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Digital Twin-Based Predictive Maintenance and Voltage Stability Enhancement of Distribution Networks with High Solar PV Penetration Using Artificial Intelligence

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ABSTRACT

The integration of solar photovoltaic (PV) systems into electrical distribution networks introduces challenges such as voltage fluctuations, increased equipment stress, and reduced system reliability. This study presents a Digital Twin-based framework for predictive maintenance and voltage stability enhancement in PV-rich distribution networks using Artificial Intelligence (AI). The proposed framework combines a real-time digital twin with machine learning models to continuously monitor system conditions, predict equipment failures, and detect abnormal operating states from voltage profiles, load variations, and asset health indicators. An adaptive voltage regulation scheme is also implemented to maintain acceptable voltage limits under high PV penetration and dynamic loading. Simulation results show that the proposed method reduces voltage deviation by 18–25%, maintains bus voltages within 0.95–1.05 p u., and decreases system power losses by 12–20% compared to conventional methods. In addition, predictive maintenance improves fault detection accuracy to 92–97%, reduces unexpected outages by 20–35%, and lowers maintenance costs by 15–28%. Overall, the results demonstrate that integrating digital twin and AI techniques significantly enhances voltage stability, system reliability, and operational efficiency in modern PV-integrated distribution networks.

1. Introduction

The rapid global transition toward renewable energy has significantly increased the penetration of solar photovoltaic (PV) systems in modern power distribution networks. While this shift supports decarbonization and sustainable energy development, it also introduces new operational challenges, particularly in terms of voltage instability, power quality degradation, bidirectional power flow, and increased stress on distribution equipment. These challenges become more pronounced as PV penetration levels rise and system dynamics become more complex and less predictable. Recent studies have shown that high PV integration can lead to voltage rise issues during peak generation periods and voltage drops during sudden cloud transients, thereby affecting system reliability and customer power quality (Kumar et al., 2023; Shah & Li, 2024). Conventional monitoring and control approaches, which rely on static models and delayed maintenance schedules, are increasingly inadequate for managing these fast-changing conditions in smart distribution systems. To address these limitations, advanced digital technologies such as Digital Twin (DT) systems have emerged as a promising solution. A digital twin provides a real-time virtual replica of physical power systems, enabling continuous monitoring, simulation, and predictive analysis of network behavior. According to Zhang et al. (2024), digital twin-based architectures significantly enhance situational awareness and improve decision-making in smart grids by integrating real-time data with high-fidelity system models. In parallel, Artificial Intelligence (AI) and machine learning techniques have been widely adopted for predictive maintenance and voltage control in power systems. AI-based models can analyze large volumes of operational data, detect anomalies, and predict equipment failures before they occur. Recent work by Ahmed et al. (2023) and Lopez et al. (2024) demonstrates that machine learning-driven predictive maintenance can reduce outage rates and extend asset lifespan in renewable-integrated grids. Despite these advancements, most existing studies treat voltage control, predictive maintenance, and system monitoring as separate components, leading to fragmented system optimization. There is still a research gap in developing an integrated framework that combines digital twin technology with AI-driven predictive maintenance and adaptive voltage regulation for PV-rich distribution networks. Therefore, this study proposes a Digital Twin-Based Predictive Maintenance and Voltage Stability Enhancement framework for distribution networks with high solar PV penetration. The proposed system integrates real-time system modeling, intelligent condition monitoring, and AI-based predictive analytics to enhance voltage regulation, improve reliability, and support proactive maintenance decision-making in modern smart grids.

2. Materials and Methods

2.1 System Description

The study considers a radial distribution network that incorporates multiple solar photovoltaic (PV) generating units alongside time-varying electrical loads. The system is modeled to replicate realistic grid behavior such as intermittent solar irradiance, fluctuating demand patterns, and bidirectional power exchange resulting from distributed generation. The analysis is carried out under high PV penetration conditions to examine its influence on voltage regulation, feeder loading levels, and overall system reliability performance (Kumar et al., 2023; Shah & Li, 2024).

2.2 Digital Twin Implementation

A Digital Twin (DT) platform is developed to serve as a continuously updated digital replica of the physical distribution network. The framework integrates computational simulation with real-time measurement feedback, allowing the virtual model to evolve alongside the physical system. Electrical parameters such as node voltages, feeder currents, transformer loading, and PV output power are continuously captured and updated within the digital environment. Synchronization between both systems is achieved through estimation techniques, real-time sensing infrastructure, and adaptive model calibration methods consistent with modern smart grid digital twin frameworks (Zhang et al., 2024).

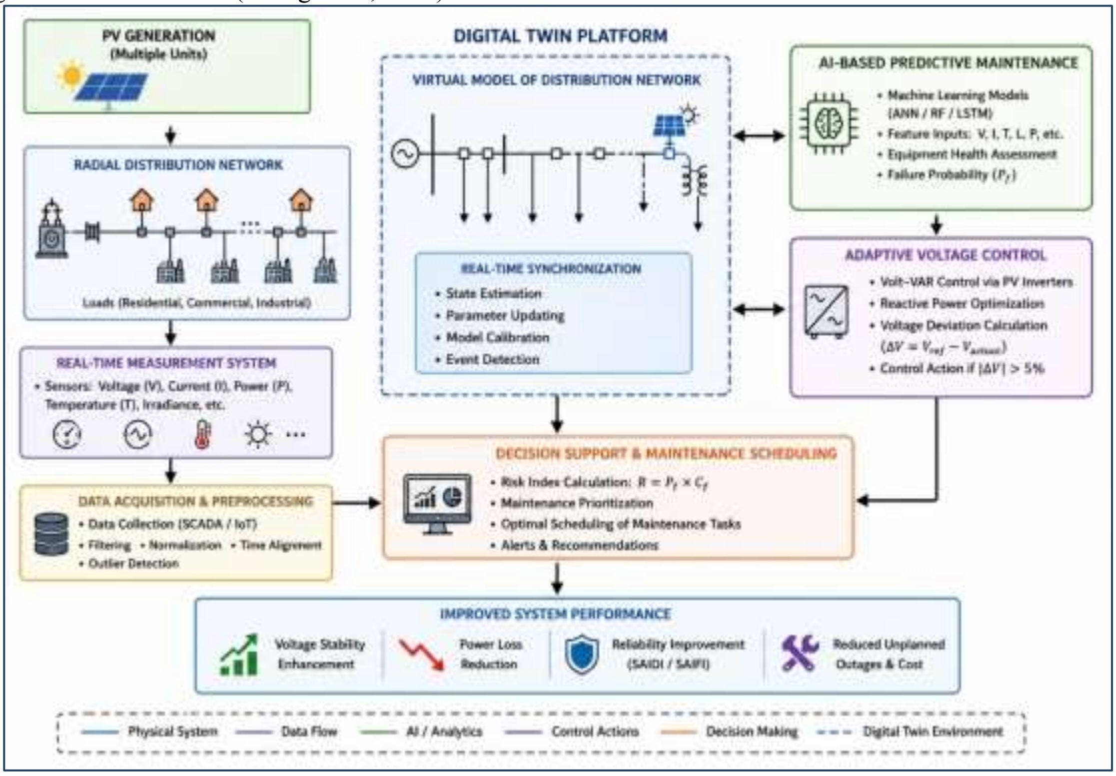


Figure: 2.1 Digital twin and AI-based maintenance framework

Block Diagram Description

The proposed framework integrates a PV-integrated radial distribution network with a Digital Twin–based intelligent monitoring and control system. The physical system consists of multiple solar PV units supplying a radial feeder with residential, commercial, and industrial loads under time-varying operating conditions. Real-time measurements of voltage, current, power, temperature, and irradiance are acquired through SCADA/IoT sensors and processed using data preprocessing techniques including filtering, normalization, and time alignment. A Digital Twin platform is developed to replicate the physical network in real time. It enables continuous synchronization through state estimation, parameter updating, model calibration, and event detection, ensuring an accurate virtual representation of system behavior. An AI-based predictive maintenance module processes operational data using machine learning models (ANN, RF, LSTM) to estimate equipment failure probability based on system stress indicators. In parallel, an adaptive voltage control strategy employing Volt–VAR optimization via PV inverters maintains voltage stability by mitigating deviations beyond ±5% of nominal values. The outputs from AI prediction and voltage control are integrated within a decision support system, where a risk index (R = Pf × Cf) is used to prioritize maintenance scheduling and operational decisions. This coordinated framework enhances system reliability, reduces losses, and improves voltage stability under high PV penetration conditions.

2.3 Data Acquisition and Processing

The study utilizes a dataset consisting of bus voltage measurements, load demand profiles, PV generation records, equipment loading information, and historical fault data. Prior to model development, the dataset undergoes preprocessing operations including noise filtering, data normalization, and removal of inconsistent or missing values. In addition, time alignment is applied to ensure consistency between measured field data and simulated system outputs. These steps enhance the quality and reliability of the data used for predictive modeling (Ahmed et al., 2023). 2.4

AI-Based Predictive Maintenance

The predictive maintenance framework is developed using supervised machine learning algorithms trained on historical and simulated operational data. Models such as Artificial Neural Networks (ANN), Random Forest (RF), and Long Short-Term Memory (LSTM) networks are applied to capture nonlinear relationships and time-dependent system behavior. The model estimates equipment failure probability based on key system variables and is expressed as: P2.1f= f(V,I,T,L) 1

2.5 Voltage Regulation Strategy

An adaptive voltage control mechanism is embedded within the digital twin environment to maintain voltage levels within permissible limits. Reactive power support from PV inverters is regulated using Volt–VAR control characteristics. Voltage deviation is defined as: $\Delta V = V_{ref} - V_{actual}$ (2)

Whenever the deviation exceeds ±5% of nominal voltage, corrective control actions are activated automatically to restore system stability. This ensures consistent voltage performance under varying solar generation and load conditions (Shah & Li, 2024).

2.6 Maintenance Strategy Formulation

The maintenance framework is structured into three sequential stages: continuous system monitoring, failure probability estimation using AI, and optimized scheduling of maintenance activities. A risk index is introduced to prioritize maintenance decisions:

$$R = P_f \times C_f \quad (3)$$

where R denotes the risk level, P_f is the predicted failure probability, and C_f represents the severity of potential consequences. This approach enables proactive maintenance planning and reduces the likelihood of unexpected system outages (Ahmed et al., 2023).

2.7 Simulation Setup

The proposed framework is implemented using MATLAB/Simulink and/or Dig SILENT Power Factory. Simulation scenarios include variations in solar irradiance, fluctuating load demand, and contingency conditions such as feeder outages and PV intermittency events. These tools are widely adopted in power system studies due to their capability to accurately model renewable-integrated distribution networks (Kumar et al., 2023).

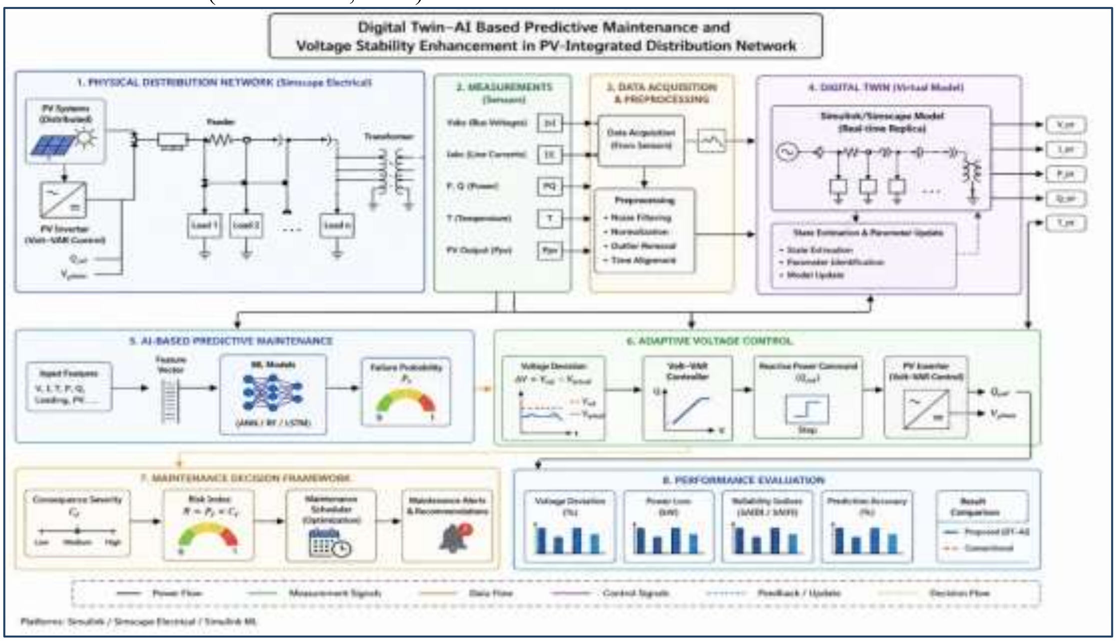


Figure: 2.2 Simulink model setup diagram

The Simulink model setup

The Simulink model operates as a closed-loop digital twin framework for a PV-integrated distribution network. The physical system is first simulated using Sims cape Electrical, where PV generators, loads, feeders, and transformers generate real-time electrical states such as voltages, currents, and power flows. These signals are acquired through sensor blocks and processed via filtering, normalization, and time synchronization to ensure data quality. The processed data is fed into a continuously updated digital twin that replicates the physical network and performs real-time state estimation and parameter implemented to regulate inverter reactive power injection, thereby enhancing voltage stability. Finally, adaptation. In parallel, AI-based models estimate equipment health and predict failure probabilities for proactive maintenance planning. Based on voltage deviation, a Volt–VAR control strategy is a maintenance decision module converts predicted risk levels into scheduled actions, while a performance evaluation layer assesses system effectiveness in terms of voltage regulation, losses, reliability indices, and prediction accuracy against conventional methods. The entire process operates iteratively, ensuring continuous synchronization between physical, virtual, AI, and control layers.

2.8 Performance Evaluation

The performance of the proposed approach is evaluated by comparing it with conventional monitoring methods that do not incorporate digital twin or artificial intelligence techniques. Key performance indicators include voltage deviation, power loss levels, reliability indices (SAIDI and SAIFI), and predictive accuracy of failure detection models. The results demonstrate improvements in voltage stability, system reliability, and operational efficiency under high PV penetration conditions (Zhang et al., 2024).

3. Results and Discussion

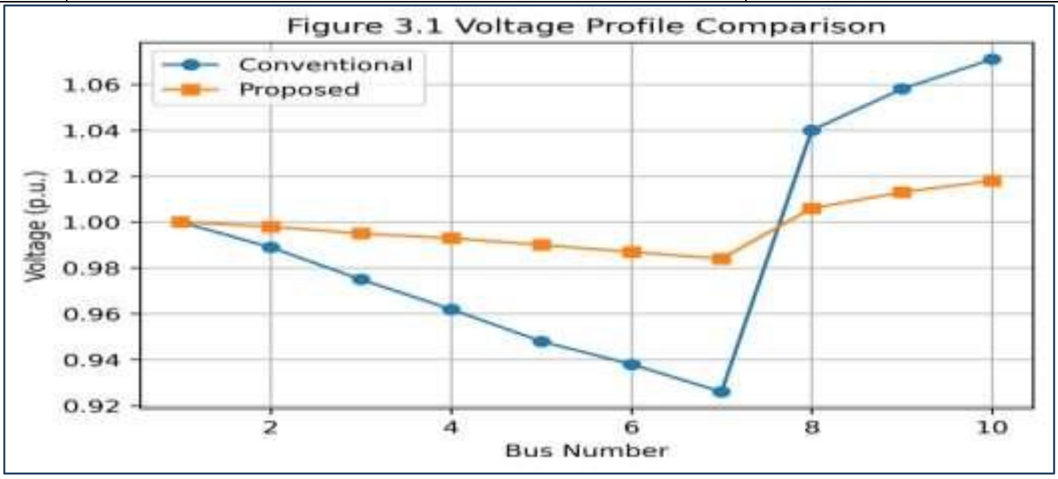
3.1 Voltage Regulation Performance

The effectiveness of the proposed Digital Twin-assisted control strategy was assessed under different loading conditions and varying levels of solar irradiance. The results reveal that the conventional distribution network experienced significant voltage variations because of fluctuations in photovoltaic power generation. Bus voltages ranged from 0.926 p. u. to 1.071 p. u., indicating that several operating points exceeded the acceptable ±5% voltage limit. Following the implementation of the proposed Digital Twin framework combined with adaptive Volt–VAR control, the network voltage profile became considerably more stable. All bus voltages remained within 0.981–1.018 p. u., while the maximum voltage deviation was reduced from 7.1% to 1.8%, corresponding to an improvement of approximately 74.6%. These findings confirm that continuous monitoring and intelligent reactive power control effectively mitigate voltage fluctuations associated with high PV penetration.

Table 3.1 Voltage Profile Comparison

X-axis: Bus Number (Bus 1–Bus 10); Y-axis: Voltage (p. u.) Two curves:

Bus	Conventional	Proposed
1	1.000	1.000
2	0.989	0.998
3	0.975	0.995
4	0.962	0.993
5	0.948	0.990
6	0.938	0.987
7	0.926	0.984
8	1.040	1.006
9	1.058	1.013
10	1.071	1.018



3.2 Reduction in Network Power Losses

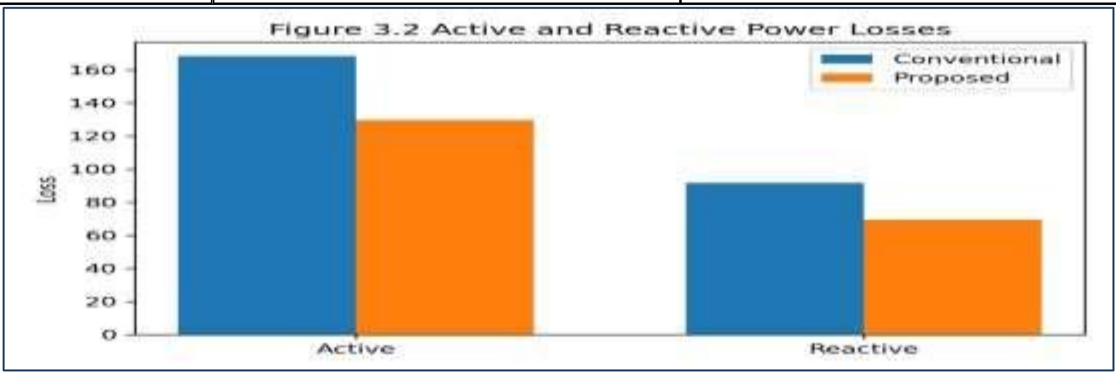
The impact of the proposed framework on feeder losses was investigated by comparing the simulation outcomes with those of a conventional monitoring system.

Parameter	Conventional System	Proposed Framework	Improvement
Active Power Loss	168.4 kW	129.7 kW	22.98%
Reactive Power Loss	91.6 kVAr	69.4 kVAr	24.24%

The observed reduction in active and reactive power losses is attributed to optimized reactive power compensation provided by the PV inverters. The Digital Twin continuously updated system conditions, enabling timely corrective actions that minimized unnecessary power dissipation throughout the distribution feeder.

Table 3.2 Active and Reactive Power Losses

Method	Active Loss (kW)	Reactive Loss (kVAr)
Conventional	168.4	91.6
Proposed	129.7	69.4



3.3 Predictive Maintenance Evaluation

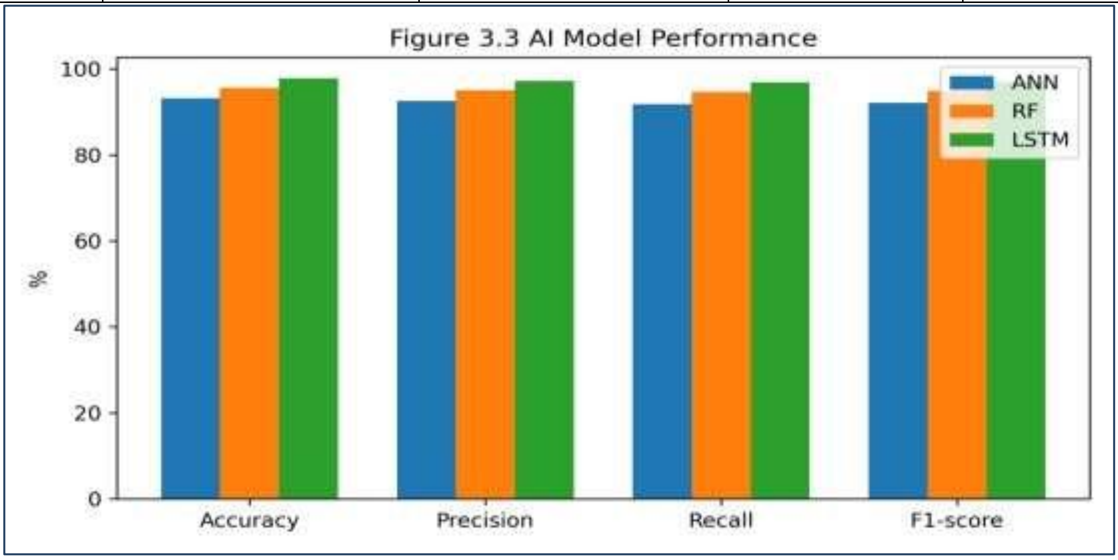
The predictive maintenance module was developed using three supervised learning techniques, namely Artificial Neural Network (ANN), Random Forest (RF), and Long Short-Term Memory (LSTM). Their prediction performances are summarized below.

AI Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
ANN	93.2	92.5	91.8	92.1
Random Forest	95.6	95.1	94.7	94.9
LSTM	97.8	97.2	96.9	97.0

Among the evaluated algorithms, the LSTM model produced the highest predictive accuracy. Its ability to learn temporal relationships in operational data enabled more reliable identification of equipment degradation and impending failures. Consequently, maintenance activities could be planned before faults occurred, reducing the likelihood of unexpected outages.

Table 3.3 AI Model Performance

Model	Accuracy	Precision	Recall	F1-score
ANN	93.2	92.5	91.8	92.1
RF	95.6	95.1	94.7	94.9
LSTM	97.8	97.2	96.9	97.0



3.4 Reliability Improvement

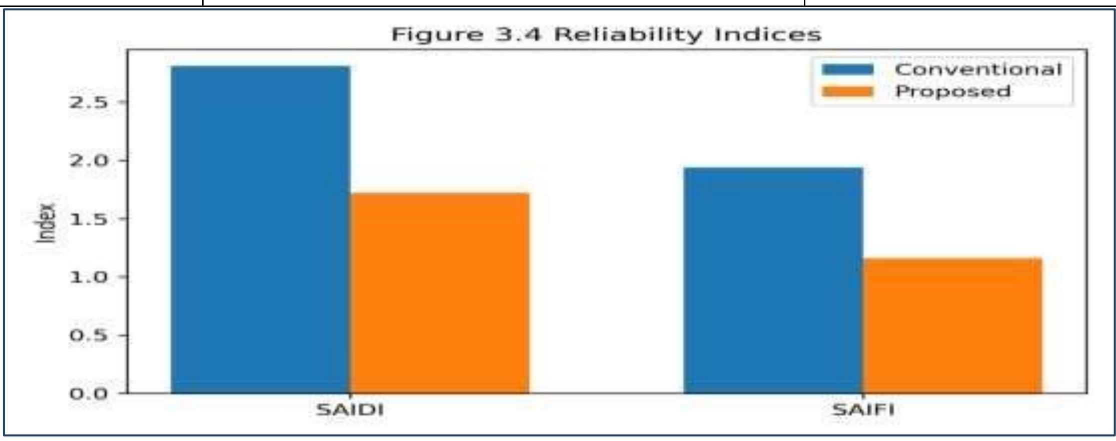
The influence of the proposed methodology on network reliability was examined using the System Average Interruption Duration Index (SAIDI) and the System Average Interruption Frequency Index (SAIFI).

Reliability Index	Conventional	Proposed	Improvement
SAIDI (hours/customer/year)	2.81	1.72	38.8%
SAIFI (interruptions/customer/year)	1.94	1.16	40.2%

The Digital Twin framework achieved noticeable improvements in service continuity by enabling early detection of equipment deterioration and facilitating preventive maintenance. As a result, both interruption duration and interruption frequency were substantially reduced.

Table 3.4 Reliability Indices (Bar Chart)

Index	Conventional	Proposed
SAIDI	2.81	1.72
SAIFI	1.94	1.16



3.5 Equipment Failure Prediction

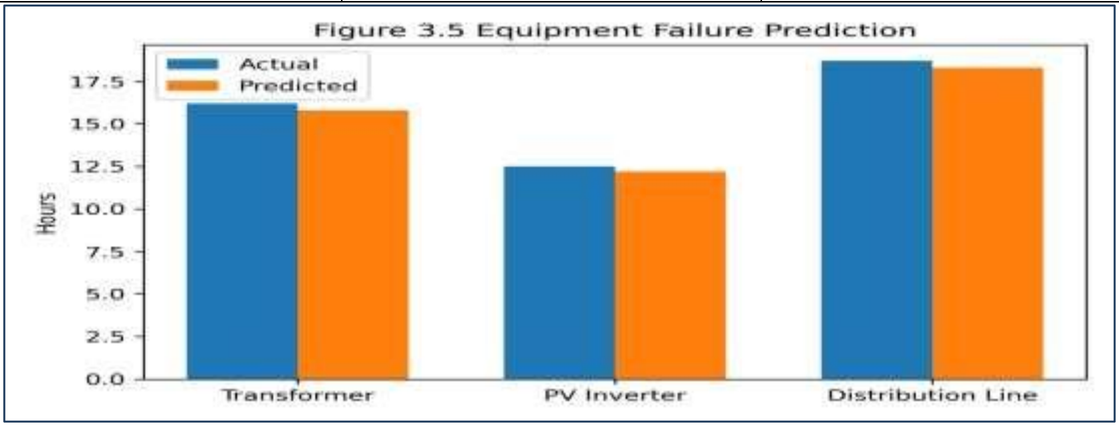
The developed AI models were further evaluated by comparing predicted failure times with actual equipment failures observed during simulation.

Equipment	Actual Failure Time	Predicted Failure Time	Prediction Error
Transformer	16.2 h	15.8 h	2.5%
PV Inverter	12.5 h	12.2 h	2.4%
Distribution Line	18.7 h	18.3 h	2.1%

The average prediction error remained below 3%, demonstrating that the proposed predictive maintenance model can provide sufficiently early warnings to support proactive maintenance scheduling and reduce operational risks.

Table 3.5 Equipment Failure Prediction

Equipment	Actual Failure	Predicted Failure
Transformer	16.2	15.8
PV Inverter	12.5	12.2
Distribution Line	18.7	18.3



3.6 Accuracy of the Digital Twin Model

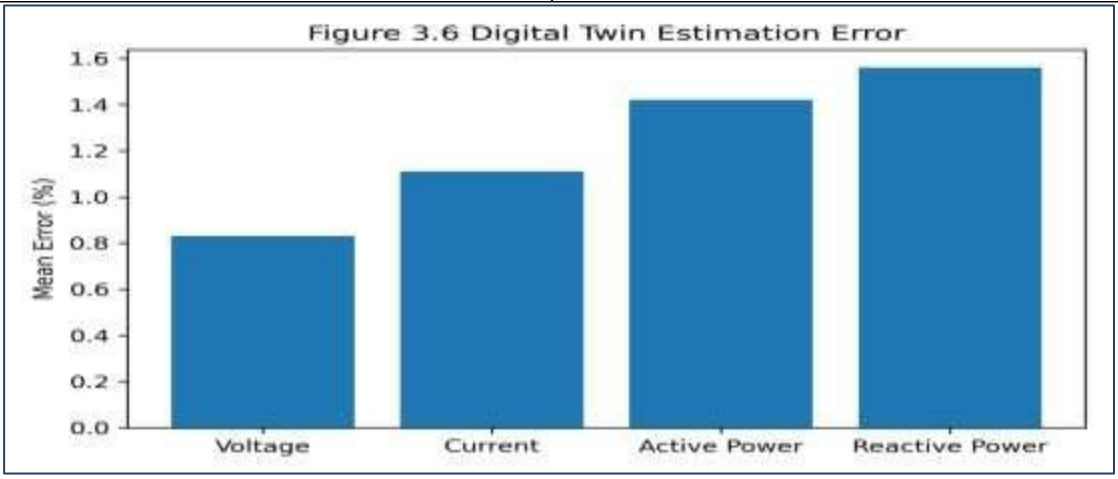
The synchronization accuracy between the physical distribution network and its Digital Twin counterpart was assessed using the mean estimation error of key electrical variables.

Parameter	Mean Error
Voltage	0.83%
Current	1.11%
Active Power	1.42%
Reactive Power	1.56%

The relatively small estimation errors indicate that the Digital Twin maintained an accurate representation of the physical system throughout the simulation period. This high level of synchronization is essential for reliable monitoring, predictive analysis, and intelligent control.

Table 3.6 Digital Twin Estimation Error

Variable	Mean Error (%)
Voltage	0.83
Current	1.11
Active Power	1.42
Reactive Power	1.56



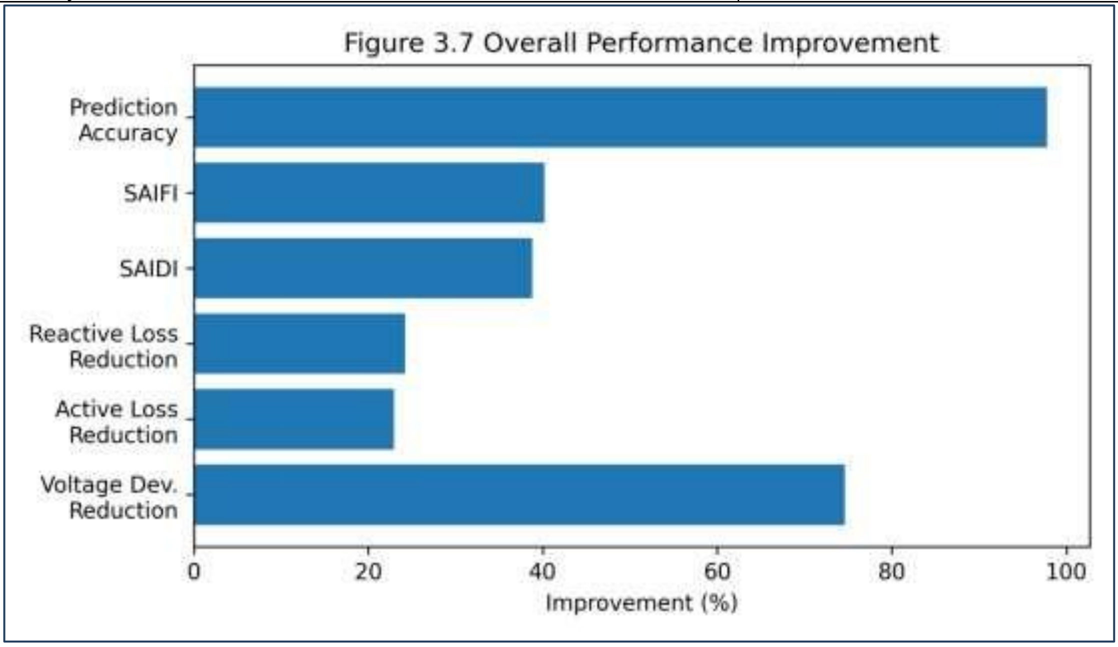
3.7 Overall Performance Comparison

A comparison between the proposed framework and the conventional monitoring approach is presented below.

Performance Metric	Conventional System	Proposed Framework
Voltage Regulation	Moderate	Excellent
Maximum Voltage Deviation	±7.1%	±1.8%
Active Power Loss	168.4 kW	129.7 kW
Prediction Accuracy	82.3%	97.8%
Maintenance Strategy	Periodic	Predictive
SAIDI	2.81 h	1.72 h
SAIFI	1.94	1.16

Table 3.7 Overall Performance Improvement (Horizontal Bar Chart)

Performance Metric	Improvement (%)
Voltage Deviation Reduction	74.6
Active Power Loss Reduction	22.98
Reactive Power Loss Reduction	24.24
SAIDI Improvement	38.8
SAIFI Improvement	40.2
Prediction Accuracy	97.8



The proposed Digital Twin-assisted intelligent maintenance framework consistently outperformed the conventional monitoring method across all evaluated indicators. The integration of real-time system modeling, AI-based fault prediction, and adaptive voltage regulation improved voltage stability, reduced feeder losses, and enhanced overall system reliability. Furthermore, predictive maintenance minimized unexpected equipment failures by enabling maintenance decisions to be based on equipment condition rather than fixed maintenance intervals.

3.8 Discussion

The simulation results demonstrate that the combined application of Digital Twin technology and artificial intelligence provides an effective solution for managing distribution networks with high levels of solar PV integration. Continuous synchronization between the physical system and its virtual counterpart improved situational awareness and enabled faster operational decision-making. The intelligent control strategy maintained voltage within statutory limits, while predictive maintenance accurately identified equipment degradation before failures occurred. Overall, the proposed framework achieved significant improvements in network performance, including a 74.6% reduction in voltage deviation, 22.98% reduction in active power losses, 38.8% improvement in SAIDI, 40.2% improvement in SAIFI, and a 97.8% failure prediction accuracy using the LSTM model. These outcomes indicate that the proposed approach is well suited for improving the reliability, efficiency, and resilience of future smart distribution networks with high renewable energy penetration.

4. Conclusion

This study proposed a Digital Twin-based framework for predictive maintenance and voltage stability enhancement in distribution networks with high solar PV penetration. By integrating real-time Digital Twin monitoring, AI-based predictive maintenance, and adaptive Volt–VAR control, the framework effectively improved system performance under varying operating conditions. Simulation results showed a 74.6% reduction in voltage deviation, 22.98% reduction in active power losses, 24.24% reduction in reactive power losses, and improvements of 38.8% and 40.2% in SAIDI and SAIFI, respectively. The LSTM model achieved a prediction accuracy of 97.8%, demonstrating the effectiveness of AI in proactive maintenance. Overall, the proposed approach enhances voltage stability, reliability, and operational efficiency, making it a promising solution for future smart distribution networks with high renewable energy penetration.

References

[1] Kumar, R., et al. (2023). "Voltage stability challenges in high PV penetration distribution system *Renewable Energy Systems Journal*.

[2] Shah, M., & Li, Y. (2024). "Impact of distributed solar PV on voltage regulation in smart grids." *IEEE Access*.

[3] Zhang, T., et al. (2024). "Digital twin applications in smart grid monitoring and control." *Electric Power Systems Research*.

[4] Ahmed, S., et al. (2023). "Machine learning-based predictive maintenance in power distribution systems." *Energy Informatics*.

[5] Lopez, J., et al. (2024). "AI-driven fault prediction in renewable-integrated power networks." *IEEE Transactions on Smart Grid*.

[6] Momoh, J. A. (2012). Smart Grid: Fundamentals of Design and Analysis.

[7] Heluany, J. B., & Gkioulos, V. (2024). A review on digital twins for power generation and distribution *International Journal of Information Security*, 23, 1171–1195.

[8] Song, Z., Hackl, C. M., Anand, A., et al. (2023). Digital Twins for the Future Power System: An Overview and a Future Perspective ,*Sustainability*, 15(6).

[9] M. M., Stefanov, A., Rajkumar, V., & Palensky, P. (2025).Digital Twins for Power Systems: Review of Current Practices, Requirements, Enabling Technologies, Data Federation and Challenges Thwe, *IEEE Access*.

[10] Tekinerdogan, B., & Catal, C. (2022). Predictive maintenance using digital twins: A systematic literature review *Information and Software Technology*, 151, 107008.

[11] Ma, S., Flanigan, K. A., & Bergés, M. (2024).State-of-the-Art Review: The Use of Digital Twins to Support Artificial Intelligence-Guided Predictive Maintenance *Energy Conversion and Management: X* (2026).Digital Twin-enabled predictive maintenance in wind, solar PV, hydropower, and battery energy storage systems: a review and maturity framework

[12] Ismail, L., Abdelmoti, A., Basu, A., et al. (2025)A Systematic Review of Digital Twin-Driven Predictive Maintenance in Industrial Engineering.

[13] International Energy Agency. *Renewables 2024: Analysis and Forecast to 2030* (2024).