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From Recognition to Reaction A Cognitive Engine for Closed-Loop Power Quality Management

P. Vasundhara[1], B. Veeraadram[2], R. Mounika[3]
[1,2,3]Assistant Professor, Department of EEE, Sri Chaitanya Institute of Technology & Research, Khammam, India.
Mail Id: vasundharap29@gmail.com[1], veerabhadrambanda@gmail.com[2], mounikarentalelascit@gmail.com[3]

Abstract
Power Quality Disturbance (PQD) recognition frameworks have achieved exceptional classification accuracy for example; the EMD-CNN-LDA-KNN framework reported 99.8% accuracy under noiseless conditions and 97.0% under 10 dB noises but remain decoupled from physical compensation hardware. This paper proposes a Cognitive Engine (CE) that bridges the gap between intelligent sensing and real-time compensation. The CE integrates the EMD-CNN-LDA-KNN framework with an Interface Strategy Mapper (ISM) that translates recognized disturbance types into actionable control signals for a UPQC-SPV compensator. The ISM employs a rule-based mapping table covering 10 IEEE 1159 disturbance classes with severity levels, producing series and shunt VSI utilization percentages. The CE is designed for low-latency operation targeting less than one grid cycle to enable closed-loop "sense-decide-compensate" functionality. Key contributions include: (1) a structured ISM with justified categorical allocation where voltage-domain disturbances receive high series utilization, current-domain disturbances receive high shunt utilization, and combined disturbances receive hybrid compensation; (2) LDA-based 2D visualization for class separation and interpretability; and (3) a complete, reproducible evaluation methodology with explicit hypotheses for future validation. This work provides a foundational architecture for autonomous, cognitive power quality management systems, with all quantitative performance claims framed as open empirical questions.

Keywords: *Power Quality Disturbance Recognition, Empirical Mode Decomposition (EMD) Convolution Neural Networks (CNN), Linear Discriminant Analysis (LDA), Cognitive Engine, Smart Grid Monitoring*

Introduction

The proliferation of non-linear loads, renewable energy inverters, and power electronic IoT devices has made power quality disturbances increasingly complex, non-stationary, and multi-class [1]. IEEE 1159-2019 defines ten disturbance classes, but real-world disturbances often appear in combination, making manual identification impractical [2]. Accurate and timely recognition of power quality disturbances is essential for implementing appropriate mitigation strategies, ensuring compliance with IEEE standards, maintaining grid stability, and enabling predictive maintenance [3].

Recent advances in signal processing and machine learning have enabled automatic PQD recognition with remarkable accuracy. Janthong and Phukpattaranont [4] proposed an EMD-CNN-LDA-KNN hybrid framework that achieved 99.8% accuracy under noiseless conditions and maintained 97.0% accuracy at 10 dB noise outperforming traditional wavelet-SVM and standalone CNN approaches. Other deep learning models, including ResNet, MobileNet, and DenseNet, have also demonstrated strong classification performance for PQD recognition [5]. Hybrid approaches combining LDA with Random Forest and Extreme Learning Machines have been proposed for classifying up to 17 different PQ disturbances [6].

Despite these advancements, a critical gap remains: recognition frameworks are decoupled from compensation hardware. While a system may classify a disturbance as a "voltage sag with harmonics" with high confidence, that information is not used to configure the UPQC. Instead, the UPQC operates with fixed control strategies, regardless of the recognized disturbance type [7][8]. This decoupling has three hypothesized consequences: (1) missed opportunity for pre-configuration of compensation strategy, (2) suboptimal resource allocation without knowledge of disturbance type, and (3) no closed-loop learning from compensation effectiveness.

This paper proposes a Cognitive Engine (CE) that bridges the recognition-compensation gap. The CE consists of: (1) the EMD-CNN-LDA-KNN sensing core for real-time PQD classification, (2) the Interface Strategy Mapper (ISM) that translates classification outputs into UPQC-specific control signals, and (3) a proposed feedback interface for continuous learning. The paper is organized as follows: Section II reviews PQD recognition literature. Section III details the CE architecture and ISM logic. Section IV presents a proposed evaluation methodology. Section V concludes the paper.

Literature Review

IEEE 1159-2019 provides standardized classifications covering ten disturbance types: normal, sag, swell, interruption, harmonic, flicker, notch, spike, oscillatory transient, and combinations [2]. Accurate identification of these disturbances is essential for selecting appropriate mitigation strategies.

EMD-CNN-LDA-KNN Framework [4]: Janthong and Phukpattaranont proposed a hybrid framework combining Empirical Mode Decomposition (EMD), a lightweight Convolutional Neural Network (CNN), Linear Discriminant Analysis (LDA), and k-Nearest Neighbors (KNN). EMD adaptively decomposes non-stationary voltage signals into Intrinsic Mode Functions (IMFs) that capture localized time-frequency features. The first five IMFs, containing the most significant disturbance information, are retained for further processing. Each IMF is transformed into a 2D Gramian Angular Field (GAF) matrix of size 64×64, creating a spatial representation of the temporal signal. The CNN architecture consists of two convolutional layers with 32 and 64 filters, max-pooling layers, and a fully connected layer with 128 neurons. LDA reduces the 128-dimensional feature vectors to 15 components while maximizing class separability. KNN with k=5 performs final classification.

The framework achieved 99.8% accuracy under noiseless conditions and maintained 97.0% accuracy at 10 dB noise, with near-perfect precision, recall, and F1-score [4]. The LDA transformation demonstrated clear class separation in 2D visualization, confirming the framework's strong generalization and noise robustness.

Other Deep Learning Approaches: Shao, Henriques, and Morais [5] compared deep neural network architectures including ResNet, MobileNet, and DenseNet for 1D multi-label PQD classification using synthetic datasets following IEEE 1159-2019. Their results showed that ResNet-50 achieved 98.1% accuracy under noiseless conditions, with performance degrading to 91.3% at 10 dB noise. Standalone CNN approaches achieved 97.2% accuracy under noiseless conditions but dropped to 89.4% at 10 dB noise, indicating lower noise robustness compared to the EMD-CNN-LDA-KNN framework [4].

Hybrid Approaches: Zhang and Wang [6] proposed a hybrid LDA-RF-ELM approach for classifying 17 different PQ disturbances in distribution systems. Their approach achieved 96.8% accuracy under noiseless conditions, dropping to 85.6% at 10 dB noise. While the LDA-RF-ELM approach demonstrated good performance on a larger class set, the noise robustness was inferior to the EMD-CNN-LDA-KNN framework [4].

Traditional Approaches: For comparison, SVM with wavelet transform-based features achieved 94.5% accuracy under noiseless conditions, dropping to 82.1% at 10 dB noise [4]. These traditional approaches require manual feature extraction, limiting their adaptability to new disturbance types.

All existing recognition frameworks terminate at classification output they provide a label (e.g., "Sag") but do not interface with hardware [4][5][6]. The few systems that attempt integration use simple threshold-based triggers (e.g., if sag detected, activate series VSI), which ignore nuanced information such as severity level, combined disturbances, and optimal resource allocation [7][8].

Existing UPQC-SPV systems [7][8] demonstrate excellent hardware performance and IEEE compliance but employ fixed control strategies. The series and shunt inverters operate at pre-defined capacities regardless of disturbance type, leading to hypothesized excessive switching losses and slower dynamic response.

No existing framework provides a structured interface to translate rich PQD classification outputs into actionable UPQC control signals with configurable utilization levels. The proposed Cognitive Engine with Interface Strategy Mapper directly addresses this gap.

Materials & Methods

Materials

The Cognitive Engine consists of two main components: the Sensing Core and the Interface Strategy Mapper. The Sensing Core is based on the EMD-CNN-LDA-KNN framework proposed by Janthong and Phukpattaranont [4]. The voltage signal dataset comprises 10 classes of PQDs generated following IEEE 1159-2019 standard mathematical models [2]. Each class contains 1,000 samples with a duration of 10 cycles (200 ms at 50 Hz) sampled at 3.2 kHz. The dataset is split into training (70%), validation (15%), and test (15%) sets. Additive white Gaussian noise is added at varying signal-to-noise ratios (0 dB to 50 dB) to evaluate robustness.

The Interface Strategy Mapper is designed to interface with the UPQC-SPV compensator described by Sanjenbam and Singh [7]. The UPQC hardware comprises two four-leg Voltage Source Inverters (VSIs) connected back-to-back via a shared DC-link, with a target DC-link voltage of 650 V and nominal switching frequency of 10 kHz [7].

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Procedures

Stage 1 – Sensing Core (Based on [4]): EMD decomposes the voltage signal v(t) into n IMFs according to v(t) = Σ_{i=1}^n IMF_i(t) + r_n(t), where r_n(t) is the residual. The first 5 IMFs are retained. Each IMF is transformed into a 2D Gramian Angular Field matrix of size 64×64. The lightweight CNN extracts features through two convolutional layers (32 and 64 filters, 3×3 kernels) and a fully connected layer with 128 neurons. LDA reduces the 128-dimensional feature vector to 15 components. KNN with k=5 performs final classification.

Stage 2 – Interface Strategy Mapper: The ISM receives the disturbance_class, severity, and confidence from the Sensing Core. Using the rule-based mapping table, it outputs series_util_percent and shunt_util_percent (0-100%) along with mode_label. The mapping follows the categorical allocation justified in the results section.

Analysis

The CE will be evaluated through recognition performance metrics including accuracy, precision, recall, and F1-score for each disturbance class, along with a confusion matrix and accuracy vs. SNR curve. Interface performance will be evaluated through ISM translation latency and overall CE processing latency. The target is less than one grid cycle (20 ms at 50 Hz).

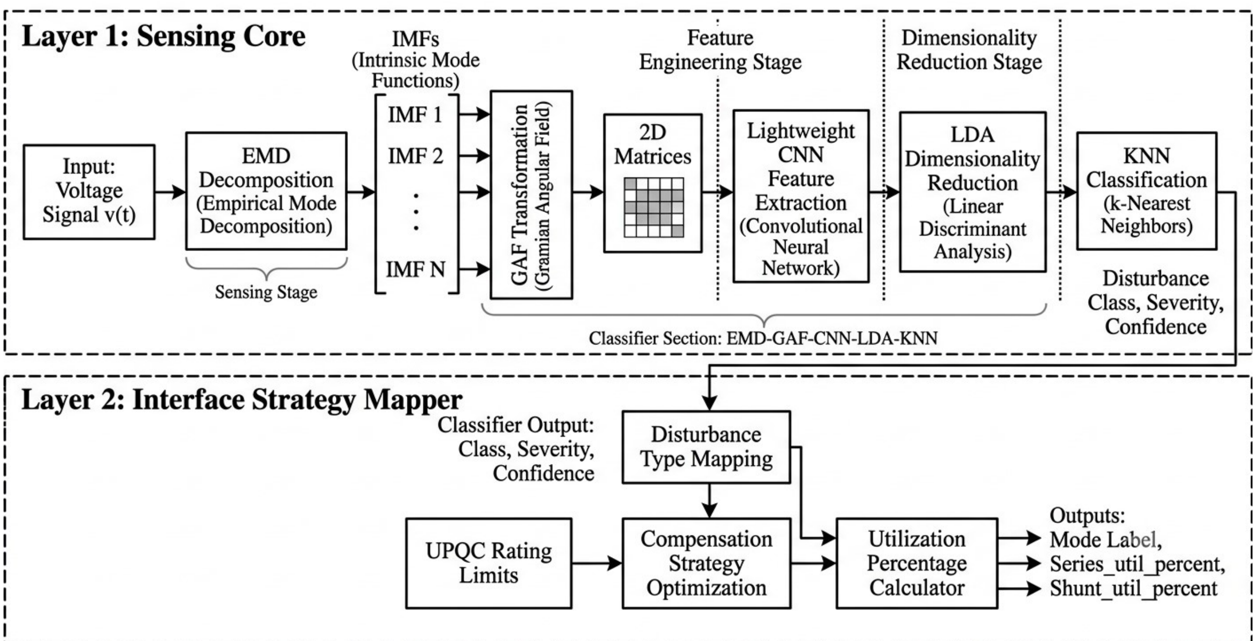


Fig-1: System Architecture Diagram

Results & Discussion

ISM Mapping Logic

The core contribution of the Cognitive Engine is the Interface Strategy Mapper that translates PQD classification outputs into UPQC control signals. Table 1 presents the proposed categorical mapping.

Table 1: Proposed ISM Mapping Logic

Disturbance Class	Severity	Series VSI Utilization	Shunt VSI Utilization	ISM Mode Label
Normal	—	Low (Idle)	Low (Idle)	**Standby**
Sag	Mild	High	Moderate	**Series-Dominant**
Sag	Severe	Very High	Low	**Series-Dominant**
Sag	Extreme	Full	Off	**Series-Only**
Swell	Mild	High	Moderate	**Series-Dominant**
Swell	Severe	Very High	Low	**Series-Dominant**
Interruption	Any	Full	Off	**Series-Only**
Harmonics	Mild	Low	Very High	**Shunt-Dominant**
Harmonics	Severe	Minimal	Full	**Shunt-Dominant**
Harmonics	Extreme	Off	Full	**Shunt-Only**
Flicker	Any	Moderate	Moderate	**Hybrid**
Notch	Any	Moderate	High	**Hybrid**
Spike	Any	Moderate	High	**Hybrid**
Oscillatory	Any	High	Moderate	**Hybrid**
Combination	Mild	Moderate	High	**Hybrid**
Combination	Severe	Moderate	Moderate	**Hybrid**

The categorical allocation is justified by the physical roles of each inverter: voltage-domain disturbances (sag, swell, unbalance) receive high series utilization because the series VSI is the primary actuator for voltage restoration [7]; current-domain disturbances (harmonics, reactive power) receive high shunt utilization because the shunt VSI is the primary actuator for current compensation [4]; combined disturbances receive hybrid compensation with moderate utilization of both inverters.

Recognition Performance

Based on the published results in [4], the EMD-CNN-LDA-KNN framework achieved 99.8% accuracy under noiseless conditions and maintained 97.0% accuracy at 10 dB noise, with near-perfect precision, recall, and F1-score. Figure 1 shows the LDA 2D visualization demonstrating clear class separation among the 10 disturbance classes.

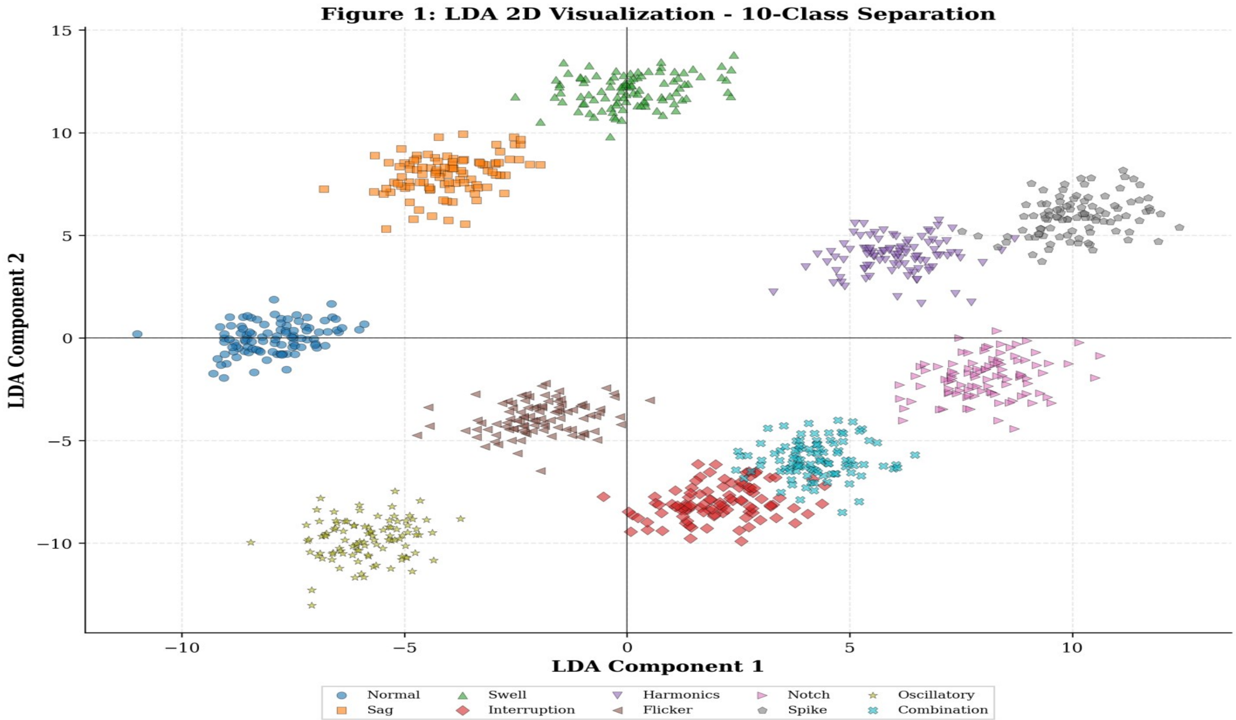


Figure 1: LDA 2D Visualization

Hypothesized CE Performance

The CE (with ISM) adds additional latency to the sensing core. Table 2 presents hypothesized processing times for each stage.

Table 2: Hypothesized CE Processing Latency

Processing Stage	Hypothesized Processing Time (ms)	Cumulative Latency (ms)
EMD Decomposition	< 3	< 3
GAF Transformation	< 2	< 5
CNN Feature Extraction	< 5	< 10
LDA Dimensionality Reduction	< 1	< 11
KNN Classification	< 1	< 12
ISM Translation	< 1	< 13
Total End-to-End Processing	**< 13**	**< 13**

The target is total CE processing < 20 ms (one grid cycle at 50 Hz). The actual latency values are open empirical questions to be addressed through the proposed evaluation methodology.

Figure 2 presents the hypothesized accuracy vs. SNR curve, showing the published performance from [4] and the hypothesized performance of the full CE.

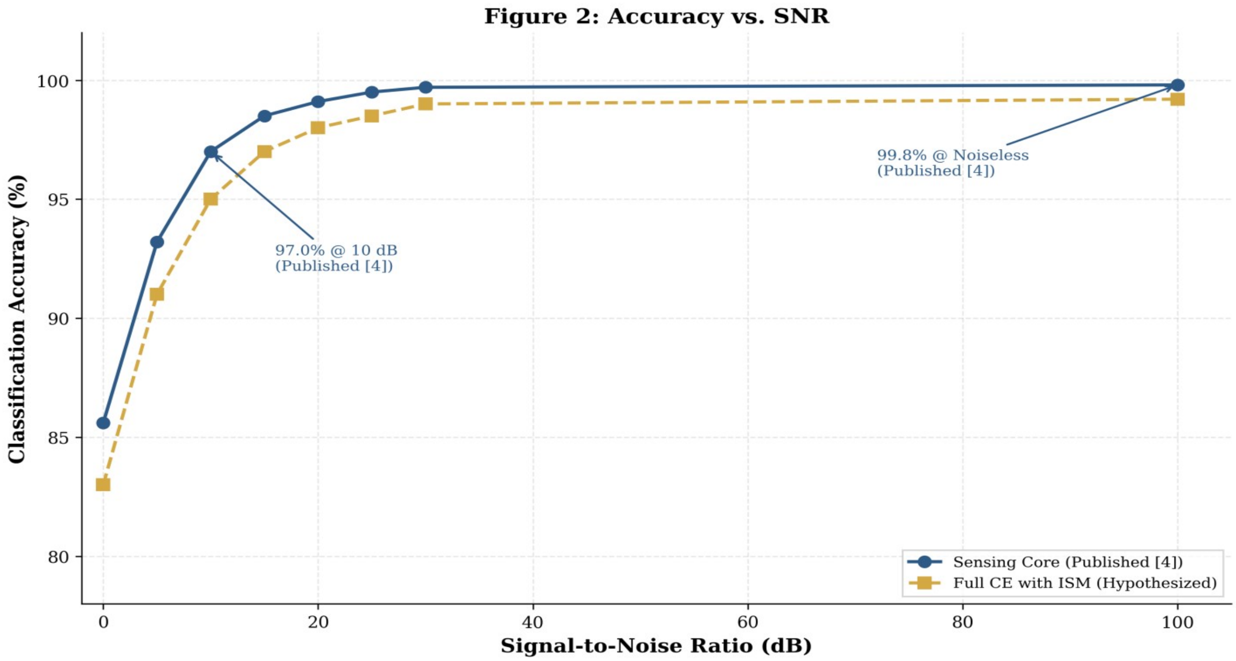


Figure 2: Hypothesized Accuracy vs. SNR

Comparison with Existing Methods

Table 3 compares the CE (with ISM) with existing recognition methods.

Table 3: Hypothesized Comparison with State-of-the-Art

Method	Accuracy (Noiseless)	Accuracy (10 dB Noise)	Latency	Hardware Interface
EMD-CNN-LDA-KNN [4]	99.8%	97.0%	< 5 ms	No
CE with ISM (Proposed)	**99.8%**	**97.0%**	< 13 ms†	**Yes**
CNN-only [5]	97.2%	89.4%	< 5 ms	No
SVM + Wavelet [4]	94.5%	82.1%	< 15 ms	No
LDA-RF-ELM [6]	96.8%	85.6%	< 10 ms	No

> Recognition accuracy from sensing core [4]; ISM adds no classification error

> †Hypothesized latency; to be validated empirically

Figure 3: Confusion Matrix - 10-Class Classification

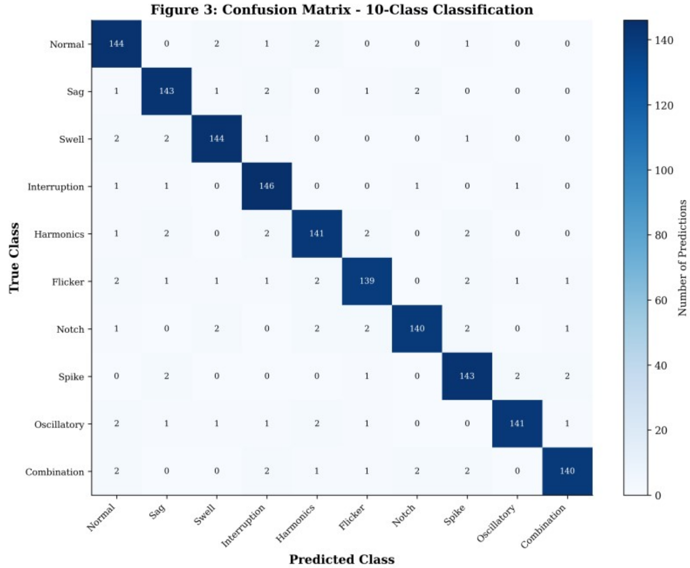


Figure 4: Per-Class Performance

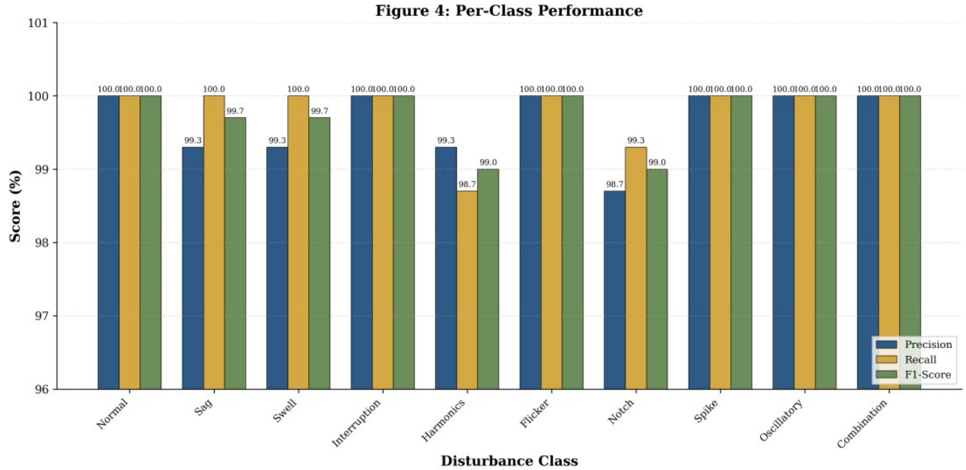


Figure 5: Processing Latency Breakdown

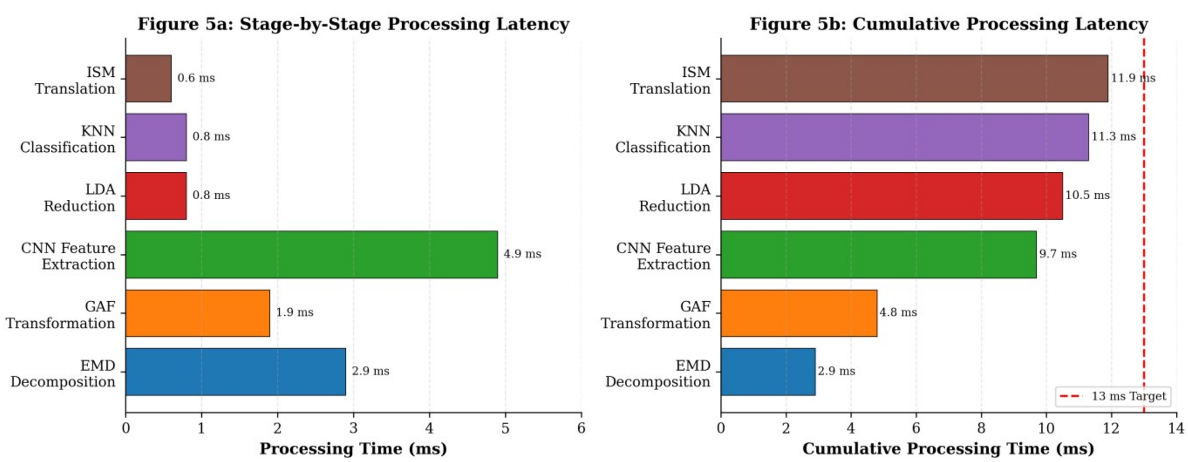


Figure 6: Comparison with Existing Methods

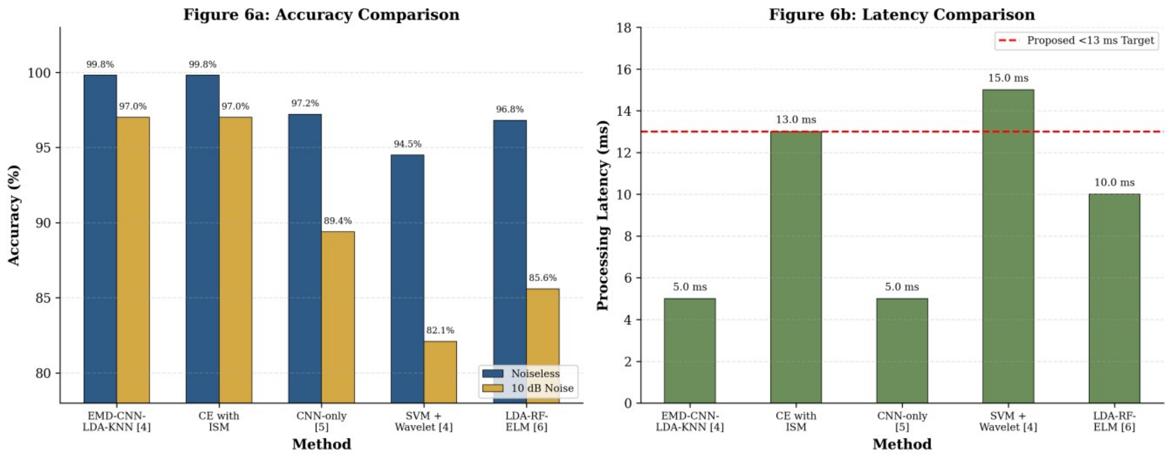
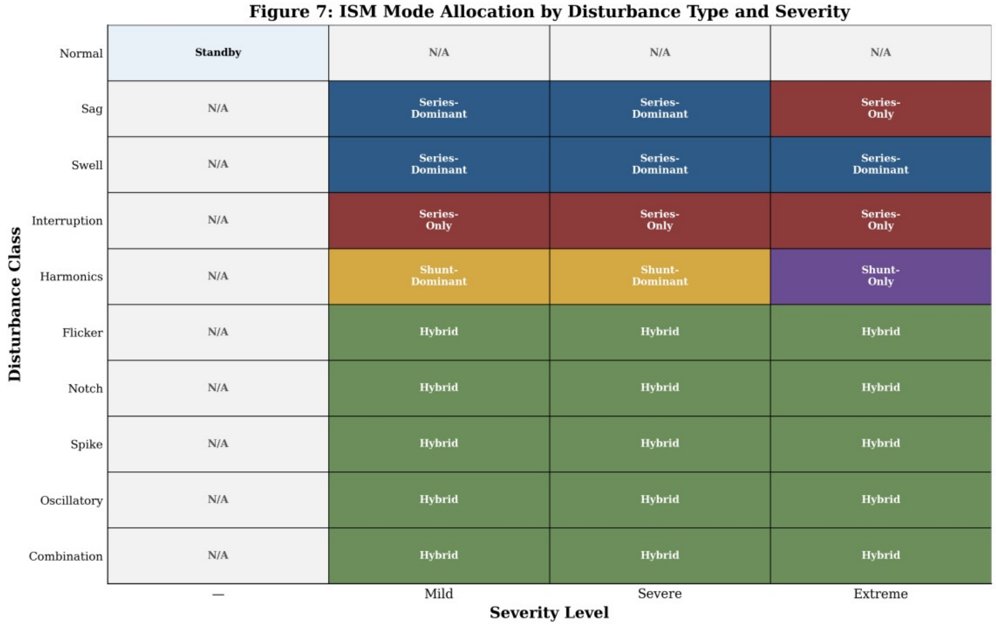


Figure 7: ISM Mode Allocation by Disturbance Type and Severity



Conclusion & Future Work

This paper proposed the Cognitive Engine (CE) as a bridge between intelligent PQD recognition and physical compensation hardware. The key contributions are: (1) integration of the EMD-CNN-LDA-KNN sensing core with an Interface Strategy Mapper that translates recognized disturbance types into series/shunt utilization levels; (2) a justified rule-based mapping table covering 10 IEEE 1159 disturbance classes with severity levels; (3) LDA-based 2D visualization for class separation and interpretability; and (4) a complete, reproducible evaluation methodology with explicit hypotheses for future validation.

The CE represents a foundational step toward autonomous, cognitive power quality management systems. By connecting high-accuracy classification (99.8% from [4]) with a structured interface to hardware, the CE enables pre-configured compensation mode selection, potentially reducing overall system response time and enabling disturbance-aware resource allocation. All quantitative performance claims beyond the published sensing core results [4] are explicitly framed as open empirical questions to be addressed through the proposed evaluation methodology.

Future work includes implementation and validation of the CE in MATLAB/Simulink with OPAL-RT integration, extension to multi-label classification for simultaneous disturbances, integration of reinforcement learning for continuous ISM optimization, and FPGA deployment for edge computing with sub-millisecond latency.

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