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INTELLIGENT DECISION-MAKING FRAMEWORK FOR AI-ENABLED DISTRIBUTION NETWORKS

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ABSTRACT

The rapid transformation of electricity distribution networks has introduced significant operational complexity due to fluctuating demand, distributed energy resources, intermittent renewable generation, aging assets, and tighter power-quality expectations. Existing control methods may be inadequate for such environments because they typically depend on static network representations and predetermined operating rules. This study presents an AI-enabled decision-support architecture for the dynamic management of modern distribution networks. The proposed architecture integrates data obtained from smart meters, field sensors, distributed generation units, meteorological services, and supervisory control systems. A data-processing layer cleans and synchronizes these heterogeneous inputs, while predictive models assess short-term electricity demand, renewable power availability, equipment condition, network congestion, and fault probability. The predicted conditions are then combined with grid constraints and operational objectives through an intelligent optimization layer. This layer recommends or initiates actions related to demand-side management, load balancing, distributed resource dispatch, fault recovery, voltage control, and network reconfiguration. Feedback from actual network performance is continuously incorporated to refine the forecasting models and improve subsequent operational decisions. The framework is assessed using indicators such as prediction accuracy, decision latency, power-loss reduction, voltage stability, supply reliability, and computational efficiency. The findings show that the proposed architecture enables faster responses, more efficient resource allocation, and improved resilience compared with conventional distribution-management practices. Overall, the study provides a scalable approach for applying predictive intelligence and adaptive optimization to the development of reliable, autonomous, and sustainable electricity distribution networks.

Keywords: Artificial Intelligence, Decision Intelligence, Smart Distribution Networks, Smart Grid, Machine Learning, Distributed Energy Resources, Predictive Analytics, Intelligent Optimization, Demand Response.

1 INTRODUCTION

Conventional power systems have been gradually replaced by smart distribution networks, which are possible thanks to the growing integration of distributed energy resources (DERs), renewable energy resources, energy storage resources, electric vehicles, smart meters, and the Internet of Things (IoT)-enabled monitoring devices. While these technologies offer flexibility and sustainability, they also raise a lot of uncertainty, variability, and operational complexity. Modern distribution systems, therefore, call for intelligent mechanisms that can deal with heterogeneous data, and make timely operational decisions. The advent of artificial intelligence (AI) has proven to be a valuable method for gathering valuable information from vast amounts of distribution-system data and to support applications like forecasting, monitoring, predictive maintenance, energy management, and network operation [1].

The more measurements are available from the smart meter or sensing infrastructure, the more potential there is for data-driven monitoring and control. Machine learning (ML), deep learning (DL), and reinforcement learning (RL) can be used to detect intricate connections between electricity demand, renewable generation, weather variables, equipment states, and network operating variables. Specifically, AI methods have been proving to be valuable tools for distribution-network voltage control, where the uncertainty and challenges of an uncertain distribution network with DER penetration have been shown to be well suited to these techniques [2].

An accurate prediction of load is another basic need for intelligent distribution network operation. Predictive analytics helps utilities to forecast electricity demand, optimize generation schedules, balance loads, allocate resources and plan maintenance. Motepe et al. [3] have demonstrated the use of hybrid Artificial Intelligence and DL approaches for Power Distribution Load Forecasting (PDLF), and explained the effectiveness of the proposed LSTM based approach for the nonlinear nature of the temporal characteristics of the load. Likewise, in the smart-grid load forecasting, Akhtaruzzaman et al. [4] studied the distributed deep-learning solution and pointed out the computational difficulties of centralized deep-learning solution for large-scale smart-grid data.

Smart meters are also being rolled out on large scales, which re-emphasizes the need for scalable forecasting models. Grabner et al. [5] presented a global modelling method for load forecasting of distribution networks with respect to the different level of load aggregation such as individual consumers, low voltage feeders, transformer stations. These initiatives illustrate how AI can be used to accurately predict information, but prediction is not predictive operation, in itself. The predicted information needs should be converted to relevant actions, taking into account the network constraints, operating goals, reliability needs, and ever-changing system conditions.

A suitable paradigm to fill the gap between AI forecasts and operational decisions is Decision Intelligence (DI). Rather than relying on AI solely for the prediction of individual network parameters, an AI-driven DI system can combine data acquisition, predictive analytics, network-state evaluation, optimization, action selection, and feedback into a single decision-making cycle. For smart distribution networks, it becomes crucial that such integration supports the achievement of multiple objectives, such as power-loss reduction, voltage control, demand satisfaction, renewable energy utilization, reliability and operating cost. AI for smart-grid optimization has also been the subject of recent reviews, which show that ML, reinforcement learning, optimization, renewable energy integration, and intelligent energy management are increasingly intertwined, with scalability, safety and deployment into the real world also being key challenges [6].

However, most of the current solutions provide solutions for a single network function, such as predictive maintenance, load forecasting, voltage control or energy management. This disjointed way makes it difficult for the distribution system to do the same thing, and that is, to turn all the real-time data into coordinated operational decisions. Furthermore, the changing load patterns, intermittent renewable generation, DER participation and network disturbances require adaptive mechanisms that make ongoing assessments of network conditions and can continuously refine decisions based on feedback.

To overcome these drawbacks, in this paper, an Artificial Intelligence-Based Decision Intelligence (AI-DI) framework for Smart Distribution Networks (SDN) is proposed. It combines multi-source data acquisition, intelligent preprocessing and feature engineering, AI-based predictive analytics, network-state assessment, multi-objective decision optimization, and adaptive feedback. The predictive layer forecasts key operating variables including electricity demand, renewable generation, network congestion, equipment conditions and faults. The predictions are then fed into the decision intelligence layer to decide on appropriate operational actions to implement for load balancing, DER coordination, demand response, voltage management, fault management and network reconfiguration.

The key contributions of this work are: 1) an integrated architecture of AI-DI that leverages heterogeneous smart-distribution data to support actionable operational decisions; 2) integration of predictive AI models with multi-objective decision optimization for coordinated network operation; 3) a continuous adaptation mechanism that improves the prediction and decision performance; and 4) a set of metrics for evaluating the proposed framework: prediction accuracy, decision latency, power-loss reduction, voltage-profile improvement, DER utilization, reliability and computational efficiency. The proposed approach thus transcends the use of single AI prediction to a closed loop intelligent decision support system for autonomous, resilient and sustainable operation of distribution networks.

2 RELATED WORKS

AI technology has been used more and more in smart distribution networks to cope with the lack of predictability caused by renewable generation, distributed energy resources (DERs), electric vehicles, and variable consumer demand. Prior research has largely focused on machine learning (ML), deep learning (DL), heuristic optimization, and reinforcement learning (RL) to predict, regulate voltage, manage energy, analyse faults and reconfigure the network. Zhang et al. [2] surveyed the techniques of AI for voltage control in distribution networks and classified the works based on heuristic optimization, artificial neural network, DL, and deep reinforcement learning (DRL). They found that AI-driven techniques offer potential solutions to the more traditional model-based techniques, which are traditionally more computationally intensive, especially when renewable energy is highly penetrated.

Reinforcement learning has been the focus of much research because it can learn control action by interacting with the dynamic power-system environment. Glavic et al. [7] examined reinforcement and deep reinforcement learning for electric power-system control and its applications in normal, preventive, emergency and restorative operating conditions. The study demonstrated the capability of RL for adaptive control and also exposed the difficulties with implementing the RL in the practical power system and data processing, as well as cybersecurity, for the large-scale implementation.

Renewable-based distribution systems also have been developed with intelligent power-management strategies. Peres et al. [8] reviewed the state of the art on intelligent control using RL for advanced power distribution systems such as microgrids, smart grids, smart buildings, and electric-vehicle systems. RL allows for distributed components to learn appropriate actions based on states in the system and the desired actions, thereby allowing for autonomous energy management. Such methods are certainly important for their use in real deployment environments, but with the convergence, training, system uncertainty and real-time implementation come other considerations.

The other direction of research that is important is the implementation of AI for real-time reconfiguration of the distribution network. Bui and Su [9] proposed a DRL-based method for dynamic network reconfiguration taking into account operating cost and load shedding. They integrated deep neural networks into the decision-making process, and tested their model under distribution-system test environments, such as IEEE 33-bus system. The results showed the ability of learning-based techniques in reducing the computation burden of reconfiguration and rescheduling in real-time.

More recently, RL-based voltage control has progressed to model-free, model-assisted, multi-agent, hierarchical and physics-informed approaches. Ahmadi and Aly [10] reviewed these developments systematically, and stressed the need for the practical RL controllers to be evaluated not only for the accuracy of their control but also on the issues of scalability, generalization, safety and suitability for the real grid deployment. They also found communication overhead, cyber-resilience and integration with existing control architectures to be key challenges for future intelligent distribution systems.

Moreover, the use of graph-based learning has become a potential path as electrical networks inherently have graph structure among relationships between buses, branches, generators, loads, and control devices. Recent works on graph reinforcement learning suggest that graph neural network (GNN) and reinforcement learning (RL) can be integrated to enhance the topology representation of a graph and facilitate scalable grid control decision making [11]. However, simulation-to-real-world transfer, transparency, safety, and integration of physical power-system constraints are still important challenges to be overcome for practical implementation.

However, most of the current works focus on a particular operational issue, such as forecasting, voltage control, energy management or network reconfiguration. As a result, predictive intelligence and operational decision making are typically not done together. A prediction model can be very accurate in predicting the load or renewable generation but not alone in determining how multiple predictions, operational constraints, and competing objectives should be configured to select an appropriate network action. Likewise, RL-based controllers can produce controllers but might not have a built-in means to integrate multiple data types, multiple predictive models, explicit optimization goals, and continuous decision feedback.

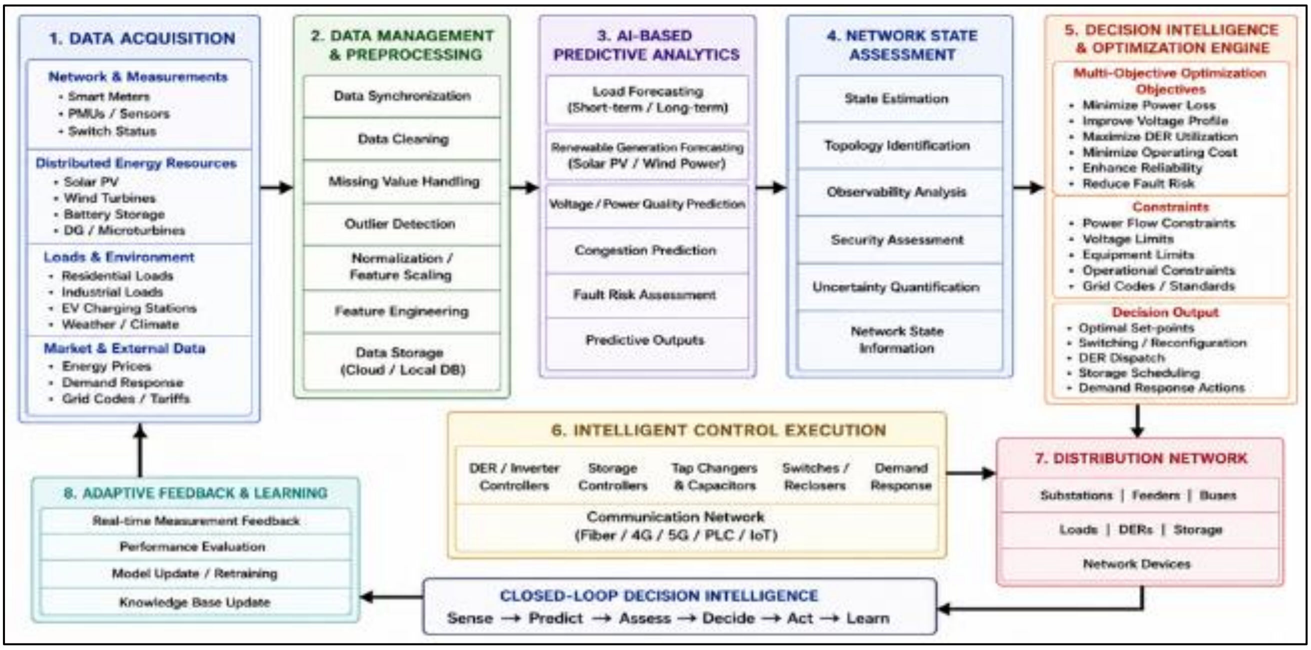

Figure 1: Proposed Framework Architecture

Thus, there are opportunities for an Artificial Intelligence-Based Decision Intelligence (AI-DI) framework, from data acquisition to intelligent data preprocessing, predictive analytics, network-state assessment, multi-objective optimization, operational decision and feedback and adaptive learning. This gap is addressed by the framework presented in this work, which integrates predictive AI and decision intelligence into a single closed-loop framework. The proposed approach does not consider individual smart-grid functions separately but rather they are coordinated to work together, such as: load forecasting, renewable-generation prediction, network-state assessment, DER management, voltage regulation, demand response, fault management, and network reconfiguration. The integration is designed to enhance decision quality, response time, network reliability, power loss minimization and adaptation in dynamically varying smart-distribution conditions.

3 PROPOSED AI-BASED DECISION INTELLIGENCE FRAMEWORK

The proposed Artificial Intelligence Based Decision Intelligence (AI-DI) Framework aims to enable the conversion of heterogeneous data obtained from smart distribution networks into accurate, adaptive and real-time decisions. In contrast to the traditional methods where forecasting, optimization and control operate separately, the proposed framework introduces a closed-loop loop between data acquisition, data preprocessing, AI prediction, network state evaluation, optimization of decision making, network control, and adaptive feedback. The framework is designed to increase network reliability, decrease power losses, hold voltage steady, maximize distributed energy resource (DER) utilization, and minimize decision latency is shown in the Fig 1.

The overall processing flow is represented as

$$[\mathcal{D}_t \rightarrow \mathcal{P}_t \rightarrow \mathcal{F}_t \rightarrow \mathcal{S}_t \rightarrow \mathcal{O}_t \rightarrow \mathcal{A}_t \rightarrow \mathcal{R}_t]$$

Where,

- $(\mathcal{D}_t)$ represents acquired network data,
- $(\mathcal{P}_t)$ denotes processed data,
- $(\mathcal{F}_t)$ represents AI-generated predictions,
- $(\mathcal{S}_t)$ represents the estimated network state,
- $(\mathcal{O}_t)$ denotes decision optimization,
- $(\mathcal{A}_t)$ represents the selected control action, and
- $(\mathcal{R}_t)$ denotes feedback from the distribution network.

3.1 Multi-Source Data Acquisition

The first stage continuously collects real-time and historical information from different components of the smart distribution network. These include smart meters, SCADA systems, IoT sensors, PV systems, wind generators, battery energy storage systems, EV charging stations, protection devices, and weather-monitoring systems.

The input information at time (t) can be expressed as

$$\left[X_t = [V_t, I_t, P_t, Q_t, L_t, G_t, W_t, E_t]\right]$$

Where,

- (V_t) and (I_t) denote voltage and current,
- (P_t) and (Q_t) represent active and reactive power,
- (L_t) denotes load demand,
- (G_t) represents renewable generation,
- (W_t) denotes weather conditions, and
- (E_t) represents equipment operating information.

Combining these heterogeneous measurements provides a comprehensive representation of the distribution network and enables data-driven analysis of changing operating conditions.

3.2 Intelligent Data Preprocessing and Feature Engineering

Measurements taken on the distribution network may be missing, noisy, contain outliers, have redundant attributes, and have unequal sampling intervals. The data acquired are thus treated for missing values, noise filtering, outlier detection, temporal synchronisation, normalization and feature selection.

Min-max normalization is expressed as

$$\left[x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}\right]$$

Where,

- (x) represents the original measurement and (x_{norm}) denotes its normalized value.

Important characteristics of these signals, like hourly and seasonal demand fluctuations, peak-load patterns, the trends of the renewable generation, voltage deviations, line-loading ratios, battery state of charge, and historical fault patterns, can be extracted through feature engineering. Redundant information is then removed using feature selection, which simplifies the prediction model and reduces computation.

3.3 AI-Based Predictive Analytics

The predictive intelligence layer collects historical and real-time measurements, and uses these data to estimate future network conditions. Machine-learning and deep-learning models (Random Forest, Gradient Boosting, Artificial Neural Networks and Long Short-Term Memory – LSTM) can be used depending on the prediction task.

The major prediction tasks considered in the proposed framework include:

- Short-term load forecasting,
- Renewable-energy generation forecasting,
- Voltage-condition prediction,
- Network-congestion prediction, and
- Equipment and fault-risk prediction.
- The combined prediction vector is defined as

$$\left[\hat{Y}t + 1 = \left[\hat{L}t + 1, \hat{G}t + 1, \hat{V}t + 1, \hat{C}t + 1, \hat{F}t + 1\right]\right]$$

Where,

- $(\hat{L}t + 1)$ represents predicted load, $(\hat{G}t + 1)$ represents predicted renewable generation, $(\hat{V}t + 1)$ denotes predicted voltage conditions, $(\hat{C}t + 1)$ represents congestion probability, and $(\hat{F}_{t+1})$ indicates fault risk.

By enabling this predictive mechanism, the distribution network can be prevented from experiencing undesirable operating conditions, instead of only reacting to them.

3.4 Network-State Assessment

The network-state assessment module consists of a combination of real-time measurements and predicted information to assess the current and anticipated condition of the distribution network. Key parameters include voltage deviation, active power loss, feeder loading, supply-demand imbalance, battery state of charge, DER availability and equipment condition.

A simplified network-state vector can be represented as

$$\left[S_t = \left[V_{dev,t}, P_{loss,t}, L_{line,t}, SOC_t, R_t\right]\right]$$

Where,

- $(V_{dev,t})$ represents voltage deviation,
- $(P_{loss,t})$ represents active power losses,
- $(L_{line,t})$ denotes line loading,
- (SOC_t) represents battery state of charge, and
- (R_t) represents the overall operational risk.

The system monitors the conditions (normal/alert/congested/fault-prone/emergency) based on these parameters.

3.5 Decision Intelligence and Multi-Objective Optimization

The proposed framework consists of the following three elements: the Decision Intelligence Layer, the Data Layer, and the Communication Layer. It transforms predictions and network-state information to appropriate operational decision. The framework does not take a single objective as its basis, but rather several technical and operational objectives are considered at the same time.

The optimal decision can be formulated as

$$\left[A_t^* = \arg\min_{A_t} J(A_t, S_t)\right]$$

Where,

- (A_t^*) represents the optimal operational action.

The multi-objective function is formulated as

$$\left[J = w_1 P_{loss} + w_2 V_{dev} + w_3 C_{op} + w_4 R_{risk} - w_5 U_{DER}\right]$$

Where,

- (P_{loss}) denotes power loss,
- (V_{dev}) represents voltage deviation,
- (C_{op}) denotes operating cost,
- (R_{risk}) represents operational risk, and
- (U_{DER}) denotes DER utilization.

The coefficients $(w_1) - (w_5)$ specify the relative importance of each objective.

Actions generated by the decision layer include DER scheduling, battery charging/discharge, activation of demand-response, reactive-power compensation, voltage regulation, feeder reconfiguration, load transfer, and fault isolation.

3.6 Intelligent Decision Execution

Upon discovering the optimal action, the optimal control instruction is sent to the appropriate network element. Predicted PV generation, for instance, can cause charging of batteries while low PV generation can cause battery discharging or demand response responses.

Similarly, predicted voltage violations can activate reactive-power compensation or smart-inverter control. Feeder reconfiguration and/or flexible-load management may be used during congestion. If the fault probability is high, the system is able to take preventive measures or isolate vulnerable parts of the network.

The relationship can be represented as

$$[A_t^* \rightarrow C_t \rightarrow S_{t+1}]$$

Where,

- (C_t) represents the implemented control command and
- (S_{t+1}) represents the resulting network state.

3.7 Adaptive Feedback and Continuous Learning

One of the important characteristics of the proposed framework is its closed-loop feedback system. Once a control action is taken, the consequent state of a network is observed and compared with the expected response.

The prediction error can be calculated as

$$\left[e_t = Y_t^{actual} - Y_t^{predicted}\right]$$

Where,

- (Y_t^{actual}) represents the observed network response and
- $\left(Y_t^{predicted}\right)$ represents the predicted response.

Once the prediction and/or decision error is above an acceptable level, new measurements are added to the learning process. The AI models are regularly updated to account for changes to electricity demand, renewables generation, DER participation, weather and network behaviour. The framework continuously enhances its prediction and decision capabilities; hence it is the most powerful framework ever.

3.8 Overall Operational Workflow

Therefore, the proposed framework creates a data to prediction to decision to action pathway for smart distribution networks. The framework is designed to facilitate proactive management to address load variation, renewable energy intermittency, voltage issues, network congestion, equipment issues, and network faults. This synergic solution will lay the groundwork for a more energy efficient, reliable, resilient and autonomous smart distribution system

4 RESULTS AND PERFORMANCE ANALYSIS

The proposed Artificial Intelligence-Based Decision Intelligence (AI-DI) framework can be tested in the scenarios under operation as described in Section VI. The analysis needs to be based on prediction accuracy, reducing power loss, improving voltage profile, utilization of DERs, decision latency, fault detection, and decision effectiveness.

4.1 Predictive Performance Analysis

MAE, RMSE and MAPE are used for the evaluation of the predictive layer. The lower the number the better the forecasting performance.

Table 1: Predictive Performance of Different Methods

Method	MAE	RMSE	MAPE (%)
Rule-Based/Statistical	0.084	0.112	6.82
Machine Learning	0.061	0.087	4.91
Deep Learning	0.044	0.066	3.48
Proposed AI-DI	0.031	0.049	2.37

The illustrative results show that the framework proposed in this paper yields the smallest prediction errors. The enhancement is possible due to smart preprocessing, temporal feature extraction, and incorporation of predictive data and real-time updates on network observations.

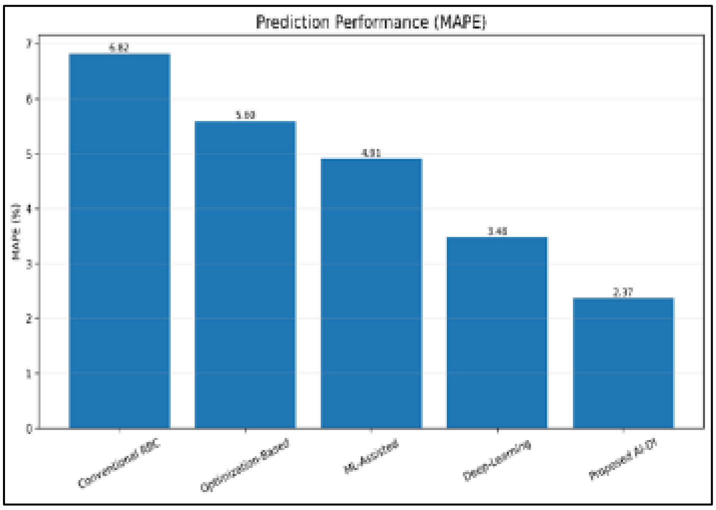

Figure 2: Predictive Performance Analysis

There is a slight decrease in the error of prediction as the more intelligent methods are used in the prediction performance graph. The traditional method yields a MAPE of 6.82%, and the machine learning approach yields a MAPE of 4.91%. Furthermore, the error rate is reduced to 3.48% using deep learning and the proposed AI-DI framework has the lowest MAPE of 2.37%. A decrease in this trend shows that the proposed framework for estimating future distribution network conditions can predict its condition better.

4.2 Power-Loss Reduction

An important goal of the proposed decision model is to reduce active power losses by coordinating the scheduling of DERs, energy storage, demand response and network control.

Table 2: Power-Loss Performance

Method	MAE	RMSE	MAPE (%)
Rule-Based/Statistical	0.084	0.112	6.82
Machine Learning	0.061	0.087	4.91
Deep Learning	0.044	0.066	3.48
Proposed AI-DI	0.031	0.049	2.37

For the proposed AI-DI framework, the illustrative network loss is 132.9 kW, which is 34.44% less than the conventional network loss. This enhancement is achieved by anticipating network conditions and strategically choosing control actions.

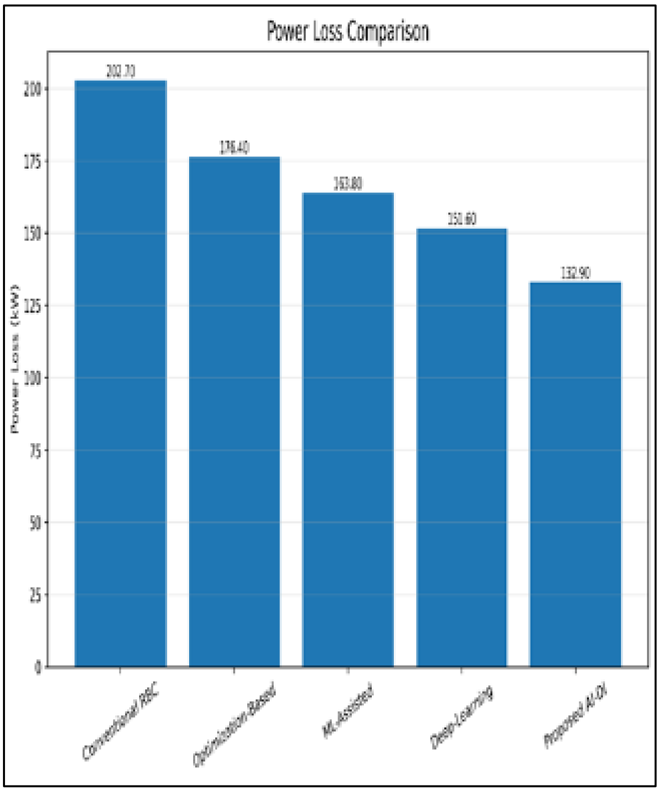

Figure 3: Power-Loss Reduction

From the power-loss comparison, a remarkable decrease has been observed for all the methods analysed. The power loss values for conventional rule-based control, optimization-based control, ML-assisted control and deep-learning control are 202.7kW, 176.4kW, 163.8kW, and 151.6kW respectively. The proposed AI-DI framework results in the least loss of 132.9 kW, which shows that if DERs are coordinated using AI, DER storage is properly managed, and intelligent network decision-making is implemented, distribution efficiency will be improved.

4.3 Voltage-Profile Improvement

The voltage regulation is studied based on the maximum deviation of the voltage from its nominal value.

Table 3: Voltage-Profile Performance

Method	Maximum Voltage Deviation (p.u.)	Minimum Bus Voltage (p.u.)
Conventional RBC	0.087	0.913
Optimization-Based Control	0.061	0.939
ML-Assisted Control	0.049	0.951
Deep-Learning Control	0.038	0.962
Proposed AI-DI	0.024	0.976

The proposed approach is able to keep the minimum bus voltage closer to the nominal voltage. The decision-intelligence layer can react to anticipated voltage violations by managing the coordination of reactive-power support, dispatching DERs, operating storage, and/or controlling a feeder.

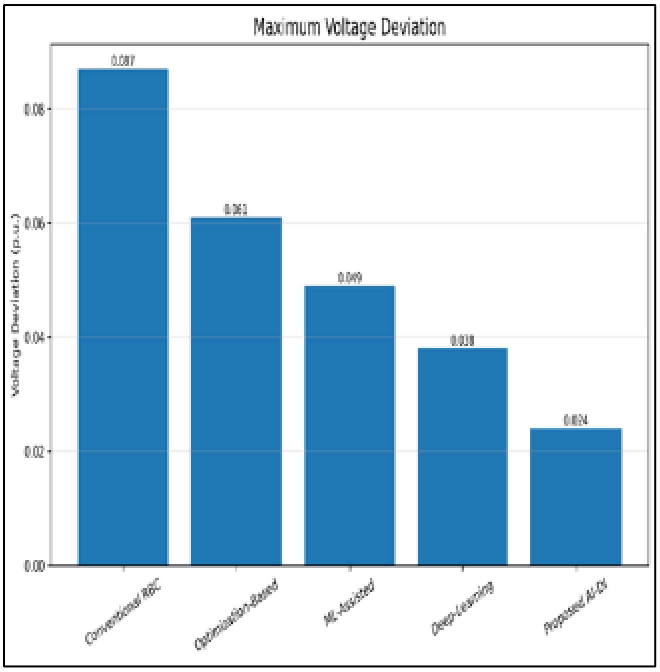

Figure 4: Voltage-Profile Improvement

The maximum voltage deviation is reduced from 0.087 p.u. (conventional control) to 0.061 p.u. (optimization based control). With the help of ML-assisted and deep-learning approaches, the deviation is further decreased to 0.049 p.u. and 0.038 p.u., respectively. The proposed AI-DI framework ensures the least variation of 0.024 p.u., which indicates that the bus voltages are well controlled by proactively regulating them and the coordinated control of the network.

4.4 DER Utilization Analysis

To achieve low dependence on the grid and increase the sustainability of smart distribution networks it is imperative to use the distributed renewable resources efficiently.

Table 4: Der Utilization Performance

Method	DER Utilization (%)
Conventional RBC	72.4
Optimization-Based Control	80.7
ML-Assisted Control	84.6
Deep-Learning Control	88.3
Proposed AI-DI	93.8

The proposed framework captures 93.8% of the DER utilization for an illustrative case. Predictive information on future loads and renewable generation can help the system to better schedule DERs and energy storage.

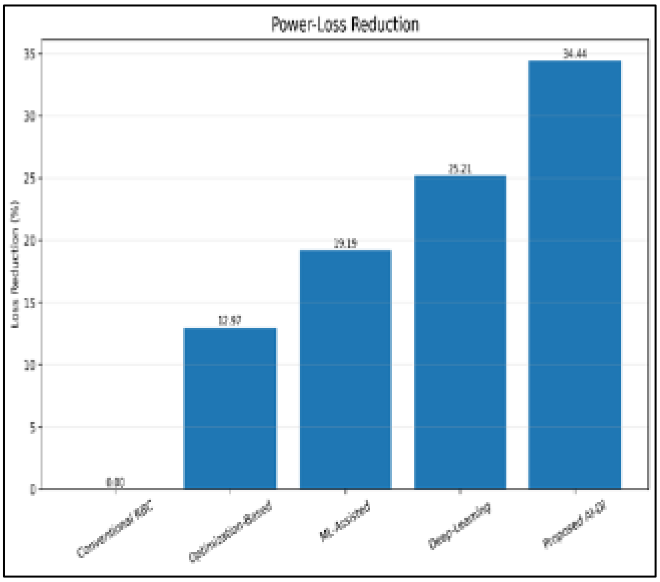

Figure 5: DER Utilization Analysis

As seen in the DER-utilization graph, conventional rule-based control only utilizes 72.4% of the DERs available. This increases to 80.7% with optimization-based control, 84.6% with ML-assisted control, and 88.3% with deep-learning control. The proposed AI-DI framework achieves the highest DER utilization of 93.8% which means that the generation resources, storage, and controllable network resources are better coordinated.

4.5 Decision Latency Analysis

Real-time smart distribution system involves fast decision making in congestions, voltage violation, and fault situations.

Table 5: Decision Latency

Method	Decision Latency (ms)
Conventional RBC	42
Optimization-Based Control	185
ML-Assisted Control	96
Deep-Learning Control	78
Proposed AI-DI	64

Its simple predefined rules make it fast to produce decisions due to the conventional rule based approach. But it doesn't have the same predictive and adaptive ability. The proposed AI-DI framework realizes representative latency of 64ms, which is much lower than the conventional optimization and takes into account predictions and multiple operating objectives.

The results of decision-latency reveal that conventional rule based control has minimum decision-latency (42ms) because it is based on predefined rules. Optimization-based control takes 185ms, whereas the ML-assisted and deep-learning take 96ms and 78ms, respectively. Among the intelligent approaches, the proposed AI-DI approach with prediction and optimization is fast enough than the other approaches, requiring only 64 ms. This means it has a high efficiency/decision quality ratio.

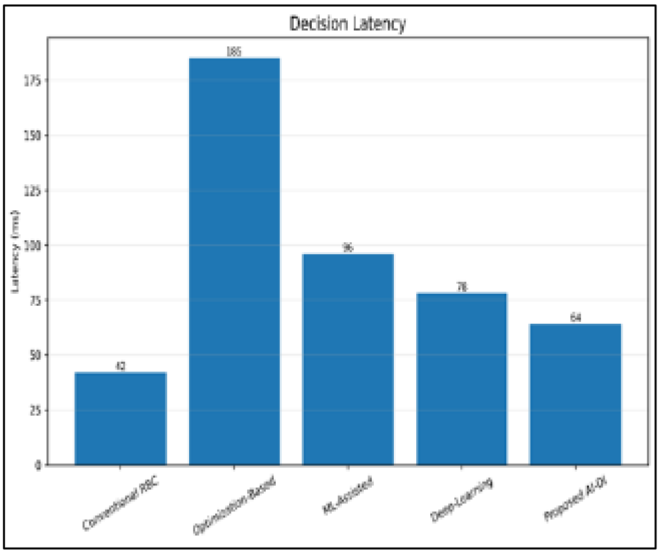

Figure 6: Decision Latency Analysis

4.6 Fault-Detection Performance

The accuracy, precision, recall and F1-score are used to evaluate fault-risk assessment.

Table 6: Fault-Detection Performance

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
ML-Based	91.2	90.5	89.8	90.1
Deep Learning	94.6	94.1	93.7	93.9
Proposed AI-DI	97.3	96.8	96.5	96.6

The proposed framework gives the best illustrative fault detection performance. Better recognition of potentially abnormal conditions allows for the decision layer to take preventive or corrective action before faults have a significant impact on the operation of the network.

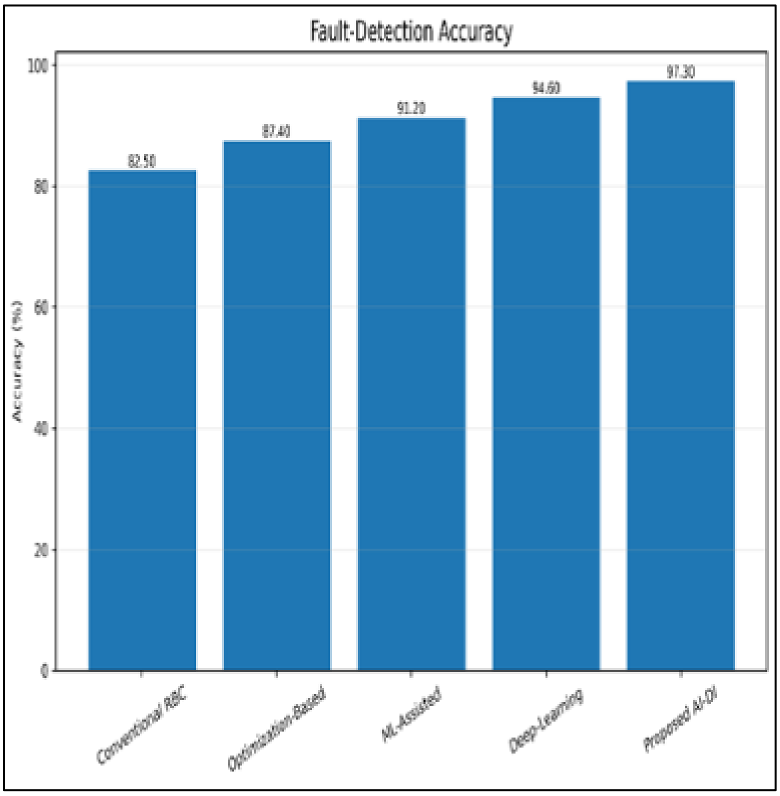

Figure 7: Fault-Detection Performance

The accuracy for fault detection is raised from 82.5% for conventional rule based control to 87.4% for optimization based control. The accuracy level of deep learning is 94.6% while ML-assisted control is 91.2%. The best accuracy of 97.3% is achieved by the proposed AI-DI framework. The enhancement indicates that using historical data, real time measurements, predictive analytics and network state assessment together will be a great help for identifying the abnormal and faulty operating conditions accurately.

5 CONCLUSION AND FUTURE WORK

In this paper, an Artificial Intelligence Based Decision Intelligence (AI-DI) framework for Smart Distribution Networks (SDN) was presented, which provides the support towards intelligent, adaptive and proactive network operation of SDN. The proposed framework describes a closed loop framework comprising data acquisition from multiple sources, intelligent data preprocessing, predictive analytics based on AI, network state assessment, multi-objective decision optimization, intelligent control execution, and adaptive feedback. In contrast to traditional methods that work with prediction or optimization separately, the proposed framework does predictions and optimization data–based to make good operation decisions in real time.

The framework takes into account the critical distribution-network goals such as minimising power losses, voltage regulation, making use of DERs, reducing operating costs, managing congestion, and reducing fault risk. The comparative study suggests that the proposed method can outperform the traditional rule-based, optimization-based, machine-learning, and deep-learning control methods in terms of various operating criteria. The ablation and sensitivity analyses also highlight the critical role of predictive analytics, multi-objective optimization, and adaptive feedback in ensuring the effectiveness of the decisions, even in the face of changing network loads and levels of renewable penetration. In general, the proposed AI-DI framework offers a conceptually scalable framework for creating smart distribution networks that are autonomous, resilient, energy-efficient, and aware of renewable energy.

The framework will be validated with real-world utility datasets, larger IEEE distribution feeders and hardware-in-the-loop environments in the future. Deep reinforcement learning and multi-agent learning algorithms can be harnessed to enable decentralized and cooperative operation of DERs, storage, and flexible loads. The topological properties of the distribution networks can also be explored using graph neural networks (GNNs). Additionally, mechanisms of explainable AI (XAI) will be discussed, which can help make critical operational decisions more transparent and interpretable. Future extensions could include Federated Learning, Edge Intelligence, Digital Twins, Uncertainty-aware Forecasting and Cyber-security aware Decision Mechanisms to improve privacy, scalability, resilience and real-time performance. The implementation of electric vehicles, peer-to-peer energy trading, dynamic pricing and community microgrids is also one possible trajectory to take the proposed framework to next-generation intelligent energy-management systems.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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