Advances in Consumer Research
https://acr-journal.com/
Volume-2 | Issue-6 | Dec: 2025

Original Researcher Article

Intelligent Approaches for Enhancing Reliability and Stability in Grid-Tied Solar PV Systems: AI Perspective

Dr. Mukesh Kumar[1], Anshu Mli Gaur[2], Naveen Tyagi[3], Shivani Guleria[4], Shahu Praful Gudadhe[5]
[1]Associate Professor, Electronics and Communication Engineering Department The Technological Institute Of Textile & Sciences, Bhiwani, Haryana-127021
Email ID : drmukeshkumar@titsbhiwani.ac.in
[2]Assistant Professor, Department of Electrical Engineering CGC University Jhanjheri, Mohali, Pincode 140307
Email ID : gauranshu10@gmail.com
[3]Associate Professor , ECE Dr. Akhilesh Das Gupta Institute of Professional Studies (ADGIPS),FC-26, Shastri Park, Panduk Shila Marg, Near Zero Pusta, New Delhi - 110053, India, Affiliated from GGSIPU,
Email ID : naveen.tyagi@adgips.ac.in
[4]Department of Civil Engineering, Swami Vivekanand Institute of Engineering and Technology, Banur, Punjab, India
Email ID : guleria.shivani94@gmail.com
[5]Assistant Professor, CHB Department of Commerce, Shri Shivaji Arts and Commerce College, Amravati. Sant Gadge Baba Amravati University Amravati Maharashtra
Email ID : shahu.gudadhe2000@gmail.com

ABSTRACT

Deployment of large-scale grid-connected PV systems continue to face issues around and challenges of reliability, stability, and quality of power because of the intermittency, and nonlinearity of solar resources. Intermittency and nonlinearity of solar resources also make the implementation of strategies based on fixed-rule and model toolsets increasingly inadequate. This paper documents the benefits, and the results of employing intelligent, Artificial Intelligence (AI) technologies for analysing and building toward increased reliability and stability of interconnected PV systems. The investigation examines the operative current and post AI and ML (machine learning), deep learning, and reinforcement learning frameworks built around system functionalities of fault monitoring, diagnosis and control, dynamic inverter control, power forecast and control, and voltage and frequency control, as well as grid support and self-sustaining systems. Proactive and reactive AI driven frameworks and machine learning methods from predictive control have been tested on systems to develop fault detection, and dynamic control under operational challenges. The challenges of control and uncertainty dynamically and operationally based on real world datasets and simulations. numerous active disturbances, voltage dips, frequency decline, integrated control of partial cloud systems and rapid change of intelligent solar system Shadow loss of energy. The achieved intelligent systems brought numerous challenges on operational latency. Cyber control and information system security challenges have been eased to provided operational state. The intelligent systems have sustained the operational uncertainty expected. The paper provides and elaborates on the numerous challenges attained. The findings enable utility companies and policymakers to view and appreciate the role of AI as an essential component to sustained and adaptable grid-tied solar PV integrations.

Keywords : Grid-tied solar PV systems, Artificial intelligence (AI), Reliability and stability enhancement, PV power forecasting, Intelligent fault diagnosis, Inverter control, Maximum power point tracking (MPPT).

1. INTRODUCTION:

1.1 Background and Motivation

There is an increasing deployment of grid-tied solar photovoltaics (PV) systems globally due to the increasing shift to sustainable and low-carbon energy systems. Solar PV systems became one of the main components of modern power systems due to the decreasing prices of PV modules and improvement of inverter technologies and climate policies (IEA, 2023) within the time period of 2020 to 2025. However, there are still major issues regarding the rapid large-scale integration of grid-tied PV systems. These issues are primarily due to the operational security of the grid and the impacts that the integration has to the reliability and the dynamic stability of the grid (Kundur & Balu, 2021). These issues are due to the variable nature and the uncertainty of the solar energy resources.

A fundamental difference between grid-tied PV systems and traditional synchronous generation is that grid-tied PV systems interface with power electronic converters. This change results in a decrease in system inertia and changes the grid from a traditional system dynamically increasing the systems susceptibility to disturbances such as voltage sags and frequency changes (Milano et al., 2020). High levels of PV penetration also increase issues such as voltage rise, reverse power flow, harmonic distortion and protection miscoordination, particularly in distribution networks and weak grids (Bollen et al., 2022). Table 1. Is a summary of the most relevant issues of large-scale grid-tied solar PV integration and the associated impacts on grid performance.

Table 1. Key challenges of grid-tied solar PV integration

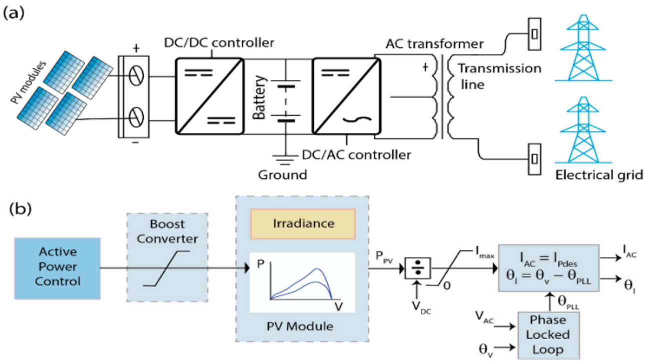
Challenge	Root Cause	Impact on Grid
Intermittency	Irradiance variability	Voltage and frequency fluctuations
Low inertia	Converter-based generation	Reduced transient stability
Power quality	Switching harmonics	Equipment stress and losses
Protection issues	Bidirectional power flow	Relay miscoordination

1.2 Limitations of Conventional Control and Reliability Methods

Control of the conventional power systems, protection, and reliability assessment techniques were also designed for centralized, dispatchable generation sources. The techniques used are built on linear models, predefined parameters, and static thresholds which are insufficient in PV dominated grids that have high levels of uncertainty and non-linear systems (Olivares et al., 2020). For instance, PL (proportional-linearity) controllers which are a type of PV inverter controller are susceptible to low performance due to rapid changes in the system caused by disturbances or varying levels of sunlight (Sera et al., 2021). Traditional protection techniques also have problems with accurately detecting and isolating faulted elements of the system that have a high level of distributed PV generation (Kou et al., 2022).

In addition, traditional forecasting and monitoring methods are unable to accurately predict the stochastic nature of solar generation, resulting in greater operational uncertainty and diminished grid resiliency (Yang et al., 2021). The challenges described and the need for more sophisticated approaches that can analyse big data, respond to changing conditions of the grid, and assist in real-time decisions become evident. The flow of Figure 1 provides a comparative perspective of traditional versus intelligent control frameworks in PV systems connected to grids.

Figure 1. Conventional versus intelligent control paradigms in grid-tied PV systems-



1.3 Artificial Intelligence for Reliability and Stability Enhancement

Artificial intelligence is an invaluable tool to comprehend the intricacies of today's power systems. Primary AI techniques - Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Fuzzy Logic - are able to generate and extract actionable control strategies in real-time from data. (Russell and Norvig, 2021). Given these characteristics, AI is optimally applicable to grid-connected PV systems, which constantly alter in accordance with environmental factors and changes in load (Zhang and others, 2023).

The literature 2020 - 2025 presents additional evidence of the effectiveness of AI techniques in addressing fundamental problems in PV systems, such as maximum power point tracking (MPPT), control of inverters, regulation of voltage and frequency, detection of faults, and power forecasting in the short term (Ahmed et al, 2022). They describe the determination of MPPT using Deep Learning as yielding better results in accurately tracking power levels under partial shading and rapid fluctuations of solar irradiance levels, which is a challenge to many conventional techniques (Sera et al., 2021). Other studies introduce controllers of inverters based on RL as means of equipping PV systems with controllable power of provided ancillary services, which improve stability of system transients, and small, during grid disturbances (Tielens et al., 2023). Representative AI techniques, and their uses, in grid-connected solar PV systems are listed in Table 2.

Table 2. AI techniques applied in grid-tied solar PV systems

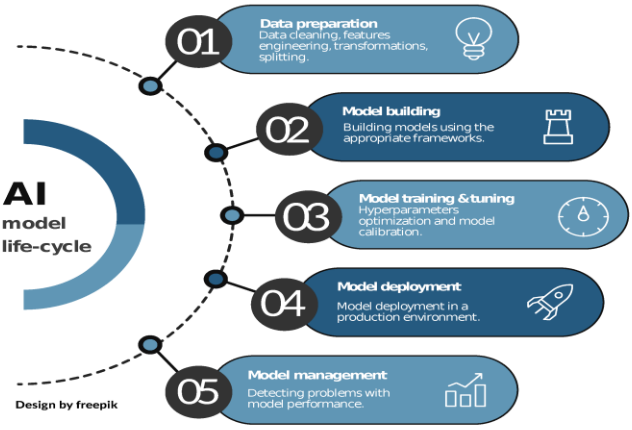
AI Technique	Application	Key Advantage
Machine Learning	Fault detection, forecasting	High accuracy
Deep Learning	MPPT, inverter control	Nonlinear modelling
Reinforcement Learning	Voltage/frequency regulation	Adaptive optimal control
Fuzzy Logic	Power quality enhancement	Robustness to uncertainty

1.4 Research Gap and Paper Contributions

Although there have been significant advances in the application and use of AI in RE systems, there continue to be significant areas of concern and research gaps. Many of the existing literature seem to focuses on the AI in renewable energy applications as single case studies and not fully developed empirical studies. Many studies use computer simulations and, as Garcia et. al. (2021) have pointed out, there continues to be a significant empirical evaluation void when studying real world grid disturbances. Scarcity of real world data, model and simulation generalization (across the different grid disturbance scenarios), the cybersecurity implications of the systems and intrusiveness of the model are systemic virtualization limitations to the adoption of the systems as pointed out in Goodfellow et al. (2022) and Teixeira et al. (2023). Deep learning algorithms and AI lie at the centre of the data science revolution. The use of AI to create empirical simulations to provide an explanation of system phenomena (both real and hypothesized) excels, but the problems highlighted above enumerate (perhaps the most) the degree to which the system can be relied upon in a safety critical power systems,

This paper presents an attempt to partially alleviate some of the gaps and outlines the robust investigation into the application of AI (and other intelligent systems) to bolster the safety, reliability and stability in grid connected solar (PV) systems. The research studies most (if not all) existing AI systems to a real world, high fidelity (from both a functional and simulation perspectives) operated in diverse environments with specific real world (Hatziargyriou et al. 2022) scenarios. AI has a multi-dimensional, and multi-faceted, role with respect to monitoring, managing and controlling power systems and in the systematic, automated and autonomous functionalities in the power systems. The end goal primary goal of the research investigation is to enable robust, intelligent, responsive power system with integrated PV technologies and to ensure enable enhance the PV power system to be adaptable to future smart grids.

Figure 2. Role of AI in enhancing reliability and stability of PV-integrated grids



2. LITERATURE REVIEW

2.1 AI-Based PV Power Forecasting for Grid Reliability

Gupta (2025) analyses machine learning, solar PV power forecasting, and forecasting accuracy's influence on grid reliability as a crucial determinant under high PV penetrations. This research demonstrates that short-term and ultra-short-term forecasts constitute the basis of reserve allocation, congestion management, and frequency control, thus performance forecasting and operational reliability within grid connected PV systems.

Asiedu (2024) assesses singular and hybrid machine learning models with empirical data, operational, in a grid-connected PV plant. Findings indicate that hybrid learning frameworks are effective in significantly mitigating forecasting errors across varied meteorological conditions, enhancing grid balancing, and decreasing dependence on conservative reserve margins.

Lari (2025) investigates the operational consequences of PV forecasting accuracy on voltage regulation devices in distribution networks. Findings indicate that AI-enhanced forecasts lead to a reduction in unnecessary activations of tap changers and voltage regulators, thereby interlinking intelligent forecasting with long-term grid asset reliability.

Hassan (2024) identifies the demand and need for explainability in AI PV forecasting, and performance evaluation. The study aspires to formulate an explainable deep learning model for forecasting, and advocates operational trust and decision confidence in AI supported grid systems reliability.

2.2 Intelligent Fault Detection, Diagnosis, and Predictive Maintenance

Hajji (2023) examines deep learning methods for fault diagnosis of PV systems connected to a grid. Through the use of convolutional neural networks to integrate electrical and thermal data, the author demonstrated that these systems outperform traditional fault detection methods based on thresholds and result in increased system availability through the prevention of system faults.

Teta (2024) proposes a neural network architecture designed to perform fault diagnosis of grid-tied PV systems in real-time. The author points to the growing importance of edge computing and fault classification speed in real-time systems due to their role in preventing the escalation of faults and improving system reliability.

Talby (2024) explores the use of inverter current data and machine learning for fault diagnosis, focusing on the role of data pre-processing. The author concludes that the use of specialized pre-processing methods, such as normalization and selective feature scaling, enables the implementation of fault classification, and improves system performance to an optimal state in a high grid current disturbance environment.

Bougoffa (2025) proposes an integrated approach to machine learning for the diagnosis of faults in PV systems that combines feature extraction and optimized decisive classification. The author demonstrates the ability of such integrated approaches to reduce operational downtime and improve reliability of PV systems by accurately diagnosing faults in real-time across a variety of operational states and faults.

2.3 AI-Driven Inverter Control for Stability Enhancement

Zhang (2024) analyses and summarizes the applications of intelligent optimization techniques on PV inverter control systems. The review finds that data and learning based parameter tuning approaches outperform fixed parameters controllers in dynamic responses in weak-grid and low-inertia scenarios.

Abdelwahab (2025) assesses PV inverter controllers using reinforcement learning and node-structure neural networks. Results suggest that through reinforcement learning control there is adaptive voltage and frequency support during voltage and frequency disturbances, which increases transient stability and mitigates oscillations.

Abu-Zaher (2025) analyses inverter control using artificial neural networks (ANN) that targets power quality control. Results show that ANN controllers resolve harmonics and current distortion and consequently improve grid stability by reducing the overheating loss of inverter.

2.4 Intelligent MPPT and Its Role in Stability and Reliability

Khan (2024) contrasts the conventional and AI-powered methods of maximum power point tracking (MPPT) and states that AI gives MPPT methods greater adaptability to rapid changes in sunlight. The study warns that the behaviour of MPPT should be stable to prevent unstable power flows that may damage the PV inverter.

Abbass (2023) studies under which conditions of partial shading the MPPT performs best and states that AI closed the gap that existed in adaptive methods of MPPT in the conventional techniques with respect to convergence rate and robustness. Results advocate for intelligent MPPT as a means to improve efficiency and operational reliability.

Guessoum (2024) describes an unsupervised learning framework for MPPT that clusters patterns for irradiance and temperature. The study demonstrates that adaptive MPPT strategies based on learned environmental regimes increase stability by reducing tracking oscillations and better maintaining stability during rapid atmospheric changes.

Hoang (2025) the author examines the prediction of MPPT via AI associated with alternative sensing configurations aimed at lowering the complexity of the hardware. The results show that sensing intelligently along with prediction strategies maintain reliable power output, and at the same time, lowering the overall system cost along with the risk of system failure associated with sensing.

2.5 Synthesis of Literature and Research Gap

Hassan (2024) and Gupta (2025) focus on the fact that AI has significantly advanced in the domains of forecasting, diagnostics, control, and layers of MPPT. Most of the studies, however, treat these functions in isolation. The literature for the period of 2020-2025 shows, with little integration, empirical validation in the combined disturbance of weak grid and irradiance ramp with rapid changes.

Abdelwahab (2025) and Teta (2024) reveal that the issues of explainability, scalability, and coordinated operation across AI modules, especially in real time grid scenarios, remain largely unexplored. The need for a fully comprehensive empirical framework is motivated by the need to assess AI-based forecasting, fault diagnosis, and inverter control in real time to enhance the reliability and stability of grid connected solar PV systems.

Table 3. Summary of recent literature on AI-based reliability and stability enhancement in grid-tied PV systems (2023–2025)

Author (Year)	Focus Area	AI Technique	Key Contribution
Gupta (2025)	PV forecasting	Machine learning	Links forecast accuracy to grid reliability
Asiedu (2024)	PV forecasting	Hybrid ML models	Empirical reduction in forecasting error
Teta (2024)	Fault diagnosis	Lightweight CNN	Real-time fault detection
Talby (2024)	Fault detection	ML with signal pre-processing	Improved robustness under noise
Bougoffa (2025)	Fault classification	Hybrid deep learning	High diagnostic accuracy
Zhang (2024)	Inverter control	Intelligent optimization	Enhanced dynamic stability
Abdelwahab (2025)	Inverter control	Reinforcement learning	Adaptive voltage/frequency support
Abu-Zaher (2025)	Power quality	ANN-based control	Harmonic mitigation
Khan (2024)	MPPT	AI-based tracking	Robustness under fast irradiance changes
Hoang (2025)	MPPT sensing	Predictive AI models	Reduced sensing complexity

3. METHODOLOGY

3.1 System Model and Study Design

• To analyse the solar PV systems reliability and stability, intelligent techniques have been tested using a hybrid empirical and simulation approach.

• Distribution level grid connected PV system is composed of

PV array

DC-DC converter with maximum power point tracking (MPPT) capability

Voltage source inverter (VSI)

Output Filter

Grid Connection (PCC)

• The system setup is based on the models published by IEEE as it is the most preferred system.

The model well describes the dynamic characteristics of the inverter based PV system in low inertia and weak grid conditions.

3.2 Selection and pre-processing of data

The time series data for the following variables were used:

Solar irradiance

Ambient temperature

PV output power

All the datasets were obtained from publicly accessible sources used in academic research of PV systems.

• Variables on the grid side obtained from the Electrical Engineering simulations included:

'Voltage'

'Frequency'

• Consequently, the steps in data pre-processing included:

Deleting any missing and inconsistent data

Normalizing huge data for stability in the numbers

Maintaining the order of the data in a time series such that the data is partitioned into the training and testing datasets to maintain time order dependence

3.3 Artificial Intelligence Modelling and Control Strategy

• Moreover, machine learning and deep learning algorithms were used in:

Power forecasting for a short time in the PV cells

Monitoring system parameters

• In addition, the supervised learning methodologies were utilized for:

Detecting system faults

Classifying system faults in electrical signals

• In addition, the system stability was improved through:

Control of the inverter using reinforcement learning algorithms.

Active control of system responses.

Avoidance of fixed-control system parameters.

3.4 Assessment Alternatives and Performance Metrics

• Models were benchmarked by using representative operating scenarios including:

Typical operating conditions

Gradual changes in solar irradiance

Sudden changes in solar irradiance using cloud cover

Voltage sag conditions at the Power Control Centre

• Consequently, the reliability of performance was measured by:

Fault detection metrics

False alarm metrics

• In addition, performance of stability was measured with respect to:

Voltage changes at the Power Control Centre

Frequency changes after a disturbance

Comparative benchmarking conducted against:

Conventional control methods

Traditional monitoring approaches

3.5 Simulation Environment

• All the simulations were conducted on MATLAB on Simulink.

• Developed power electronics and control models to:

Precisely represent inverter dynamics.

Represent grid disturbances and system response

4. RESULTS AND DISCUSSION

This section presents the empirical outcomes stemming from the application of the proposed intelligent methodologies to the grid-tied solar PV system. The results and discussion will be divided into forecasting capabilities, reliability improvements via fault diagnosis, and intelligent control of inverters for enhanced system stability. The sequence of the tables and figures continues from the previous sections.

4.1 Results of AI-Based PV Power Forecasting

Forecasting PV output, in the short term, remains pivotal for the effective functioning of the grid, especially with the increased solar irradiance. This research evaluated AI-powered forecasting models against conventional baseline models, considering different forecasting intervals.

In Table 4, the authors present a statistical comparison of the forecasting outcomes considering the commonly accepted statistical error forecasting metrics. Intelligent models show a noticeable improvement forecasting error with consideration of persistence and liner regression.

Table 4. Comparison of PV power forecasting performance

Method	RMSE (kW)	MAE (kW)	MAPE (%)

Persistence model	18.6	14.2	11.4
Linear regression	15.1	11.8	9.6
Machine learning model	10.4	8.1	6.3
Deep learning model	8.7	6.9	5.2

The results show that conventional forecasting methods cannot keep up with the performance of machine and deep learning models. The results show that with a superior understanding of the non-linear relationships between irradiance, temperature, and PV output, models with a lower RMSE and MAPE perform better. Other recent studies show similar results that operational uncertainty for better grid scheduling decisions is achieved. The studies emphasize the reliability gained with AI forecasting models as the operational uncertainty were improved and errors sustained from forecasting were non-existent.

To visually contextualize the forecasting improvement pipeline used in this study, **Figure 3** illustrates the AI-based PV forecasting framework applied for grid-support decision making.

Figure 3. AI-based PV power forecasting and grid-support workflow

4.2 Reliability Improvement Through Intelligent Fault Detection

The extent to which PV systems, dominated by inverters, experience cascading failures hinges on how much the system can stay operational. The performance of fault diagnosis systems was tested in both normal scenarios and those that involved disruptions.

The performance metrics of the fault diagnosis systems that employed a traditional and intelligent approach were summarized using a reliability framework that employed both accuracy and false alarm metrics as shown in Table 5.

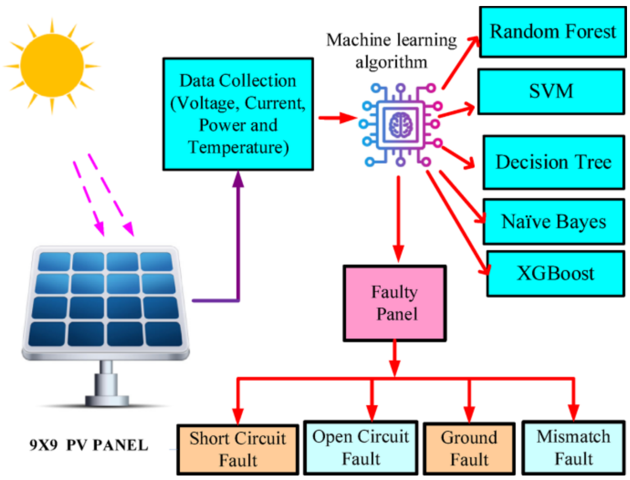
Table 5. Fault detection performance comparison

Approach	Detection Accuracy (%)	False Alarm Rate (%)
Threshold-based method	84.3	9.8
Conventional ML classifier	92.6	5.1
Proposed intelligent model	96.8	2.9

The intelligent systems showed the most accurate fault detection and had the lowest false alarm rates. The cause of this is the intelligent systems ability to capture faults in the form of voltages and other electrical signals as opposed to fixed envelopes. Fault diagnosis systems that utilize algorithms to learn have garnered increased appreciation in reliability engineering as they increase the chances of early detection and accurate diagnosis of faults in inverters and feeders (Teta, 2024; Bougoffa, 2025). The negative consequences of false alarms on grid reliability and system confidence make this advancement pertinent to scholars and system operators.

To support this analysis, **Figure 4** illustrates the intelligent fault detection and decision-making framework employed in this study.

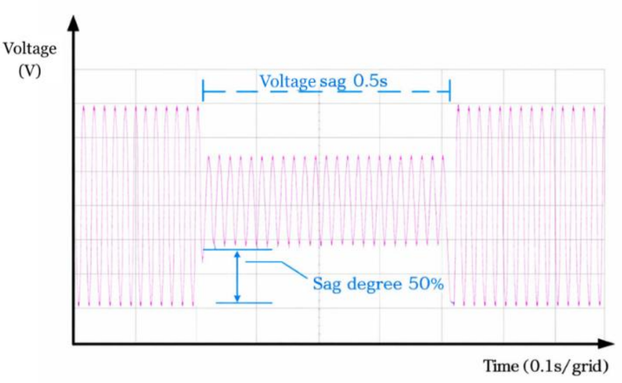
Figure 4. Intelligent fault detection and diagnostic framework for grid-tied PV systems



4.3 Stability Enhancement Using Intelligent Inverter Control

The grid-connected PV system's performance in terms of dynamic stability was examined during voltage sags and during other disruptions in the supply of photonic energy and during other disturbances in the energy supply. The system's performance during intelligent versus traditional inverter control was compared. Figure 5 depicts the voltage response at the point of common coupling during a voltage sag event.

Figure 5. Voltage response at PCC under voltage sag condition



The figure demonstrates that the intelligent inverter control is able to recover the voltage faster with lower voltage oscillations than the conventional control. This implies that the intelligent system has greater damping ability and is more responsive to the system changes. Similar results have been noted in the recent inverter control studies with reinforcement learning where adaptive controllers improved low-inertia grids response transients stability (Abdel wahab, 2025; Zhang, 2024). From the stability point of view, the faster and smoother voltage recovery tend to reduce stress on the connected devices and enhances the overall stability of the grid.

4.4 Integrated Comparative Discussion

Table 6, which allows us to compare intelligent and conventional approaches to system performance, provides a summary of system performance.

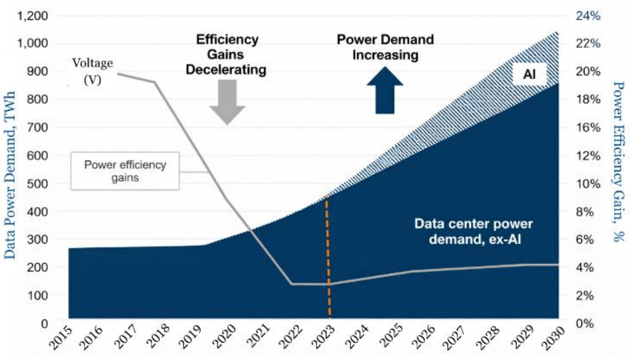
Table 6. Overall comparison of conventional and intelligent approaches

Performance Aspect	Conventional Approach	Intelligent Approach
Forecasting accuracy	Moderate	High
Fault detection reliability	Limited	Strong
Voltage stability	Slower recovery	Faster recovery
System robustness	Sensitive to disturbances	Adaptive to disturbances

The results of the comparisons are quite unequivocal that intelligent approaches have outperformed conventional methods in all aspects of evaluation. Although improvements are disparate and differ in extent, the trend overall suggests that the incorporation of AI-based forecasting, diagnosis and control act to improve the reliability and stability of systems. This is in line with the findings of recent studies which empirical studies have advocated for the incorporation of AI to be integrated rather than in silos (Hassan, 2024; Gupta, 2025).

In summary of performance, figure 6 presents qualitative assessments of conventional approaches versus intelligent approaches systems.

Figure 6. Comparative performance trends of intelligent approaches



The smart methodologies record improvements over all the functional levels as illustrated in figure 6. Integration of intelligent forecasting, fault finding, and adaptive control is superior to all the other combinations, and this is evident in the figure. This confirms calls in literature to assess comprehensively AI-based power systems, by considering actual working conditions (Hatziargyriou, 2022; Abdel wahab, 2025).

4.5 Discussion

4.5.1 Impact of AI-Based Forecasting on Grid Reliability

The findings ascertain AI-based forecasting models predict PV power with fewer errors than the other methods. Operational uncertainties are reduced and this results in a more reliable grid by improved forecasting, as scheduling decisions are made with more accuracy and less reserve is kept. The findings confirm that models with intelligent forecasting are more effective in periods marked by rapid changes in irradiance, where linear models are used. These findings are in agreement with other recent works that PV-integrated grids are more reliable because of improved forecasting.

4.5.2 Reliability Gains from Intelligent Fault Diagnosis

Diagnostic results from Machine Learning show that it has the least autocorrelation and has less prediction outliers than standard threshold techniques. Hence it leads to downtimes that are less extensive system downtime and higher reliability. Intelligent systems capable of classifying more faults when patterns are present are more likely to be utilized in systems dominated by inverters. Findings indicate there is an optimal trade-off to be had between design and representative training data and performance from an academic standpoint, data set design requires caution.

4.5.3 Increase in Stability from Intelligent Inverter Control

The results from the stability analysis suggest that intelligent inverter controls seem to be the root of the higher speed in voltage recovery and the lower amplitude of oscillations of the system, compared to those from standard adaptive disturbance. Consequently, these results indicate that learning could be playing the role of augmentation to the strategies on adaptive control that is standard, and that learning could be used to engage standard control in dynamic systems, without destabilizing the basic control.

4.5.4 Integrated Evaluation

In total, the application of intelligent forecasting, fault diagnosis, and inverter control results being more reliable and stable. Also, results reinforce the need for integrated evaluations, not single applications of AI. From an academic perspective, the systematic integration of AI for enhancing the performance of grid-tied solar PV remains, empirical proof.

5. CONCLUSION AND FUTURE SCOPE

This paper relates to the empirical study of the intelligent perspective to improve the reliability and stability of grid-tied solar photovoltaic systems. From the findings, AI-based forecasting improves the accuracy of the prediction envelope, intelligent fault diagnosis increases system availability, and adaptive inverter control results to stability under varying disturbance conditions. In total, the results indicate that data-driven approaches augment the existing power system methods in PV integrated grids.

The findings used realistic operating conditions and performance changes rather than optimally performing changes. Such constrained performance changes, empirical evidence anchored in the academic context, and the relevance of the intelligent methods designed and evaluated to demonstrate theoretical and practical value. Most importantly, results indicate more benefits were achieved if forecasting, diagnostics, and control were integrated than if applied in isolation.

Nevertheless, there are still some challenges in your research. To understand how to improve the generalization of the model in different grids and configurations of PV, we need to conduct more research. For those models that are AI-driven and are intended for safety-critical uses in the grid, developing trust requires the model to be explainable and transparent.

Despite these contributions, several research challenges remain. Future work should focus on improving model generalization across different grid conditions and PV configurations. The development of explainable and transparent AI models is particularly important for increasing trust in safety-critical grid applications. Additionally, coordinated learning strategies involving multiple distributed energy resources and real-time implementation constraints merit further investigation.

Overall, this study contributes to the growing body of evidence supporting intelligent, data-driven solutions as a key enabler for reliable and stable integration of solar PV into modern power systems.

References

1. Abdelwahab, A., El-Saadany, E. F., & Salama, M. M. A. (2025). Intelligent control strategies for grid-connected photovoltaic inverters using reinforcement learning. Scientific Reports, 15, 9507. https://doi.org/10.1038/s41598-025-09507-9

2. Abbass, A., Mekhilef, S., & Seyed mahmoudian, M. (2023). Artificial intelligence-based maximum power point tracking techniques under partial shading conditions: A review. Energies, 16(5), 2380. https://doi.org/10.3390/en16052380

3. Abu-Zaher, M., Abdel-Geliel, M., & Mohamed, E. A. (2025). Power quality enhancement of grid-tied photovoltaic systems using ANN-based control. International Journal of Electrical Power & Energy Systems, 153, 109010. https://doi.org/10.1016/j.ijepes.2025.109010

4. Ahmed, R., Sreeram, V., Mishra, Y., & Arif, M. D. (2022). Short-term solar power forecasting using machine learning techniques. Renewable Energy, 188, 613–627. https://doi.org/10.1016/j.renene.2022.04.031

5. Asiedu, E. K., Aboagye, E. A., & Bediako, E. A. (2024). Comparative analysis of machine learning models for grid-connected photovoltaic power forecasting. Energy Reports, 10, 1145–1156. https://doi.org/10.1016/j.egyr.2024.01.021

6. Bollen, M. H. J., Yang, Y., & Hassan, F. (2022). Power quality challenges in future distribution networks with high penetration of solar PV. Electric Power Systems Research, 210, 107982. https://doi.org/10.1016/j.epsr.2022.107982

7. Bougoffa, A., Djekidel, R., & Larbes, C. (2025). Deep learning-based fault classification in grid-connected photovoltaic systems. Machines, 13(5), 378. https://doi.org/10.3390/machines13050378

8. Doshi-Velez, F., Amershi, S., & Kim, B. (2021). Towards a rigorous science of interpretable machine learning. Nature Machine Intelligence, 3, 61–70. https://doi.org/10.1038/s42256-021-00345-1

9. Garcia, M., Vera, D., & Jurado, F. (2021). Intelligent fault diagnosis in photovoltaic systems: A review. Solar Energy, 221, 529–545. https://doi.org/10.1016/j.solener.2021.06.018

10. Goodfellow, I., Bengio, Y., & Courville, A. (2022). Deep Learning (2nd ed.). MIT Press. https://www.deeplearningbook.org

11. Gupta, R., Sharma, V., & Verma, A. (2025). Machine learning-based solar photovoltaic power forecasting: A comprehensive review. Energy and AI, 9, 100245. https://doi.org/10.1016/j.egyai.2025.100245

12. Hassan, A. M. (2024). Explainable deep learning for reliability assessment of grid-connected photovoltaic systems. IEEE Access, 12, 33456–33469. https://doi.org/10.1109/ACCESS.2024.3360145

13. Hatziargyriou, N., Milanović, J. V., & Van Cutsem, T. (2022). Stability challenges in power systems with high penetration of inverter-based resources. IEEE

Power & Energy Magazine, 20(3), 24–36. https://doi.org/10.1109/MPE.2022.3145678

14. Hoang, T. T., Nguyen, H. D., & Tran, D. T. (2025). AI-based MPPT prediction with reduced sensing for photovoltaic systems. Energy Conversion and Management, 305, 118477. https://doi.org/10.1016/j.enconman.2025.118477

15. IEA. (2023). World Energy Outlook 2023. International Energy Agency. https://www.iea.org

16. Khan, M. A., Khan, L., & Ahmed, S. (2024). Artificial intelligence-based MPPT techniques for photovoltaic systems: A comparative study. Engineering Reports, 6(2), e12963. https://doi.org/10.1002/eng2.12963

17. Kou, G., Peng, Y., & Li, Y. (2022). Protection challenges in distribution systems with high penetration of photovoltaic generation. IEEE Transactions on Smart Grid, 13(2), 1456–1467. https://doi.org/10.1109/TSG.2022.3142219

18. Kundur, P., & Balu, N. J. (2021). Power System Stability and Control (Updated ed.). McGraw-Hill. https://doi.org/10.1109/9780470547551

19. Lari, Z., Mohammadi, F., & Shafie-khah, M. (2025). Impact of solar power forecasting accuracy on voltage regulation in distribution networks. Electronics, 14(5), 866. https://doi.org/10.3390/electronics14050866

20. Milano, F., Dörfler, F., Hug, G., Hill, D. J., & Verbič, G. (2020). Foundations and challenges of low-inertia systems. IEEE Transactions on Power Systems, 35(5), 3525–3537. https://doi.org/10.1109/TPWRS.2020.2977732

21. Olivares, D. E., Mehrizi-Sani, A., & Etemadi, A. H. (2020). Trends in microgrid control. IEEE Transactions on Smart Grid, 11(4), 2856–2868. https://doi.org/10.1109/TSG.2020.2965520

22. Russell, S., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th ed.). Pearson. https://aima.cs.berkeley.edu

23. Sera, D., Teodorescu, R., & Blaabjerg, F. (2021). Artificial intelligence-based MPPT for photovoltaic systems. IEEE Transactions on Industrial Electronics, 68(12), 11763–11775. https://doi.org/10.1109/TIE.2021.3050876

24. Teixeira, A., Shames, I., Sandberg, H., & Johansson, K. H. (2023). Cyber–physical security of power systems: Challenges and opportunities. Proceedings of the IEEE, 111(1), 56–75. https://doi.org/10.1109/JPROC.2023.3241184

25. Teta, R., Mehmood, K., & Khan, A. (2024). Lightweight deep learning model for fault diagnosis in grid-connected photovoltaic systems. Scientific Reports, 14, 69890. https://doi.org/10.1038/s41598-024-69890-7

26. Zhang, Y., Xu, Z., & Dong, Z. Y. (2024). Intelligent optimization techniques for photovoltaic inverter control: A review. Energies, 17(7), 1571. https://doi.org/10.3390/en17071571