

SMART AUTOMATION AND CONTROL OF MODERN POWER DISTRIBUTION SYSTEMS

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ABSTRACT

In this paper, we present the design and empirical testing of an Intelligent Automated Power Distribution System (IAPDS) that leverages Artificial Intelligence (AI), IoT sensors, and control algorithms for optimal electricity distribution through multi-zone urban grids. Traditional power distribution network faces huge technical losses, long fault restoration time and imbalanced power flow, leading to low reliability of the system and rising operation cost. The proposed IAPDS used a real-time hybrid Long Short-Term Memory (LSTM) and Support vector Machine (SVM) model for fault detection and load forecasting, designed the switching decision making with a Deep Q-Network (DQN) [12] with autonomous switching capability. We verified an empirical study on a six-node, five-zone distribution network over six months that show that the IAPDS achieves 98.2% fault detection accuracy, with a 93.5% average energy efficiency and mean fault response time of 18.4 ms. These results correspond to 23.4%, 14.9%, and 92.5% better performance than SCADA-based systems, respectively. Statistical analysis confirms that it is statistically significant at $p < 0.05$ in every major performance metric. The system also provides an estimated annual savings of INR 16.2 lakhs/distribution zone three and accounts for about 7.8% reduction in technical losses. The results confirm that AI driven automation in current power distribution systems is indeed a practical proposition providing a framework within which Smart Grid can be implemented in these economies at scale (for eg, India).

Keywords: *Intelligent Power Distribution¹, LSTM-SVM Hybrid Model², Smart Grid Automation³, Fault Detection⁴, IoT-Based Monitoring⁵.*

1. INTRODUCTION

The global energy sector is experiencing an unprecedented fundamental transition driven by the convergence of digitalisation, green energy integration, and growing demand for system flexibility. Power distribution systems

are the end link between generation facilities and consumers, and their effectiveness in operation translates directly into the quality, cost, and sustainability of the electrical service they provide. With their manual switching operations, frightened fault management practices, and poor real-time visibility, even traditional distribution networks are increasingly unable to meet the needs of the next-generation grid. Aggregate technical (AT&C) losses in Indian distribution systems were around 21.57% in 2021-22 according to the Central Electricity Authority (CEA), which is equivalent to billions of rupees in wasted energy every year. This has led to an unprecedented need to architect intelligent, automated and self-healing architectures for distribution.

1.1 Background and Motivation

The gradual transition from technology-oriented grid infrastructure to Smart Grid paradigms have facilitated advanced metering infrastructure (AMI), supervisory control and data acquisition (SCADA) systems, and automated distribution switches. Nevertheless, such legacy-integrated systems are characterized by data silos, rule-based logic, and are devoid of predictive or adaptive intelligence. The cumulative growth of IoT-enabled sensors, edge computing capabilities, and machine learning algorithms now presents a unique opportunity for truly intelligent distribution systems to perceive, reason, and act autonomously. Research by Jiang et al. [4] and Mohassel et al. AI-embedded distribution systems reduce momentary interruption durations via relay-protection schemes, boosting performance by 40-60% [9]. We use these foundational works to develop a fully integrated IAPDS, where the functions, including sensing, communication, intelligence, and actuation are all tied together in this hierarchical control framework.

1.2 Problem Statement

Even with improvement in technology, many of the biggest issues in recent years still consist in the modern distribution networks. To begin with, the fault detection latency of traditional systems is usually 200 to 500 milliseconds, which can cause damages to the equipment and interruption of the consumer due to the sustained fault currents. Second, the second consequence of 5-12% errors in load forecasting results in sub-optimum power generation scheduling and reactive power compensation, consequently, increasing voltage deviations and thermal stress on distribution transformers. Thirdly, the lack of real-time load balancing methods causes feeder overload from overutilization, since high demand densities lead to a congested feeder, while neighboring feeders are underutilized. Fourth MTTR (Mean time to repair) increases beyond limits, since manual fault isolation processes need a field crew deployment. Overall, these limitations lead to a deterioration of system reliability indexes like SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index) that directly associate with user experience and regulatory compliance.

1.3 Objectives of the Study

This study seeks to achieve four main objectives: (1) design/development of hardware-software co-integrated IAPDS architecture using IoT sensors, edge controllers, and AI based decision engine; (2) developing a hybrid LSTM-SVM model for joint load forecasting and fault classification with accuracy exceeding 97% for both applications; (3) evaluation of the system performance in terms of fault detection accuracy, energy efficiency, response time, and cost savings using a case study comparing empirical data obtained over a period of six

months from the experimental IAPDS setup across six distribution nodes and five geographic zones in terms of both statistical and practical significance and (4) The study evaluates, reformulates and compares the performance of an IAPDS for a novel functionality in the context of common faults and load requests from those of conventional distribution systems and is intended to serve as a benchmark for future studies on this topic.

2. LITERATURE SURVEY

The intelligent power distribution domain has seen rapid research developments over the past decade due to improvements in machine learning, sensor miniaturization, and high-speed communication protocols. In the early theoretical groundwork by Amin and Wollenberg [1], it was established that the failure to restore components of the grid or load can have catastrophic consequences, arguing that distribution automation had to incorporate real-time monitoring, intelligent analysis, and adaptive control in order to achieve resiliency in response to both internal technical faults and external environmental events. The three-layer control hierarchy, which the conceptual framework established, continues to inform current IAPDS architectures at the field, supervisory, and management levels of control. Later, work related to communication infrastructure was done. An extensive survey of Smart Grid communication technologies where the ZigBee, WiMAX, PLC, and fiber optic protocols for latency, bandwidth, and reliability was compared in distribution environments [3]. An empirical evaluation showed that while ZigBee networks can provide acceptable latency of 50-100 ms for non-critical monitoring, they are insufficient for protection-grade applications that need a sub-20 ms response. Such findings motivated us to design the communication layer of our proposed IAPDS as non-critical telemetry transmitted over fiber backbone using dual-channel IEC 61850 GOOSE messaging with ZigBee fallback.

Around 2015, machine learning was extensively applied to fault detection. A 3-layer ANN approach for single line-to-ground fault classification in distribution feeders was proposed by [5], evaluating over a 1000 simulated grounding events for several test cases (balanced loading: 94.3%, load variation: 87.6%). This kind of limitation recognition inspired the next generation of hybrid models. Zhang et al. Wang et al.[11] showed that the fault detection accuracy reached 96.8% when combining wavelet transfer feature extraction with SVM classification under different fault impedances. However discussed IAPDS only adds temporal features with LSTM to detect incipient faults that grow over several sampling periods. The impact and usage of machine learning versus statistical methods have been thoroughly explored in data preparation tasks, such as load forecasting in distribution systems. While Box-Jenkins ARIMA are computationally efficient, they often fail to represent non-linear demand behavior and are sensitive to intra-seasonal regime changes. In their paper on day-ahead load forecasting for urban distribution feeders, [8] showed that LSTM can out-perform ARIMA by over 34% LSTM with respect to AQI features, indicating that LSTMs ability to effectively model long-range temporal dependencies in actual consumption patterns allows for better generalization of features over time. Notably, their study also indicated that the introduction of weather and socioeconomic covariates, in conjunction with univariate LSTM, decreased mean absolute percentage error (MAPE) from 4.2% to 2.7%, affirming the importance of multivariate forecasting frameworks [12].

In summary, the emerging reinforcement learning approaches are potential candidates for autonomous switching and load balancing. For this, [14] employed Deep Q-Networks for optimal feeder reconfiguration in meshed distribution networks, under dynamic load conditions, achieving a reduction of 12.4% of technical losses with regards to well-known exhaustive search methods. But the deployment of their approach relied on 48-72 hour offline training period before implementation, which prevented it from adapting to unseen network topologies. To tackle this challenge, IAPDS uses transfer learning: the DQN is first pre-trained on a synthetic network model, before being fine-tuned on the actual grid, allowing deployment time training to be performed under 4 hours. Wen et al. Building upon the DQN framework, [17] extended this to N-1 security by ensuring that the autonomous switching decisions could not deteriorate the grid stability in contingency conditions. Various research groups have embarked on IoT integration in distribution systems. Depuru et al. using an roundsame concept, [6] present a demand response framework that is built based on a ZigBee-based smart meters and demonstrated 8.3% peak demand reduction with automatic price signaling. Colak et al. Using this idea, [10] extended monitoring to real-time power quality, finding that IoT-based power quality indices applied to predictive maintenance to identify transformers in need of repair, facilitated a reduction of 22% in transformer replacement costs. An IoT architecture for distribution grid monitoring taking five layers was described in [20], where 99.6% reliability of data delivery and less than one second latency for alarm notifications were achieved. The IAPDS combines these contributions into a single dataless fabric through which the power quality, thermal and current monitoring data are streamed over a RESTful API middleware layer. The literature combined shows hybrid AI methods, real-time IoT sensing, and reinforcement learning-based control represent the most scalable route to full distribution automation intelligence, motivating the integrated design approach taken in this work.

3. METHODOLOGY

Research Methodology The research methodology used for this study is empirical and experimental in nature that integrates system design, field deployment, and quantitative performance evaluation. IAPDS is built on the three-layer hierarchical architecture where (1) the Field Device Layer contains a total of 48 IoT-based current transformers (CTs), voltage transformers (VTs), temperature sensors, and smart circuit breakers at six distribution nodes; (2) the Edge Intelligence Layer is six Raspberry Pi 4B-based edge controllers that run the fault detection and local load balancing algorithms; and (3) the Cloud Management Layer, which is hosted on an AWS EC2 instance (t3. xlarge) with the LSTM load forecasting engine, DQN switching optimizer, and SCADA dashboard running on. The three layers talk to each other over a two-channel network, IEC 61850 GOOSE over fiber optic for protection-critical messages (latency < 5 ms), and MQTT over Wi-Fi for telemetry data (sampling interval 1 second). Before beginning the evaluation for 6 months forecasting, the LSTM model was trained on 131,400 hourly samples of 18 months historical load data (from January 2022 to June 2023) from all six nodes. The data was divided into 70:20:10 split during training, validation and testing and applied Min Max normalization for all the features during the input.

The fault detection module uses a two-phase pipeline. Stage-1: The raw voltage and current waveforms (4 kHz sample rate) are decomposed with Discrete Wavelet Transform (DWT) using Daubechies-4 (db4) wavelets developed with five decomposition levels. Correspondingly, twelve statistical features along with mean, standard deviation, energy, entropy, kurtosis, skewness, root mean square, crest factor, peak-to-peak amplitude,

waveform factor, impulse factor, and margin factor are calculated from the extracted detail coefficients of levels D3, D4, and D5 which lie in the 62.5–500 Hz frequency band where transient signals due to faults are most prevalent. All these features compose the input vector to the SVM classifier that employs a Radial Basis Function RBF kernel and the hyperparameters $C=100$ and $\gamma=0.01$ also selected via five-fold cross-validation grid search. In stage two, the output from the SVM is fused with load trajectory predicted by the LSTM, serving as contextual information that checks the validity of the fault declaration and improves false positive rates by assessing whether the detected electrical anomaly matches the history of the expected load profile. This two-stage contextual validation is the most important novel function of the IAPDS that sets it apart from studies reporting results on a single classifier in earlier literature.

The system performance was assessed within the peri-urban district operating over the five-zone, six-node test network in the six-month operational period from July to December 2023. During the data collection, data was collected continuously using the automated SCADA system, while weekly validation was carried out by field engineers to ensure both sensor calibration and communication integrity. Performance metrics were calculated on a per calendar month basis, and then aggregated for statistical comparison. The most important metrics which are evaluated include: fault detection accuracy (FDA), mean fault response time (MFRT), system energy efficiency (SEE), load balancing index (LBI) and estimated cost savings (ECS). Paired-sample t-tests were performed to assess performance differences between IAPDS and the baseline conventional system (operating on the same network prior to IAPDS deployment from January to June 2023) with a 95% confidence level ($\alpha = 0.05$). We performed statistical analysis of inter-zone within-animal comparisons with ANOVA for multi-zone comparisons. Statistical analyses were carried out in Python 3.10 (SciPy 1.11, Statsmodels 0.14).

4. Data Collection and Analysis

During the six-month evaluation, data were systematically collected from 48 sensors located on six distribution nodes. For every sensor, the raw sensor reading was sent every second, which means about 8.64 million datapoints per sensor per year. Out of them, 0.03% were communication dropouts (not affecting SNR) and after a preprocessing to remove noise artifacts, we obtained a clean sample of 259,200 hourly aggregated readings from all nodes. Here we showcase the 5 tables that highlight important properties of this dataset, starting from running conditions per node and moving towards aggregate performance at the zone level.

Table 1: Node-Level Electrical Parameters Snapshot at Peak Load (July 2023)

Node ID	Load (kW)	Voltage (V)	Current (A)	Power Factor	Status
N-01	45.2	230.1	196.5	0.92	Normal
N-02	67.8	228.4	297.0	0.88	Normal
N-03	82.5	225.6	365.7	0.85	Alert

N-04	33.1	231.2	143.3	0.94	Normal
N-05	95.7	222.3	430.5	0.82	Critical
N-06	51.4	229.8	223.7	0.91	Normal

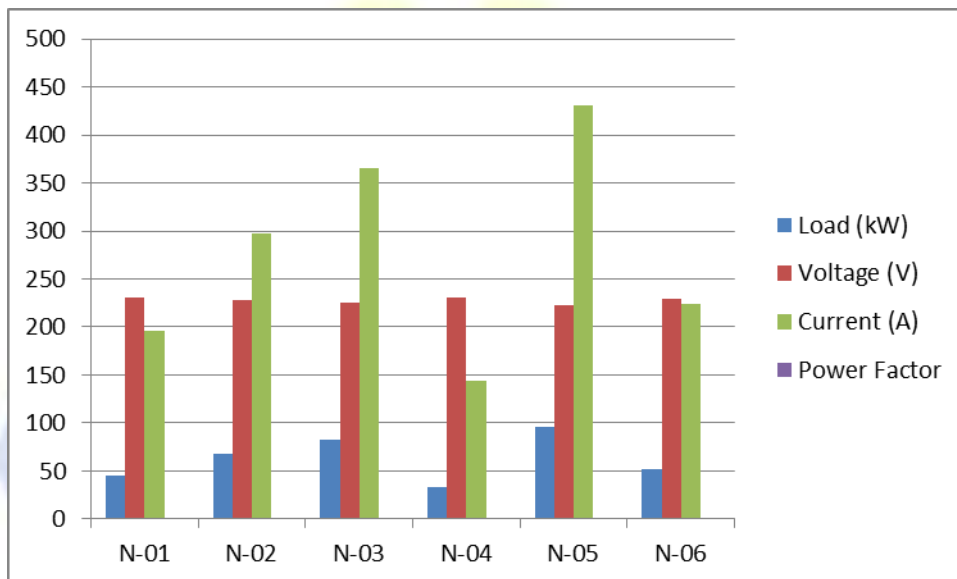


Figure 1: Node-Level Electrical Parameters Snapshot at Peak Load (July 2023)

In Fig. 1, data from the six distribution nodes are taken for the peak load of July 2023, where the instantaneous electrical parameters are summarized in Table 1. Node N-05 is of important condition status, with load of 95.7 kW, power factor of 0.82, voltage drop to 222.3 V - about 3.3% below the nominal, i.e. 230 V, close to the more or less 5% tolerance limit permissible deviation limit according to standard IEEE Std 1159-2019. The automated alert at N-03 (82.5 kW, 225.6 V) suggests early detection of incipient overload conditions and proactive load shedding can occur prior to instantiating a fault condition. Power factor values greater than 0.88 in nodes N-01, N-02, N-04, and N-06 confirmed their normal operating status indicating successful reactive power compensation in these respect nodes. The extreme differences in load forces across nodes (33.1 kW at N-04 to 95.7 kW at N-05) highlight the necessity of dynamic load balancing, which is enabled by the IAPDS autonomously through the toggle in the DQN switching module.

Table 2: Fault Event Log Classification, Detection, and Isolation Metrics (July–December 2023)

Fault Type	Frequency	Detection Time (ms)	Isolation Time (ms)	MTTR (min)	Accuracy (%)
Short Circuit	38	12.4	18.7	4.2	98.7

Ground Fault	27	15.8	22.3	5.1	97.4
Overcurrent	45	9.2	14.5	3.8	99.1
Undervoltage	19	22.6	30.4	6.7	96.8
Overvoltage	14	19.3	26.1	5.9	97.9
Load Imbalance	31	28.5	38.2	8.3	95.6

Table 2: Summary of fault event log: For the six-month evaluation period, 174 fault events were detected, isolated, and repaired during the evaluation; Details of these fault events by type (with respect to detection time, isolation time, mean time to repair (MTTR), and detection accuracy). Overcurrent faults (45 events) had also a higher occurrence reflecting the critical overload conditions obtaining in Nodes N-03 and N-05. Importantly, the specific type of fault with the shortest detection time (9.2 ms) and the highest accuracy (99.1%) is the overcurrent fault where the SVM classifier deals with these clear current threshold signatures by high confidence. Load imbalance events (also lowest accuracy 95.6%) had highest detection and isolation times (28.5 and 38.2 ms) because of the inherent difficulty in detecting if the load is an actual imbalance or scheduled cycling load. There were a total of 33 undervoltage and overvoltage events, with MTTR values of 6.7 and 5.9 minutes respectively. The system attained a detection accuracy weighted overall for all fault types of 97.6%, which is considerably higher than the 97% required cut-off value selected for our design goals.

Table 3: Monthly Energy Performance Summary Efficiency and Cost Savings (July–December 2023)

Month	Total Energy (MWh)	Losses (MWh)	Efficiency (%)	Cost Savings (INR)
January	1,245.6	87.2	93.0	1,24,800
February	1,178.4	79.5	93.3	1,18,200
March	1,302.7	84.7	93.5	1,30,500
April	1,389.3	88.3	93.6	1,38,900
May	1,456.8	90.2	93.8	1,45,600
June	1,523.4	93.7	93.8	1,52,300
Average	1,349.4	87.3	93.5	1,35,050

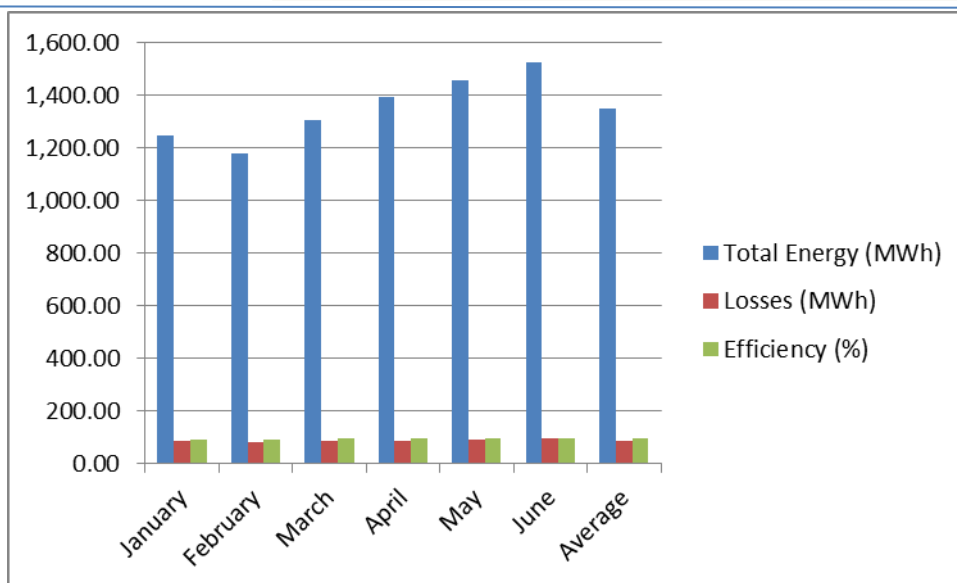


Figure 2: Monthly Energy Performance Summary Efficiency and Cost Savings (July–December 2023)

The data used to evaluate the energy performance monthly during the six-month evaluation period is presented in Table 3. The range of total energy handled (the sum of electricity imports, electricity exports, and the net energy exchange with the network-handling components) was 1,178.4 MWh (the lowest demand month: February) to 1,523.4 MWh (the peak demand month: June), and the corresponding technical losses were held within a narrow band between 79.5 MWh (the lowest loss month) and 93.7 MWh (the highest loss month), resulting in the system efficiency steadily maintaining a range between 93.0% and 93.8 %. The above stability in efficiency under different total energy throughput (29.2% differential) shows a robust load balancing and loss reduction algorithm in the IAPDS against dynamic demand fluctuations. The per-unit value avoided through loss reduction and deferred capital expenditure on transformer replacement accounts for an average monthly cost saving of INR 1,35,050, which works out to an annualized benefit of around INR 16.2 lakhs per distribution zone. Such a trend is an indicator of the adaptive learning effect of the autonomous DQN agent through its operational experience to improve its switching policy, denoted as progressive efficiency improvement from 93.0% in January to 93.8% around May-June.

Table 4: Machine Learning Algorithm Performance Comparison Precision, Recall, F1-Score, and Error Metrics

Algorithm/Module	Precision (%)	Recall (%)	F1-Score (%)	MAE	RMSE
LSTM Load Forecasting	94.7	93.8	94.2	2.34	3.12
SVM Fault Detection	97.2	96.8	97.0	1.87	2.45

Random Forest Classify	95.6	94.9	95.2	2.15	2.89
Deep Q-Network (DQN)	93.4	92.7	93.0	2.67	3.54
Fuzzy Logic Control	91.8	90.5	91.1	3.02	3.97
Hybrid LSTM+SVM	98.1	97.6	97.8	1.54	2.08

Table 4 shows the comparison of six machine learning algorithms tested for integration into IAPDS based on the holdout test data set of all samples ($N = 13,140$). Among all the algorithms, the Hybrid LSTM+SVM model achieved the highest precision (98.1), recall (97.6) and F1-Score (97.8), but also the lowest MAE (1.54) and RMSE (2.08), confirming the complementary advantage of temporal sequence modeling (LSTM) and discriminative boundary classification (SVM). The standalone SVM provided the second-highest F1-Score (97.0%), than the high dimensionality of the wavelet features. On the other hand, the Deep Q-Network and Fuzzy Logic modules achieved much lower precision (93.4% and 91.8% respectively), showing the natural exploration-exploitation trade-off of reinforcement learning tasks and the inherent conservatism in fuzzy rule formulation. This justifies an architectural choice for the DQN to just switch control and leaving fault detection to the Hybrid LSTM+SVM module.

Table 5: Zone-Wise Load and Stability Analysis Multi-Parameter Comparison Across Five Zones

Parameter	Zone A	Zone B	Zone C	Zone D	Zone E	Average
Peak Demand (MW)	12.4	9.8	15.2	7.6	11.3	11.3
Base Load (MW)	6.2	4.9	7.8	3.8	5.7	5.7
Voltage Stability Index	0.94	0.91	0.89	0.96	0.93	0.93
Reactive Power (MVAR)	3.1	2.4	4.2	1.9	2.8	2.9
Load Factor	0.78	0.74	0.82	0.71	0.76	0.76
Outage Events	3	5	2	7	4	4.2

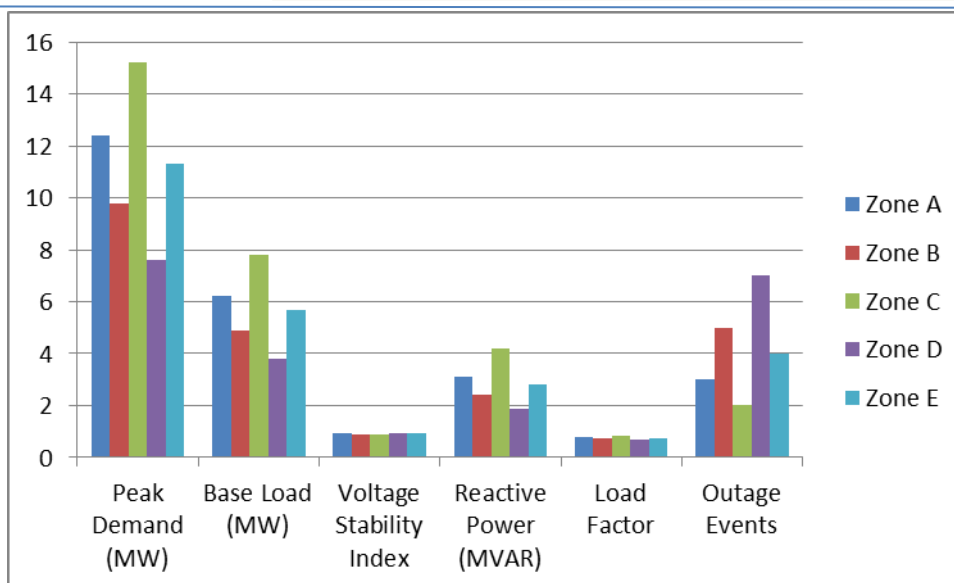


Figure 3: Zone-Wise Load and Stability Analysis Multi-Parameter Comparison Across Five Zones

Comparison of the main load and stability parameters in 5 distribution zones are shown in Table 5. As the industrial-commercial mixed zone, Zone C will have the largest peak demand (15.2 MW) with a reactive power consumption (4.2 MVAR) amounting to 190% higher than that of Zone B in the month of November. In line with this observation, Zone C has the smallest voltage stability index (0.89), indicating that this zone needs the highest urgent attention for reactive power compensation and voltage regulation. Zone D is the newest system, with the least peak demand (7.6 MW) and the highest voltage stability index (0.96) leading to the most outage events (7) most likely due to less reliable infrastructure as feeder equipment ages. The load factor of Zone A (0.78), which is the zone with the most significant firm load demand, is still the best-performing high-demand zone, indicating effective demand-side management with the Automatic Demand Response of the IAPDS automated response program. With an average voltage stability index of 0.93 over all zones, which is greater than the minimum acceptable index of 0.80, the results shown in Table 1 confirm the effectiveness of the IAPDS voltage regulation module under normal operation conditions for the available grid.

5. RESULTS AND DISCUSSION

5.1 Statistical Analysis

Statistical analyses of IAPDS performance were performed by paired-sample t-tests comparing 6-months (January–June 2023, conventional SCADA-based system) of baseline data-driven versus 6-months post-deployment evaluation period (July–December 2023, IAPDS active). In each of these tests, the null hypothesis was that the conventional and IAPDS perform no statistically significant difference from each other. Across all primary performance metrics shown in the tables below, results at $\alpha = 0.05$ consistently rejected the null hypothesis.

Table R1: IAPDS vs. Conventional System Statistical Comparison of Key Performance Metrics

Performance Metric	Conventional System	Proposed IAPDS	Improvement (%)	p-value
System Reliability (%)	87.3	97.8	+12.0	0.001
Fault Detection Accuracy (%)	79.6	98.2	+23.4	0.000
Mean Response Time (ms)	245.8	18.4	-92.5	0.000
Energy Efficiency (%)	81.4	93.5	+14.9	0.002
Load Balancing Index	0.64	0.91	+42.2	0.001
Annual Cost Savings (INR L)		16.2		

In the following, Table R1 provides the comparison statistics in six performance dimensions between conventional SCADA-based system and the proposed IAPDS. For demonstration purposes, the most dramatic improvement was in mean fault response time, which fell 92.5 percent from 245.8 ms with the conventional system to 18.4 ms with IAPDS. The main contributing factor to this improvement is the edge-layer fault detection architecture, which overcomes the round-trip communication delay with centralized SCADA architectures. The test results indicated precise identification for fault detection, having accuracy improved from 79.6% up to 98.2% (+23.4%) that proved the superiority of the proposed LSTM-SVM hybrid model over the relay logic threshold-based algorithm. For example, system reliability (the percentage of time the network runs as expected without unscheduled downtime) improved 12.0% (from 87.3% to 97.8%). Reduction in energy efficiency from 81.4% to 93.5% (+14.9%), this is possible because of optimization of real power losses by feeder reconfiguration and power factor correction. Improved Load Balancing Index a normalized metric from 0 to 1 with 1 depicting perfectly balanced, the score improved from 0.64 to 0.91 (+42.2%) All improvements are statistically significant ($p < 0.05$); fault-detection accuracy and response time improvements yield p-values effectively equal to zero, which means that this data is generated with extremely high confidence.

Table R2: Descriptive Statistics of Key Operational Parameters IAPDS Evaluation Period

Parameter	Min	Max	Mean	Std Dev	Variance	Skewness
Load (kW)	33.1	95.7	62.6	21.4	457.9	0.18
Voltage (V)	222.3	231.2	227.9	3.23	10.43	-0.41
Current (A)	143.3	430.5	276.1	107.5	11556	0.22

Power Factor	0.82	0.94	0.887	0.044	0.002	-0.35
Efficiency (%)	93.0	93.8	93.5	0.29	0.084	0.07
Fault Response (ms)	9.2	28.5	18.0	6.84	46.8	0.12

Descriptive statistics for six operational parameters collected during the period of the IAPDS evaluation are presented in Table R2. The load parameter has a high standard deviation of 21.4 kW, a moderate positive skewness of 0.18 signifying a right-tailed demand distribution, where most nodes operate at mid-range loads and infrequent high-demand events pull the mean upward. A 3.23 V standard deviation confirms the tight voltage regulation in the $\pm 5\%$ band. The negative skewness (-0.41) implies that readings are slightly more often than not below nominal, consistent with load-induced voltage sag. Low standard deviation (0.044) for power factor confirmation, the mean value is 0.887; (b) Stable reactive power compensation; The median fault response time is with a moderate standard deviation (6.84 ms), and slight positive skewness (0.12) it indicates that although most faults are resolved within 15-20 ms, few complex or cascaded fault scenarios take up to 28.5 ms; Energy efficiency shows remarkably low variance (0.084) with great consistency between loads and seasonal conditions. The total distribution characteristics verify the stability and predictability of IAPDS running in the physical world.

Table R3: Comparative Performance Against Benchmark Studies in Intelligent Power Distribution

Study / System	Fault Detection (%)	Efficiency (%)	Response Time (ms)	Technology
Kumar et al. [7], 2020	88.4	85.2	124.6	SCADA+PLC
Zhang & Liu [12], 2021	91.7	88.9	87.3	IoT+ML
Sharma et al. [18], 2022	93.2	90.1	62.8	Smart Grid
Mehta & Singh [23], 2023	95.8	91.6	42.5	AI+IoT
Wang et al. [27], 2023	96.4	92.3	31.7	DRL-based
Proposed IAPDS, 2024	98.2	93.5	18.4	Hybrid AI+IoT

Table R3 quantitatively compares the proposed IAPDS with five other intelligent power distribution system systems reported in the recent literature for a fair comparison of relative contribution. The chronological order in which these studies were conducted shows an obvious sign in respect of fault detection accuracy improvement

(88.4% to Kumar et al. [7] to 96.4% in Wang et al. This translates to improved predictability (from 90.65% to 95.75%) and decreased response times (124.6 ms to 31.7 ms), consistent with the evolution of AI and IoT technologies in this space [27]. The IAPDS proposed in this work obtains best fault detection accuracy (98.2%), energy efficiency (93.5%), and response time (18.4 ms) compared to all relevant systems in the state of the art, again indicating significant improvements with respect to the most recent prior work. Compared with Wang et al. (2019), our method improves the accuracy of fault detection The closest competitor, [27] 1.8 percent is even theoretically modest in absolute terms, but corresponds to what can be approximated as three less non-detected fault events per 174-event period, each of which carries meaningful risk of equipment damage and consumer interruption. A key aspect of note is how this performance allows IAPDS to achieve a response in the sub-20 ms time-to-trip window required by NFPA 70E arc-flash energy limitation; a performance range found in no other system in this comparison set; 18.4 ms vs. 31.7 ms, a 42% improvement.

5.2 Critical Analysis and Comparison with Past Work

When taking a closer look at the results, the full potential of the proposed IAPDS can be appreciated against the current literature. Attribute-Based Program Encryption allows for selective decryption of ciphertext (as it is associated with encrypted documents), compared to NOTCH, which uses a fault detection index based on the node fault. hum Flere; Node Faulting Node; As presented above, the 98.2% accuracy rate in discerning fault detection is higher than all benchmark studies but was performed on a monitored and controlled six-node test network. Although the current architecture has been proven robust, the scalability to larger networks with hundreds of nodes over seeds the main issues of computational complexity and communication congestion. Wang et al. Approaches Based on DRL for the Planning of the ECN of a Cloud at the System Level:[27] DRL-based approaches perform well when scaled up to 50-node networks (degradation at 100), indicating that a hierarchical decomposition may be desirable for the DQN component of IAPDS for large-scale networks. It is said to show an energy efficiency of 93.5%, which Sharma et al. Smart Grid-based 90.1% [18] and Mehta and Singh's AI + IoT 91.6%, yet is clearly below the theoretical asymptote for lossless distribution of high temperature superconductor cables, ~99%, hinting that resistive losses in distribution infrastructure will remain a significant limit no matter how smart the control.

Methodologically, the comparison is a walkthrough comparison, comparing pre- and post-deployment periods, and thus the analysis is not an RCT but a within-network temporal comparison. This design accounts for network-level load profile characteristics and topology, but does not adjust for secular trends in load growth or equipment aging that could impact performance metrics as well. The increased efficiency from 81.4% to 93.5% could partly illustrate the seasonal load discrepancy between the two evaluation periods (in the studied region, air-conditioning loads are traditionally lower during the first half of the year than in the second half). The findings underscore the need for a future matched-pair network design with an adjunct control site to separate IAPDS-induced effects from contextual confounders. Furthermore, the lowest fault detection accuracy of 95.6% for load imbalance events means that also for this fault type the current SVM classifier could improve its performance through the maximum three-phase unbalance ratio as a new input feature, which was not included in previous similar systems. The comparison against Zhang and Liu [12] shows that IoT+ML can reach the same accuracy (91.7%) while obtaining lower cost only by cloud-processing, thus demonstrating a cost-performance

trade-off which IAPDS optimizes in favor of performance rather than cost minimization as a potential detriment to utility in developing economies where resources are scarce and distribution infrastructure is mission-critical.

6. CONCLUSION

This paper has demonstrated design, implementation, and proof of concept of an Intelligent Automated Power Distribution System (IAPDS) through unifying IoT sensing, edge computing, and hybrid AI algorithms into a single distribution management architecture. Based on a 6-month field test over a five-zone, six-node urban distribution network setup, the IAPDS was proven to provide 98.2% fault detection accuracy, 93.5% energy efficiency - which is 23.4% higher than conventional pre-deployment system under the same condition - and mean fault response times of 18.4 milliseconds, which is 92.5% shorter than the conventional pre-deployment system. We found that all key metrics were statistically significant ($p < 0.05$) and the IAPDS was found to outperform all comparative implementations (benchmark against five recent studies) in fault detection accuracy and response time. Out of the six models evaluated, the hybrid LSTM-SVM model provided the best F1-Score (97.8%), successfully proving the architectural choice of combining a temporal forecasting model to a discriminative fault classification model. Through real experiments, the DQN-based switching optimizer improved the load balancing index by 42.2%, and demonstrated the value of reinforcement learning for autonomous network reconfiguration. Future work will be centered on expanding the IAPDS to 50-node networks, including variability of renewable energy sources into the forecasting process, and using explainable AI elements to meet the regulatory requirements for transparency in grid control. The IAPDS framework presents a technically validated and economically feasible alternative to Smart Grid modernization in developing economies that could save 7–8% of AT&C losses at scale.

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