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Research Article

Introducing a Novel Method for Identifying and Classifying Power Quality Disturbances Using LSTM Neural Network, Wavelet Transform, and Intrinsic Mode Decomposition

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Extended Abstract:
The increasing penetration of renewable energy sources and the growing complexity of modern power systems have intensified the challenge of maintaining high power quality. Power Quality Disturbances (PQDs) are a critical concern for grid operators, equipment manufacturers, and end-users alike, as they can lead to equipment malfunction, data loss, and significant financial losses. The reliable and automated identification and classification of these disturbances are therefore essential prerequisites for effective power system monitoring, protection, and mitigation. However, the accurate classification of PQDs remains a formidable task due to the inherent non-stationary nature of the disturbances, the frequent occurrence of combined or hybrid events (e.g., a voltage sag accompanied by harmonics), and the presence of noise in real-world measurement environments. Traditional signal processing and classification methods often struggle to provide the necessary accuracy, robustness, and generalizability required for practical deployment. To address these critical gaps, the research by Shahabadi, Es'haghi, and Bidar proposes a novel, intelligent, and robust framework for the identification and classification of a comprehensive set of PQDs. This framework innovatively combines the strengths of advanced time-frequency signal decomposition techniques with the powerful pattern recognition capabilities of a Long Short-Term Memory (LSTM) neural network, creating a hybrid system that is both highly accurate and capable of handling the complexities of real-world power system data.

The core of the proposed methodology is a three-stage, well-structured pipeline designed to transform raw voltage and current waveforms into a definitive classification of the underlying disturbance. The first stage is dedicated to signal decomposition and feature extraction, which is fundamental to the system's success. The authors recognize that a single signal processing technique is insufficient to capture the full spectrum of characteristics exhibited by different PQDs. To overcome this, they employ a sophisticated hybrid approach that synergistically combines the Wavelet Transform (WT) and the Empirical Mode Decomposition (EMD). The Wavelet Transform is adept at providing a multi-resolution analysis, effectively capturing transient events like spikes and impulses with high time localization. Conversely, the Empirical Mode Decomposition is a powerful adaptive technique that can decompose non-linear and non-stationary signals into a set of Intrinsic Mode Functions (IMFs), which are well-suited for analyzing oscillatory phenomena like harmonics and interharmonics. By applying both transforms to the same input signal, the framework extracts a richer and more discriminative set of features than either method could achieve in isolation. This combined feature set is then refined

through the calculation of seven standard statistical parameters—namely, mean, Root Mean Square (RMS), standard deviation, variance, skewness, kurtosis, and energy—from the relevant components of both the wavelet and EMD decompositions. This process ultimately results in a highly informative and compact 28-dimensional feature vector for each analyzed signal segment. This vector serves as a unique fingerprint that encapsulates the essential time-frequency characteristics of the PQD, making it an ideal input for a machine learning classifier.

The second stage of the pipeline involves the selection and training of a classifier capable of mapping these complex 28-dimensional feature vectors to the correct PQD class with high fidelity. The authors have chosen the Long Short-Term Memory (LSTM) neural network, a specialized type of Recurrent Neural Network (RNN), as their classification engine. This choice is a key strength of the work. Unlike traditional feedforward neural networks or even standard RNNs, LSTMs are explicitly designed to learn and remember long-term dependencies in sequential data while mitigating the common problems of vanishing and exploding gradients. In the context of PQD classification, the feature vector can be treated as a sequence of data points, and the LSTM's architecture is perfectly suited to analyze the temporal relationships and patterns within this sequence to make an informed decision. The LSTM model is trained on a large and diverse dataset of simulated PQD signals, which includes a comprehensive set of 18 distinct disturbance types. This set is meticulously designed to cover all major categories of PQDs as defined by the IEEE Std. 1159, including not only single, isolated events like pure voltage sags, swells, harmonics, and flicker, but also a critical and challenging array of combined or hybrid disturbances, such as a sag with harmonics or a swell with flicker. Furthermore, the "normal" or undisturbed sinusoidal condition is included as its own class, allowing the classifier to distinguish between a healthy system and one experiencing any form of anomaly. This comprehensive training dataset ensures that the model is robust and generalizes well to a wide variety of real-world scenarios.

The final and most crucial stage is the rigorous evaluation and validation of the proposed framework. The authors conduct a series of simulation experiments in the MATLAB/Simulink environment to test the performance of their GWOSMC-LSTM-WT-EMD (or simply, the proposed hybrid) model. The results are exceptionally compelling and provide strong empirical evidence of the framework's superiority. The trained LSTM model demonstrates a very high classification accuracy, successfully identifying and categorizing both isolated and combined PQDs with a high degree of precision. The paper explicitly notes that the model's performance is robust even in the presence of noise, which is a testament to the effectiveness of the feature extraction process in filtering out irrelevant information and focusing on the core discriminative characteristics of each disturbance. The use of the 28-dimensional feature vector, derived from the dual decomposition strategy, is shown to be a decisive factor in the model's success, as it provides the LSTM with a richer and more nuanced representation of the input signal than a simpler, single-method approach would.

In conclusion, this research by Shahabadi et al. makes a significant and practical contribution to the field of power quality monitoring. By proposing and validating a novel hybrid framework that integrates Wavelet Transform, Empirical Mode Decomposition, and a Long Short-Term Memory neural network, the authors have developed a powerful tool for the accurate and robust classification of a comprehensive set of power quality disturbances. The framework's ability to handle the complexities of combined events and its demonstrated high accuracy in simulations position it as a highly promising solution for real-world power system applications. The methodology provides a clear and effective blueprint for leveraging advanced signal processing and deep learning to solve complex engineering problems, and its success suggests that this approach could be a cornerstone for the next generation of intelligent power quality monitoring and diagnostic systems. The work not only advances the state-of-the-art in PQD classification but also offers a reliable and scalable solution that can enhance the resilience, reliability, and overall health of modern and future power grids.

Keywords: Power Quality Disturbance, Wavelet Transform, Empirical Mode Decomposition, LSTM Neural Network

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