SG) has significantly improved grid reliability and energy management efficiency. However, the massive data generated by various devices in smart grids, such as smart meters and IoT devices, poses significant challenges to traditional data processing methods. To address these challenges, deep learning techniques are widely applied in power system data analysis, particularly in the construction of high-precision prediction models. Deep learning models, such as Multi-Layer Perceptrons (MLP), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRU), excel in short-term load forecasting. These models can capture complex nonlinear relationships in time series data, significantly improving load forecasting accuracy. Additionally, deep learning models such as Deep Belief Networks (DBN) and Conditional Deep Belief Networks (CDBN) are used for medium- and long-term load forecasting, providing crucial support for power system resource planning and scheduling.

In the field of renewable energy, deep learning models such as Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN) are widely applied in photovoltaic and wind power forecasting. These models combine historical generation data and meteorological data to predict renewable energy generation accurately. This helps power systems formulate optimal generation plans to address renewable energy's intermittency and instability [9]. Artificial intelligence and machine learning technologies hold significant application value in smart power distribution systems. The neural network architecture is shown in Fig. 3. Accurate prediction of power load is a critical factor in ensuring the smooth and uninterrupted operation of the system, while the stability of the power grid relies on its ability to precisely forecast daily electricity demand. When using six traditional prediction methods (including SVM, LR, DT, RF, NB, KNN, and soft voting), the prediction accuracy ranges between 81% and 82%. However, when employing deep neural networks for prediction, the accuracy increases to 95.60%. Therefore, it can be concluded that the accuracy of estimation using synthetic neural networks or other deep learning techniques far surpasses that of traditional methods [10].

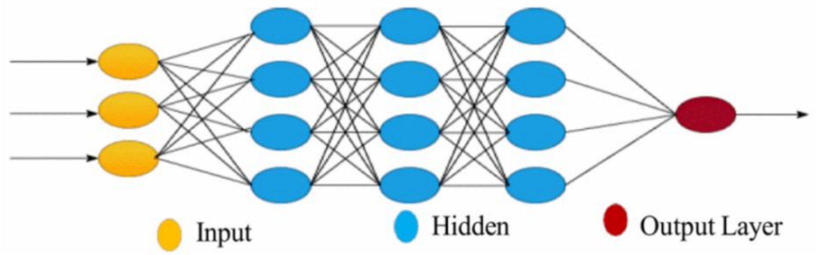

Fig. 3. Neural network architecture [10].

4 Conclusion

The application of digital signal processing (DSP) techniques in smart grids has proven to be highly effective in addressing key challenges related to power quality, fault diagnosis, and system stability. Digital low-pass filters enhance zero-crossing detection accuracy, and adaptive filters complement this by improving noise reduction and harmonic suppression. Kalman filtering, particularly the Distributed Quaternion Kalman Filter (DQKF), offers superior frequency estimation under unbalanced grid conditions. Wavelet transform, combined with Discrete Wavelet Transform (DWT) and Multi-Resolution Analysis (MRA), provides robust solutions for detecting and mitigating voltage sags and swells. Sparse signal processing techniques, like CS, facilitate efficient compression and recovery of power big data, paving the way for more scalable and low-cost power system operations. Deep learning models, such as MLPs and LSTMs, provide high-accuracy load forecasting and renewable energy generation prediction, crucial for optimizing smart grid operations under variable conditions. The integration of DSP with deep learning significantly improves accuracy, adaptability, and computational efficiency, particularly in handling complex, dynamic power grid scenarios. These advancements provide robust solutions for the evolving demands of smart grids, ensuring reliable and efficient power distribution. Future research should optimize these techniques for real-time applications, such as real-time frequency regulation, and explore their potential in edge computing and secure blockchain-based data transmission.

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