



Research article

Artificial Intelligence-driven maximum power point estimation for enhanced adaptive power regulation in rooftop PV systems



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ABSTRACT

This paper presents a novel framework for improving grid stability in rooftop photovoltaic (PV) systems by integrating an AI-based Maximum Power Point (MPP) estimation model with a newly designed adaptive power regulation (APR) strategy. The primary objective is to operate the inverter-based power conditioning unit dynamically based on the real-time load demand of individual buildings, ensuring that power injection aligns with local consumption while avoiding grid disturbances. A second-order polynomial regression model is trained on historical PV voltage and current data to estimate the MPP without environmental sensors. This estimated MPP informs an RHS-based APR controller that curtails surplus power by shifting operation away from the MPP during periods of excess generation. A real-time scenario involving a 2 MW rooftop PV deployment across 20 buildings demonstrates the necessity of such regulation, with simulation studies in MATLAB/Simulink showing up to 21% curtailment, voltage reduction from 250 V to 231 V, and frequency deviation controlled within ± 0.2 Hz. The proposed method achieves $< 2\%$ power tracking error, 0.01 s dynamic response, and steady-state oscillation below 0.5%. Hardware implementation on a 1 kW rooftop setup using an NI myRIO controller confirms reliable performance under irradiance fluctuations, with THD maintained at 4.76% in compliance with IEEE 519 standards. These results validate the effectiveness of combining lightweight AI-based estimation with real-time, load-aware adaptive power regulation to enhance inverter performance and ensure grid compliance in distributed solar applications.

1. Introduction

1.1. Research background

In recent years, rooftop photovoltaic systems have emerged as a key driver in the global transition toward decentralized energy generation. By 2024, global rooftop PV capacity exceeded 250 GW, marking a significant shift in energy infrastructure from centralized production to distributed micro-generation [1]. Residential, commercial, and institutional buildings are increasingly transforming into prosumers both consuming and generating electricity thereby altering traditional grid dynamics [2].

India, as one of the largest and fastest-growing energy markets, plays a pivotal role in this transformation. The nation ranks fifth in global power generation capacity, with an installed base of 444,756 MW, and third in terms of transmission infrastructure [3]. A combination of rapid electrification, industrial growth, and a population exceeding 1.4 billion has

driven per capita electricity consumption to 1331 kWh, with projections indicating a continued upward trend [4]. Solar energy is central to India's renewable strategy, supported by approximately 300 sunny days annually and a solar potential exceeding 5 EWh per year [5]. The Ministry of New and Renewable Energy (MNRE) and the Solar Energy Corporation of India (SECI) are actively promoting grid-connected rooftop PV systems and large-scale solar parks [6]. As of May 2024, India's renewable energy portfolio reached 146.65 GW, with rooftop solar contributing 15.08 GW to the 84.27 GW total solar PV capacity [7]. The rooftop segment is dominated by commercial and industrial consumers, accounting for nearly 80% of installations [8].

1.2. Extensive literature survey

Despite their growing adoption, rooftop PV systems present notable operational challenges, particularly at the grid edge. Their intermittent

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Nomenclature*Abbreviation*

AI-APR	Artificial Intelligence-based Adaptive Power Regulation
APR	Adaptive Power Regulation
DC	Direct Current
LV	Low Voltage
MPP	Maximum Power Point
MPPT	Maximum Power Point Tracking
PCU	Power Conditioning Unit
PI	Proportional–Integral
PV	Photovoltaic
QPSO	Quantum-behaved Particle Swarm Optimization
RES	Renewable Energy Sources
RHS	Right-Hand Side
RTSPV	Rooftop Solar Photovoltaic
SDG	Sustainable Development Goal
SPWM	Sinusoidal Pulse Width Modulation
THD	Total Harmonic Distortion

Symbols and Notations

V_{pv}	PV array voltageV
I_{pv}	PV array currentA
$P_{pv}(t)$	Instantaneous PV powerW
$\hat{P}_{mp}(t + \tau)$	Estimated maximum power at horizon τ W
$R_f(t)$	Reserve fraction–

$\hat{L}(t + \tau)$	Forecasted load demand at horizon τ W
$P_{target}(t)$	Target power referenceW
$e(t)$	Power tracking errorW
$u(t)$	Control signal (duty ratio input)–
$K_p(t)$	Adaptive proportional gain–
$K_i(t)$	Adaptive integral gain–
V_{dc}	DC link voltageV
f	Grid frequencyHz
H	Inertia constants
δ	Load anglerad
P_m	Mechanical input powerW
P_e	Electrical output powerW
K_D	Damping constant–
THD	Total Harmonic Distortion%

Units

A	Ampere
V	Volt
W	Watt
Hz	Hertz
rad	Radian
rad/s	Radian per second
s	Second
F	Farad
H	Henry
%	Percentage

output, coupled with dynamic local loads, introduces issues such as power fluctuations, reverse power flow, and voltage rise in low-voltage (LV) distribution networks [9]. These conditions can cause non-compliance with grid codes such as IEEE 929, IEEE 1547, and Rule 21, often resulting in inverter shutdowns and energy losses [10].

To address such problems, several mitigation techniques have been explored. These include demand-side load control [11], integration of battery energy storage systems [12], and PV disconnection schemes [13]. However, storage-based solutions entail high costs and complex control strategies. As an alternative, active power regulation implemented either through load management or inverter-level control has gained traction due to its cost-effectiveness and scalability [14].

Multiple inverter-based control approaches have been proposed, such as Direct Power Control (DPC) [15], current reference tracking [16], and inductor current reference strategies [17]. While these techniques offer basic control over PV output, they often fall short in handling rapid environmental changes or adapting to diverse operating conditions. To improve performance, algorithms for PV power limit control [18] and Flexible Power Point Tracking (FPPT) [19] have been developed. Nevertheless, these algorithms introduce additional computational complexity and require high-speed processing capabilities, limiting their suitability for embedded inverter platforms.

Recent advances in artificial intelligence have significantly improved the performance of photovoltaic energy management systems by enabling adaptive prediction, intelligent optimization, and robust decision-making under varying operating conditions. Advanced AI models have demonstrated superior capability in handling nonlinear system dynamics and enhancing renewable energy applications through data-driven learning and optimization techniques [20]. Furthermore, machine learning-based intelligent control strategies have shown improved accuracy in maximum power point estimation, adaptive power regulation, and energy forecasting, thereby enhancing the efficiency and reliability of PV systems operating under dynamic environmental conditions [21,22]. Motivated by these developments, the present work proposes an Artificial Intelligence-Driven Maximum Power Point

Estimation framework that integrates adaptive learning with inverter power regulation to improve energy harvesting and ensure stable operation of rooftop PV systems under rapidly changing irradiance and load conditions

1.3. Research gaps and challenges

Despite significant progress in power control strategies for rooftop PV systems, several critical limitations persist. Many existing algorithms exhibit strong dependence on environmental sensors such as irradiance and temperature sensors, which not only increase system cost but also introduce points of failure that reduce overall robustness. Additionally, numerous control methods rely on iterative or multi-stage logic, imposing a computational burden that exceeds the processing capabilities of typical commercial inverters. Stability under low-power reference conditions remains a concern, as many controllers fail to operate reliably during periods of low irradiance. Moreover, compliance with regional policy constraints such as Tamil Nadu's 999 kWp injection cap is often overlooked, limiting real-world applicability. Most importantly, many existing approaches regulate PV output without considering real-time variations in building load demand, leading to inefficiencies and increased curtailment. These challenges highlight the pressing need for a control strategy that is simultaneously sensorless, computationally lightweight, regulation-compliant, and responsive to both generation and consumption dynamics.

1.4. Motivation

Commercial rooftop PV systems commonly operate under strict grid constraints and variable load conditions. In many cases, inverters automatically disconnect when generation exceeds acceptable injection limits leading to underutilization of solar energy and reduced return on investment. These issues are particularly acute in the Indian context, where diverse climatic conditions, non-uniform load profiles, and evolving grid policies demand a more nuanced and adaptive approach.

The motivation behind this work is to design a simple, real-time, and regulation-compliant control strategy that dynamically adjusts power output based on both PV availability and building load demand. Such a system would reduce the risk of disconnection, minimize curtailment, and ensure grid stability all without requiring extensive sensing infrastructure or expensive hardware upgrades.

1.5. Major contributions and novelties

This paper proposes a lightweight, scalable Adaptive Power Regulation (APR) framework tailored for rooftop SPV systems. Its major contributions are as follows:

1. Sensorless MPP Estimation: A second-order polynomial model estimates the Maximum Power Point using only PV voltage and current, removing the need for irradiance or temperature sensors.
2. Non-iterative control logic: The proposed regulation scheme avoids complex computations, making it compatible with commercially available inverters.
3. Real-time load-aware operation: A reserve estimation block adapts power injection based on predicted short-term load trends at the building level.
4. Regulatory integration: The system enforces regional injection caps and utility constraints, supporting compliance with policies such as India's 1 MWp net metering limit.
5. Stability under low power reference: The APR logic ensures reliable operation even under low-irradiance or low-demand scenarios, a critical need in urban residential applications.

Together, these features make the proposed APR strategy highly suitable for large-scale deployment in distributed rooftop solar networks.

1.6. Organization of the paper

The remainder of this paper is organized as follows: Section I introduces the context, research gaps, and key contributions of the study. Section II outlines the motivation for adaptive power regulation in rooftop solar PV systems, emphasizing the limitations of conventional inverter protection strategies. Section III presents a case study of a distributed rooftop PV system, highlighting the operational challenges that necessitate adaptive power control. Section IV describes the proposed Adaptive Power Regulation (APR) strategy, including the AI-based sensorless MPP estimation, predictive load forecasting, reserve calculation, and RHS curtailment control logic. Section V discusses the simulation and experimental validation of the AI-APR framework, detailing real-time testing, performance metrics, and dynamic stability analysis. Section VI provides a comprehensive comparative evaluation of the proposed AI-APR method against conventional APR techniques in terms of accuracy, complexity, and adaptability. Finally, Section VII concludes the paper and outlines potential future directions.

2. Motivation for adaptive power regulation in rooftop SPV systems

2.1. Need for active power control in solar photovoltaic (SPV) systems

The importance of Adaptive Power Regulation implementation in the SPV system is covered in this section. Regulating voltage and frequency effectively keeps the grid reliable and stable. Otherwise, frequency variations can affect industrial motors and other equipment, cause turbine governor obstruction, and lessen system stiffness [23]. Furthermore, as emphasizes, going beyond a certain voltage fluctuation threshold might interfere with the functioning of consumer equipment in the network, which includes motors, lighting systems, and electronics [24].

2.2. Grid overloading

In the peak midday hours, when radiation and temperature levels are high, temperature plays a crucial role in affecting the production of PV panel voltage [25]. Eq. (1) explains the connection between voltage fluctuation and its dependencies.

$$|\Delta V| = \frac{R}{V_R} dP + \frac{X}{V_R} dQ \quad (1)$$

Where R represents the resistance within the circuit, V_R denotes the receiving end voltage [V], and $X(\Omega)$ signifies the voltage fluctuations $\Delta V[V]$. P denotes active power (W), and Q represents reactive power (W). In the current grid infrastructure, the parameters of resistance, receiving end voltage, and inductive reactance remain constant, while the levels of active and reactive power fluctuate over time. Within the low voltage (LV) grid, the R/X ratio typically exhibits a higher value due to the relatively shorter length of grid cables. As a result, the term R/V_R in Eq. (1) plays a critical role, significantly impacting the magnitude of voltage fluctuations [10].

2.3. Due to sudden passing

Short-term fluctuations in solar radiation, primarily influenced by cloud movements, can swiftly transition a solar energy generation plant from operating at maximum capacity to minimal generation, or vice versa, within seconds [26]. These sudden changes in power generation, induced by cloud movements, present operational challenges for solar PV power plants and the management of electrical grids [27]. As a proactive measure, grid operators may need to explore implementing strategies like utilizing voltage limiters to mitigate these challenges effectively.

2.4. Aging of existing power system

Aging is attributed to mechanical damage in generators, insulation depletion in transformers and reactors, and erosion of metal structures such as underground cable sheathing. If the solar PV system in aged buildings is connected to weak grid networks, which commonly have high impedance, typically above 1 mH, it can cause instability during sudden peak power generation periods. This instability can significantly impact grid-tied systems, potentially leading to grid current distortion [28]. To adhere to the recommendations set forth in the IEEE 519–1992 standards, it is strongly advised to ensure that a power system maintains a total harmonic distortion current (THD) below 5%.

2.5. Participation of frequency regulation

Eq. 2, commonly known as the swing equation, establishes a direct correlation between active power and frequency [29]. This Eq. 2 illustrates that any active power imbalance will cause frequency deviations in a power system operated by synchronous generation

$$2.H. \frac{d^2\delta}{dt^2} = P_m - P_e - K_D. \frac{d\delta}{dt} \quad (2)$$

Here, H represents the inertia constant, δ denotes the load angle, P_e signifies the electromagnetic power, P_m represents the mechanical power, and K_D stands for the damping factor. To mitigate frequency variations, it is imperative to adjust the power injection of power plants. In conventional power plants such as thermal, gas, oil, and nuclear facilities, the regulation of grid frequency relies on turbine input, involving intricate mechanical processes [30]. Conversely, in the case of SPV-based power plants, frequency regulation is accomplished by controlling the duty cycle of the Power Electronics Converters, making the participation of solar power plants in frequency regulation easier, as highlighted in [31].

2.6. Limitations of existing commercial inverter protection schemes

Commercial Power Conditioning Units (PCUs) are typically equipped with basic protection mechanisms designed to prevent damage and maintain grid stability. These include under/over-voltage and under/over-frequency tripping functions, which operate within pre-defined thresholds. For instance, synchronization is maintained within 80%–110% of the rated voltage (230 V/415 V) and 47.5 Hz–50.5 Hz frequency range. When these limits are exceeded, the inverter disconnects from the grid and remains offline for a mandatory reconnection period, often up to two seconds. While these safety features are essential, they contribute to energy curtailment, suboptimal grid utilization, and delayed dynamic response, particularly during transient disturbances. Moreover, such PCUs lack predictive or adaptive capabilities, rendering them incapable of modulating power injection based on real-time consumption trends or short-term demand forecasts. This reactive behavior limits their effectiveness in high-penetration rooftop PV scenarios where rapid power fluctuations and localized demand mismatches are common.

2.7. Need for adaptive power regulation in rooftop PV systems

Rooftop SPV systems increasingly face challenges due to mismatched generation and load:

2.7.1. Oversupply and Load Mismatch

Systems are often oversized for maximum savings, leading to surplus generation during midday. This causes backfeed into the grid, resulting in voltage rise and potential equipment stress [32].

2.7.2. Storage and export limitations

Battery storage raises system costs and still cannot fully address surplus during peak solar hours. Regulatory caps like the 999 kWp injection limit in Tamil Nadu—further restrict export options [9]. Such constraints can destabilize weak LV grids prone to voltage and frequency deviations.

2.7.3. Economic and regulatory constraints

Despite offering lower LCOE (INR 2.5–4/kWh), rooftop SPV must navigate diverse state policies. Unregulated injection during peak periods can threaten grid stability [33].

These issues clearly call for an intelligent power regulation strategy that dynamically aligns generation with demand and complies with grid codes. The following section presents a real-world case study that motivates the development of the proposed AI-enhanced APR framework.

3. Case study on a distributed rooftop PV system emphasizing the necessity of adaptive power regulation

This section outlines a real-world scenario that highlights the need for Adaptive Power Regulation (APR). An educational institute in Tamil Nadu, India (Latitude: 10° 45' 46.80" N, Longitude: 78° 49' 4.80" E) is planning to install a 2 MWp rooftop solar photovoltaic (RTSPV) system across its hostel and lecture hall buildings. Following standard rooftop sizing guidelines, approximately 10 square meters of usable area is required for every 1 kW_p of installed capacity, resulting in a total rooftop space requirement of 20,000 square meters. The proposed system is distributed in nature, with each building receiving a PV installation sized according to its energy consumption. These systems are to be connected to the respective low-tension (LT) panels, which operate at 415 V. The campus electrical infrastructure is built around an 11 kV underground (UG) ring main system, with backup supply from a high-tension (HT) diesel generator. Voltage step-down to the LT side is facilitated by four transformers with ratings of 200 kVA, 250 kVA, 500 kVA, and 1000 kVA. The combined peak daytime load across the campus is estimated to be around 1.3 MW. For safe and reliable operation, it is necessary to ensure that the total PV capacity installed across the site does not exceed the transformer capacities or the average daytime demand, especially during hours of peak generation.

To evaluate the operational feasibility of the proposed RTSPV system, real-time solar radiation data was recorded at the campus site. As depicted in Fig. 1, irradiance levels rise steadily through the morning and peak around midday. Using this solar profile, the energy output from the 2 MWp system was simulated using MATLAB/Simulink, as shown in Fig. 2. Meanwhile, the actual load demand for the same day was obtained from the institute's electrical maintenance department and is presented in Fig. 3. Comparing Figs. 2 and 3, it becomes evident that during the early morning (8:00 a.m. – 10:30 a.m.) and late afternoon (1:30 p.m. – 5:00 p.m.), the generation is insufficient to meet demand. However, between 10:30 a.m. and 1:30 p.m., a generation surplus occurs.

This surplus leads to two primary concerns. First, excess injection into the LT panels may cause voltage rise, particularly in buildings using older cables, switches, and distribution boards not rated for extended overvoltage conditions. Second, exporting the surplus energy to the grid is constrained by Tamil Nadu state regulations that cap LT-side solar injection at 999 kW_p per service connection. Although battery energy storage was considered as a mitigation option, it was ruled out due to high capital costs and limited scalability. Consequently, there is a clear need for a cost-effective and responsive power regulation mechanism that can curtail excess generation in real time, based on actual load and transformer capacity. This case study therefore supports the necessity of implementing an Adaptive Power Regulation scheme for reliable and grid-compliant operation of distributed rooftop PV systems.

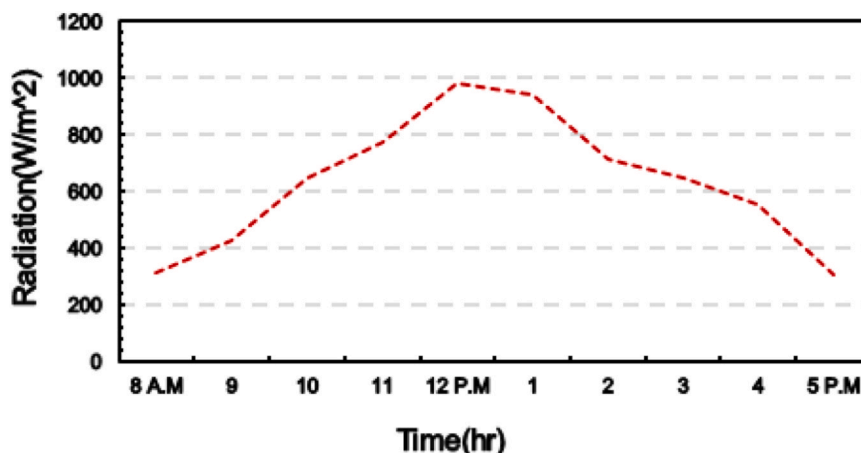


Fig. 1. Solar radiation falls on the educational institute specific day.

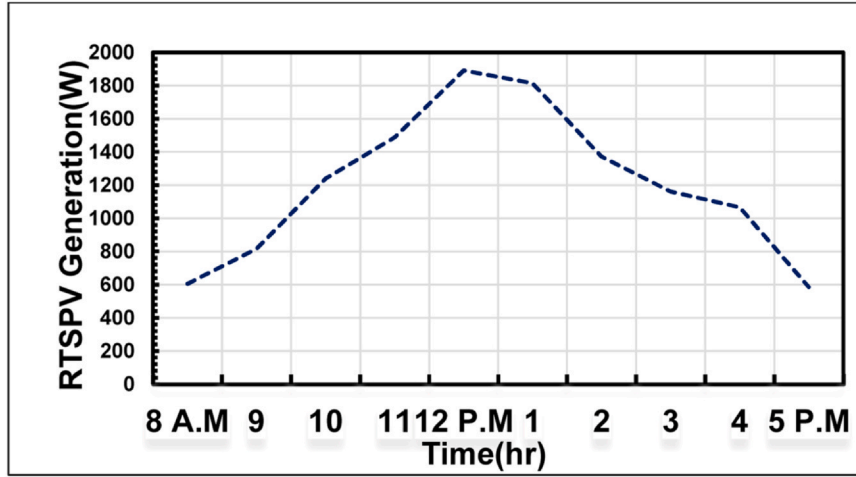


Fig. 2. Solar PV energy generation by 2MWp roof top system in the education institute.

4. Proposed adaptive power regulation strategy and AI-based MPP estimation

4.1. AI-driven real-time control loop

To address the operational limitations identified in grid-connected institutional rooftop photovoltaic (RTSPV) systems particularly those related to midday power surplus, grid export caps, and inflexible inverter control this work proposes an AI-enhanced Adaptive Power Regulation (AI-APR) framework. The proposed architecture offers a lightweight, computationally efficient solution designed to operate in real time and adapt dynamically to changing solar irradiance and load conditions. Its goal is to improve power quality, optimize energy utilization, and ensure compliance with grid codes without requiring energy storage systems or complex multi-mode control schemes. As illustrated in Fig. 4, the framework integrates a real-time control loop within the power conditioning unit (PCU). This loop modulates the active power output of the inverter by responding to both instantaneous and short-term forecasted load demand. Central to the architecture is an AI-based maximum power point (MPP) estimation unit, which replaces traditional MPPT algorithms that rely on irradiance and temperature sensors or circuit-model-based tracking. The estimation process is data-driven, relying solely on two real-time electrical measurements: PV voltage (V_{pv}) and current (I_{pv}). The MPP estimator employs a second-order polynomial regression model trained on historical operational data. This regression model maps V_{pv} and I_{pv} to the estimated available maximum power $\hat{P}_{mp}(t + \tau)$ at a short future time horizon τ , and is expressed as:

$$\hat{P}_{mp}(t + \tau) = a_0 + a_1 V_{pv} + a_2 I_{pv} + a_3 V_{pv}^2 + a_4 I_{pv}^2 + a_5 V_{pv} I_{pv} \quad (3)$$

This formulation eliminates the need for environmental sensors and provides a fast, reliable estimate of available PV power, making it well-suited for embedded implementation in rooftop PV systems requiring adaptive curtailment and grid-friendly operation.

Where, a_0 to a_5 are pre-trained coefficients and τ denotes a short-term forecasting horizon. This model enables fast, sensor-independent estimation, simplifying embedded integration and improving real-time decision-making. Once the available maximum power $\hat{P}_{mp}(t + \tau)$ is estimated, the system computes a reserve fraction $R_f(t)$ to determine the portion of power that can be curtailed. This is based on the difference between the estimated power and the forecasted load $\hat{L}(t + \tau)$, expressed as:

$$R_f(t) = \frac{\hat{P}_{mp}(t + \tau) - \hat{L}(t + \tau)}{\hat{P}_{mp}(t + \tau)} + \alpha \cdot \epsilon(t) \quad (4)$$

Here, α is a correction gain and $\epsilon(t)$ is the instantaneous power tracking error. The forecasted load $\hat{L}(t + \tau)$ is obtained by analyzing historical site-specific load data and constructing a daily load curve using optimization techniques. Metaheuristic algorithms such as Quantum-behaved Particle Swarm Optimization (QPSO) are employed to tune the model parameters for accurate forecasting. The resulting load curve enables the controller to anticipate future demand conditions and proactively adjust power injection targets. Based on the computed reserve, the power target for grid injection is calculated as:

$$P_{\text{target}}(t) = \hat{P}_{mp}(t + \tau) \cdot (1 - R_f(t)) \quad (5)$$

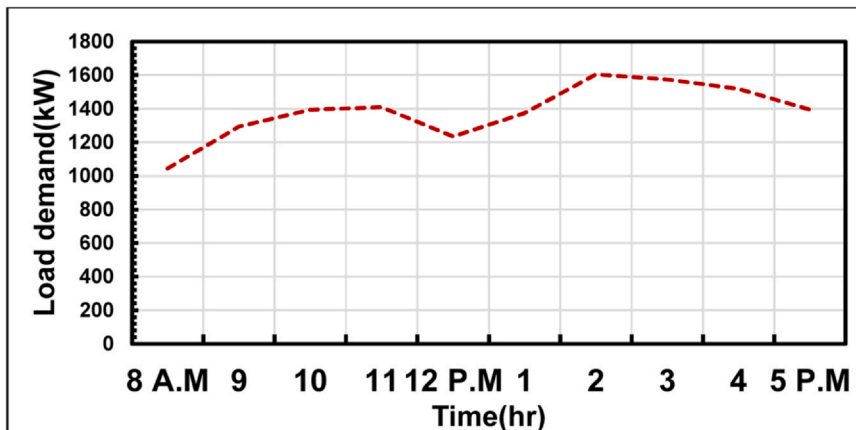


Fig. 3. Load demand on the educational institute for a specific day.

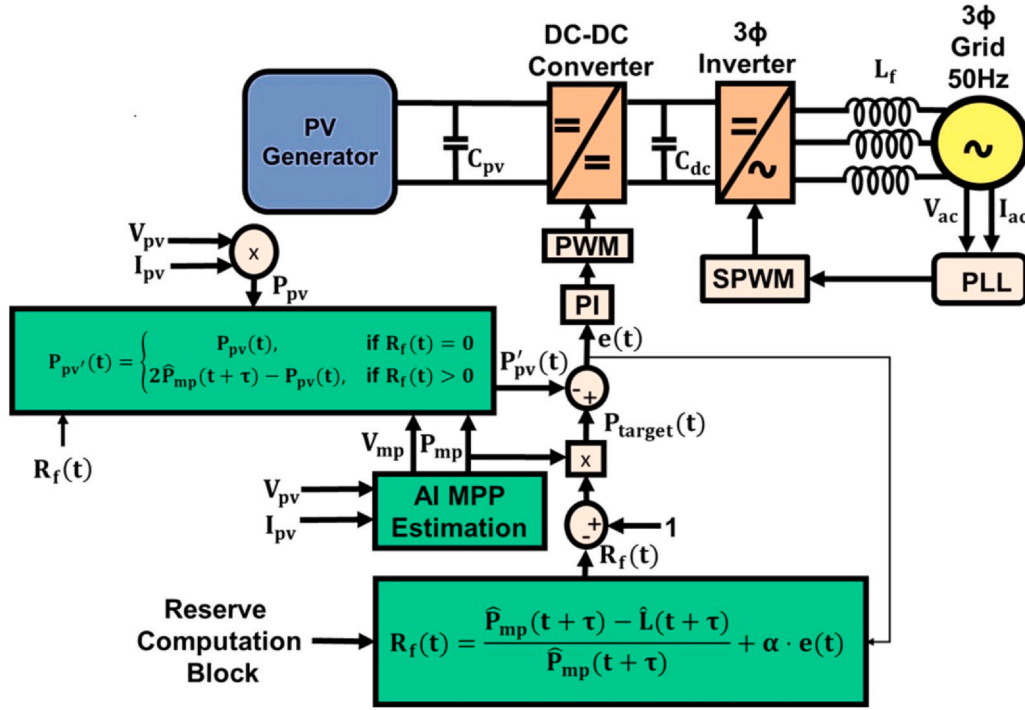


Fig. 4. Proposed AI-APR framework for rooftop PV systems.

The system continuously compares the actual measured PV power $P_{pv}(t)$ with the computed target, generating the tracking error:

$$e(t) = R_{\text{target}}(t) - P_{pv}(t) \quad (6)$$

This error is processed by an adaptive proportional–integral (PI) controller, which generates a control signal:

$$u(t) = K_p(t) \cdot e(t) + K_i(t) \cdot \int e(t) dt \quad (7)$$

where $K_p(t)$ and $K_i(t)$ are adaptive gains. The controller output $u(t)$ modulates the duty cycle of a 20 kHz DC-DC boost converter, thereby maintaining the DC-link voltage within operating limits. A novel contribution of the AI-APR framework is the incorporation of Right-Hand Side (RHS) power operating logic. Under surplus generation conditions ($R_f(t) > 0$), the system intentionally shifts the PV operating point toward the right of the MPP on the PV curve by adjusting the converter duty cycle resulting in increased voltage and reduced current. This mitigates surplus injection and avoids inverter shutdowns. The RHS logic is expressed as:

$$P_{pv'}(t) = \begin{cases} P_{pv}(t), & \text{if } R_f(t) = 0 \\ 2\hat{P}_{mp}(t + \tau) - P_{pv}(t), & \text{if } R_f(t) > 0 \end{cases} \quad (8)$$

This strategy enables smooth and continuous curtailment aligned with grid export limitations, particularly during peak irradiance periods. By avoiding abrupt inverter disconnection events, it contributes to more stable converter operation and consistent power quality. The regulated DC output is interfaced with the grid through a sinusoidal pulse-width modulation (SPWM) inverter, which facilitates current injection at unity power factor and maintains total harmonic distortion (THD) below 5%, in accordance with IEEE 519 standards. The proposed AI-APR framework integrates real-time power estimation, predictive load forecasting, and adaptive control to deliver a robust, regulation-compliant solution for rooftop SPV systems. By incorporating RHS logic into the control loop, the system can modulate the PV operating point under surplus conditions without instability. Additionally, the use of optimization-based daily load profiles enables the controller to anticipate variations in demand and proactively adjust power injection. Together, these features enhance the framework's ability to respond dynamically to environmental and load fluctuations. As a result, the AI-APR architecture improves energy

efficiency, ensures grid compatibility, and supports secure integration of distributed rooftop PV systems making it particularly well-suited for decentralized, real-time applications.

4.2. AI-based MPP estimation vs conventional analytical model: A comparative analysis

Accurate estimation of the maximum power point (MPP) is crucial for efficient photovoltaic (PV) energy harvesting, particularly in grid-connected systems where real-time regulation is required. Traditionally, MPP estimation has relied on analytical methods rooted in circuit-level modeling of the PV module. These conventional approaches begin with measurements of the PV terminal voltage (V_{pv}) and current (I_{pv}), which are then applied to the single-diode equivalent circuit of the PV system. The light-generated current (I_L) is computed using the diode equation as:

$$I_L = I_{ph} + I_0 \left(\exp \left(\frac{V_{pv}}{n_a V_t} \right) - 1 \right) \quad (9)$$

Neglecting shunt resistance, the voltage at maximum power point (V_{1m}) is derived using the Lambert-W function:

$$V_{1m} = n_a V_t \left(W \left(\frac{I_L \cdot \exp(1)}{I_L} \right) - 1 \right) \quad (10)$$

The corresponding current and voltage at MPP are adjusted using series and shunt resistances as follows:

$$V_{mp} = V_{1m} - \left(I_m - \frac{V_{1m}}{R_{sh}} \right) R_s, \quad I_{mp} = I_{1m} - \frac{V_{1m}}{R_{sh}} \quad (11)$$

and the maximum power is then calculated by:

$$P_{mp} = V_{mp} \cdot I_{mp} \quad (12)$$

While these equations provide detailed modeling, they rely on parameters such as I_0 , R_s , R_{sh} , V_t , n , and T , which are often difficult to measure in real-world conditions. Moreover, the use of exponential and Lambert-W functions makes the computation resource-intensive, limiting their suitability for real-time embedded control applications.

MPP estimation in PV systems has been addressed through several approaches, including perturbation-based MPPT, incremental

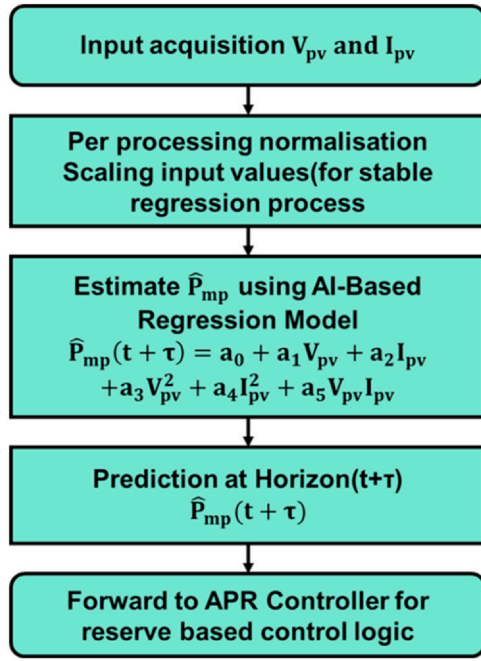


Fig. 5. AI-Based MPP Estimation Process for Predictive Power Control.

conductance, fractional open-circuit/short-circuit methods, metaheuristic optimization, analytical equivalent-circuit models, and data-driven learning models. In the present work, the comparison is restricted to analytical sensorless MPP-estimation methods because the proposed estimator is designed to replace parameter-dependent analytical computation inside an embedded APR controller.

In contrast, the proposed AI-based MPP estimation model offers a simplified and efficient alternative. As shown in Fig. 5, the method uses only V_{pv} and I_{pv} as inputs to a second-order polynomial regression model, eliminating the need for environmental or internal physical parameters. Recent studies have demonstrated the growing potential of machine learning techniques for photovoltaic power prediction and estimation owing to their ability to capture nonlinear relationships and improve prediction accuracy under varying environmental conditions [34–36]. The regression equation is given by:

$$\hat{P}_{mp} = a_0 + a_1 V_{pv} + a_2 I_{pv} + a_3 V_{pv}^2 + a_4 I_{pv}^2 + a_5 V_{pv} I_{pv} \quad (13)$$

Here, a_0 to a_5 are pre-trained coefficients obtained through offline training using historical PV data. The estimated power $\hat{P}_{mp}$ corresponds to a predicted MPP at a short-term future horizon τ , expressed as:

$$\hat{P}_{mp}(t + \tau) \approx \text{Estimated peak power at horizon } \tau \quad (14)$$

This model significantly reduces computational complexity and is well suited for real-time deployment on embedded platforms such as NI myRIO, STM32, or Raspberry Pi. The estimated $\hat{P}_{mp}(t + \tau)$ is then fed into the Adaptive Power Regulation (APR) control loop, where it is compared against forecasted load to determine the reserve fraction and define the

power injection target. This integration supports a closed-loop control structure that is responsive to both generation variability and grid constraints. A detailed comparison of the conventional analytical model and the proposed AI-based estimation method is presented in Table 1, highlighting key differences in input requirements, computational burden, real-time applicability, and adaptability to varying environmental conditions.

While the conventional model offers detailed insights into PV behavior, its computational complexity and parameter dependence limit real-time applicability. In contrast, the proposed AI-based estimator provides a fast and scalable solution using only voltage and current inputs, making it well-suited for adaptive regulation in rooftop PV systems. To validate the proposed AI-APR framework, simulation studies are carried out based on the earlier institutional case study, incorporating real-world irradiance and load conditions. In addition, hardware-level testing is conducted to evaluate the controller's real-time responsiveness, power curtailment accuracy, and stability under dynamic operating scenarios. These validations collectively demonstrate the practical effectiveness of the system prior to deployment.

4.3. Training of the AI-based MPP estimator

The AI-based MPP estimator was trained offline using PV voltage-current-power samples collected under different irradiance and temperature operating conditions. The input variables were the measured PV voltage (V_{pv}) and PV current (I_{pv}), while the target output was the reference maximum available PV power ($P_{mpp,ref}$). For each irradiance-temperature condition, the reference MPP was obtained from the corresponding PV characteristic curve by identifying the maximum value of $P_{pv} = V_{pv} \times I_{pv}$. The measured samples were screened to remove incomplete readings, switching transients and sensor spikes. The remaining samples were normalized before regression to prevent scale dominance between voltage and current variables.

A second-order polynomial regression model was selected because it offers a practical compromise between estimation accuracy and embedded implementation simplicity. The model includes linear, quadratic and cross-product terms of V_{pv} and I_{pv} . The coefficients were identified offline using least-squares regression on the training subset and were then fixed during real-time controller implementation. The trained estimator receives only V_{pv} and I_{pv} during operation and produces the estimated available maximum power for the APR reserve computation block.

The dataset was divided into training, validation and testing subsets. The training subset was used to identify the regression coefficients, the validation subset was used to check model generalization and avoid overfitting, and the testing subset was used only for final accuracy evaluation. The trained model was embedded in the AI-APR controller and executed at the controller sampling rate to provide a real-time estimate of available PV power.

4.4. Replicability of the proposed AI-APR framework

Although the proposed AI-APR framework has been demonstrated using a 2 MWp rooftop PV installation under Indian operating conditions, the methodology is readily transferable to other countries. The control

Table 1

Comparison of Representative Analytical Sensorless MPP Estimation Model and the proposed AI-Based MPP Estimation Method.

Feature	Representative Analytical Sensorless MPP Estimation Model[37]	Proposed AI-Based Estimation
Inputs Required	$V_{pv}, I_{pv}, T, I_0, R_s, R_{sh}$	V_{pv}, I_{pv} only
Model Type	Physics-based, nonlinear exponential	Data-driven, polynomial regression
Computational Complexity	High (exponentials, Lambert-W)	Low (basic arithmetic)
Real-Time Applicability	Limited in embedded systems	Highly suitable for embedded platforms
Sensor Dependency	Requires temperature and irradiance sensors	None beyond voltage and current
Adaptability	Moderate; depends on fixed parameters	High; generalizes across varying conditions
Output	V_{mp}, I_{mp}, P_{mp}	$\hat{P}_{mp}(t + \tau)$

architecture is independent of geographical location and relies primarily on measured PV voltage and current for AI-based maximum power estimation. To deploy the framework in a different country, only the local PV module characteristics, historical weather data, load profiles, inverter ratings, and applicable grid code requirements need to be incorporated during the offline training stage. Once the regression model is retrained using locally representative operating data, the online implementation remains unchanged. Consequently, the proposed framework can be effectively applied to educational campuses, commercial buildings, industrial facilities, and distributed rooftop PV installations across diverse climatic regions while complying with local grid regulations.

5. Simulation and Experimental Validation of the Proposed AI-APR Framework

5.1. Simulation under Dynamic Conditions

To evaluate the effectiveness of the proposed AI-APR system, a comprehensive simulation study was carried out on a 2 MW_p rooftop solar photovoltaic (RTSPV) installation. The system, comprising 20 educational buildings each equipped with a 100 kW_p PV array, was modelled in MATLAB/Simulink to reflect realistic rooftop deployment and control architecture. The simulation accounted for dynamic environmental inputs and varying load conditions throughout a representative sunny day. The results, illustrated in Figs. 6 to 13,

highlight the operational improvements achieved through the AI-based control approach, including enhanced power tracking, regulated curtailment, and stable grid interaction. The key electrical and control parameters used in the simulation analysis are summarized in Table 2.

Fig. 6 illustrates the hourly variation of solar irradiance and ambient temperature throughout a representative sunny day. The irradiance rises from approximately 350 W/m² at 8:00 a.m., peaks at 980 W/m² by noon, and declines steadily thereafter. Correspondingly, ambient temperature increases from early morning and reaches a maximum of 43°C around midday. These parameters serve as dynamic environmental inputs to the AI-based maximum power point (MPP) estimator within the proposed APR framework.

Fig. 7 presents the total energy generated by the 2 MW_p RTSPV system as predicted by the AI-based MPP estimator. The estimation is driven solely by real-time voltage (V_{pv}) and current (I_{pv}) inputs processed through a trained polynomial regression model. The generation curve mirrors the irradiance pattern observed in Fig. 7, peaking at approximately 2000 kW between 12:00 p.m. and 1:00 p.m., confirming the estimator's capability to track power accurately without direct irradiance or temperature sensors.

Before integrating the proposed polynomial regression model into the Adaptive Power Regulation (APR) framework, the estimator was validated independently to verify its ability to predict the available maximum power. Fig. 7 compares the reference MPP obtained from the photovoltaic model with the AI-estimated MPP under identical operating conditions.

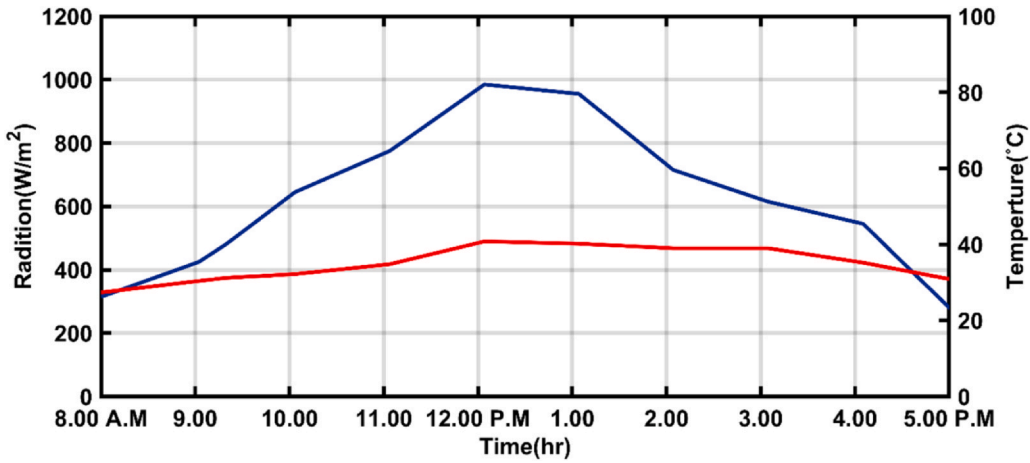


Fig. 6. Hourly Variation of Solar Irradiance and Ambient Temperature.

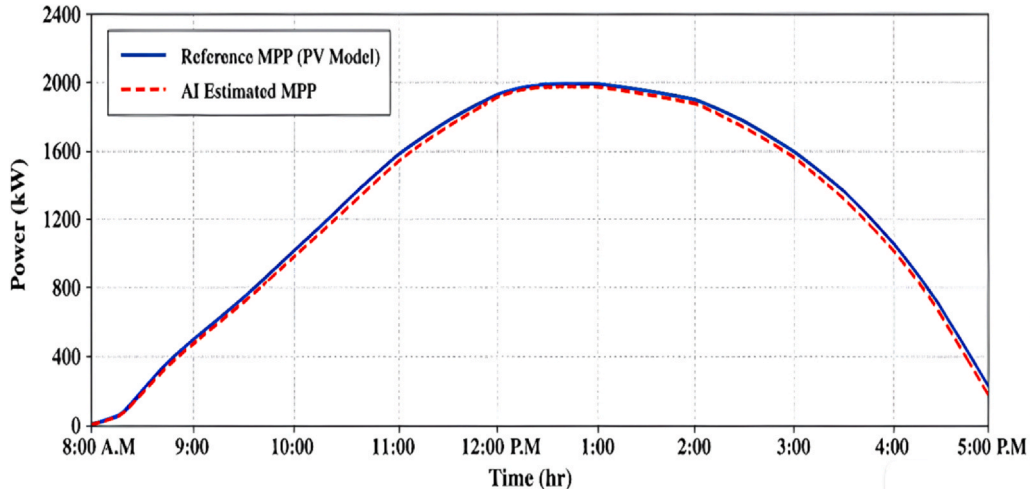


Fig. 7. Daily PV Energy Generation Predicted by AI-Based MPP Estimator.

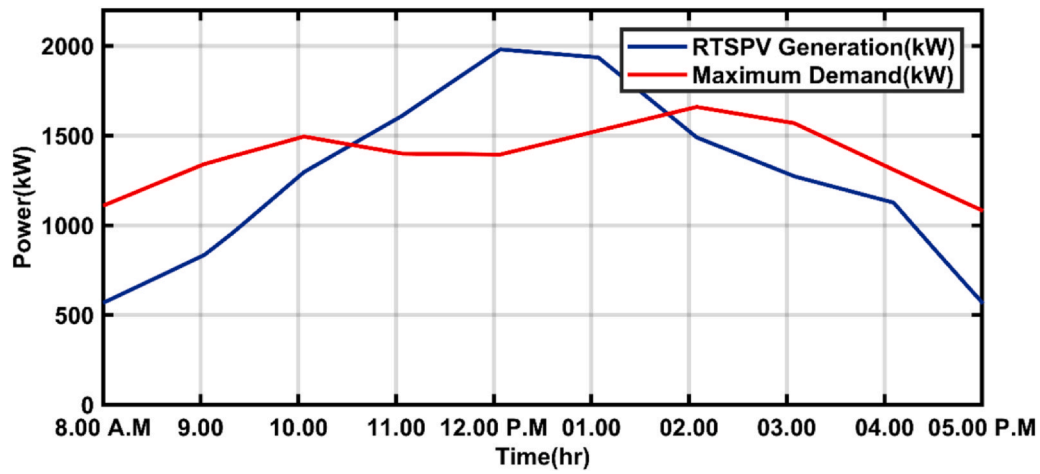


Fig. 8. Comparison between AI-Estimated PV Generation and Institutional Load Demand.

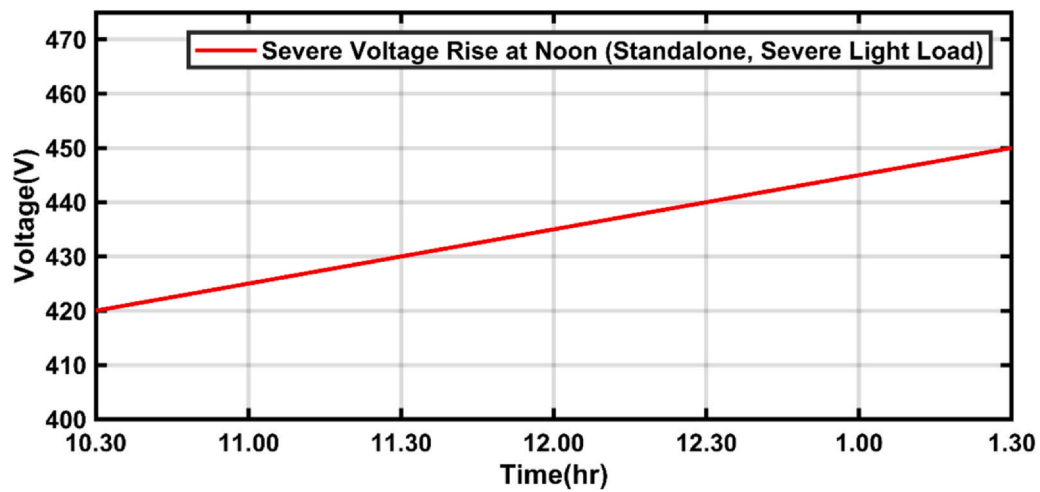


Fig. 9. LT Panel Voltage Rise without Regulation during Surplus Period.

The close overlap between the two curves throughout the operating period demonstrates that the proposed estimator accurately tracks the available maximum power under varying irradiance levels. Minor deviations are observed only during rapid irradiance transitions, while excellent agreement is maintained during steady-state operation. These results confirm

that the estimated MPP can be reliably used as the available-power reference for reserve computation and adaptive power regulation.

Fig. 8 compares the AI-estimated PV generation with the institutional load demand. A mismatch is evident, especially in the early morning (8:00 a.m.–10:30 a.m.) and late afternoon (1:45

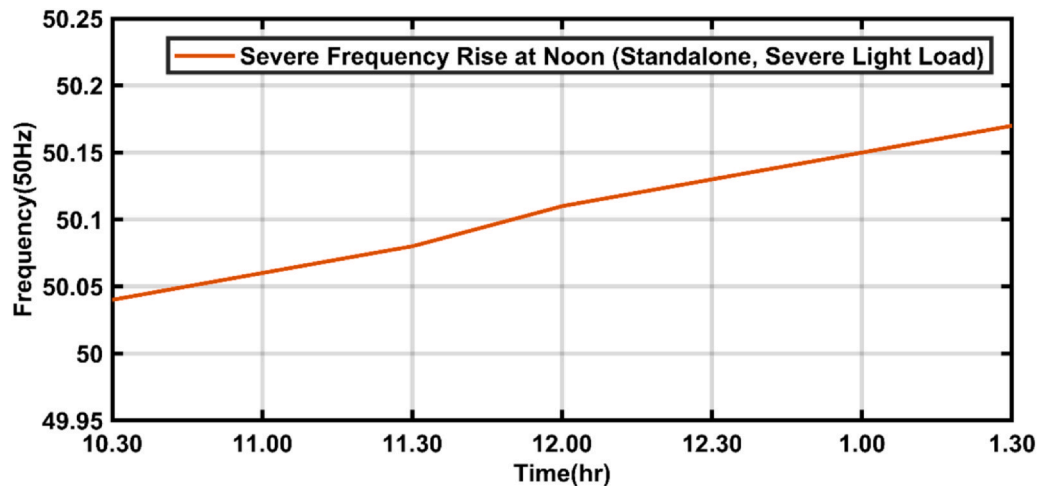


Fig. 10. Grid Frequency Drift Under Surplus Generation without APR.

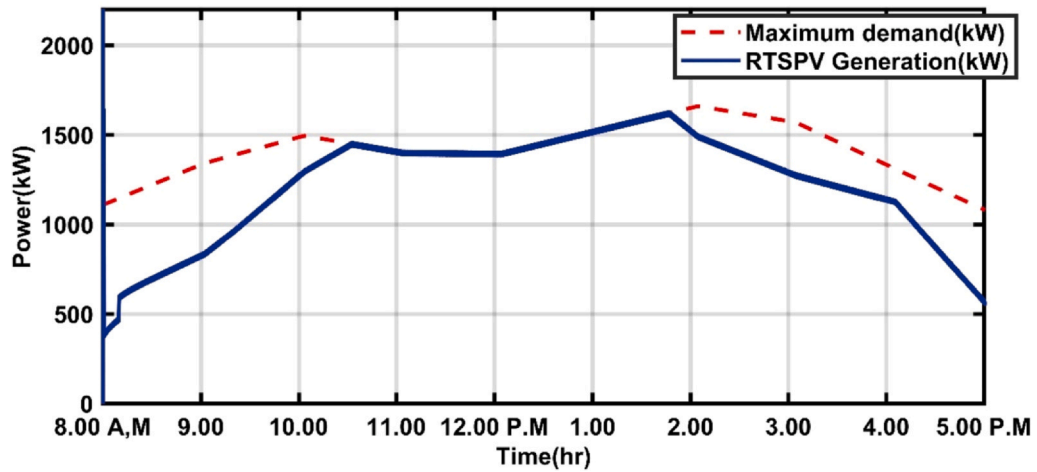


Fig. 11. Regulated PV Output after Applying AI-APR Controller.

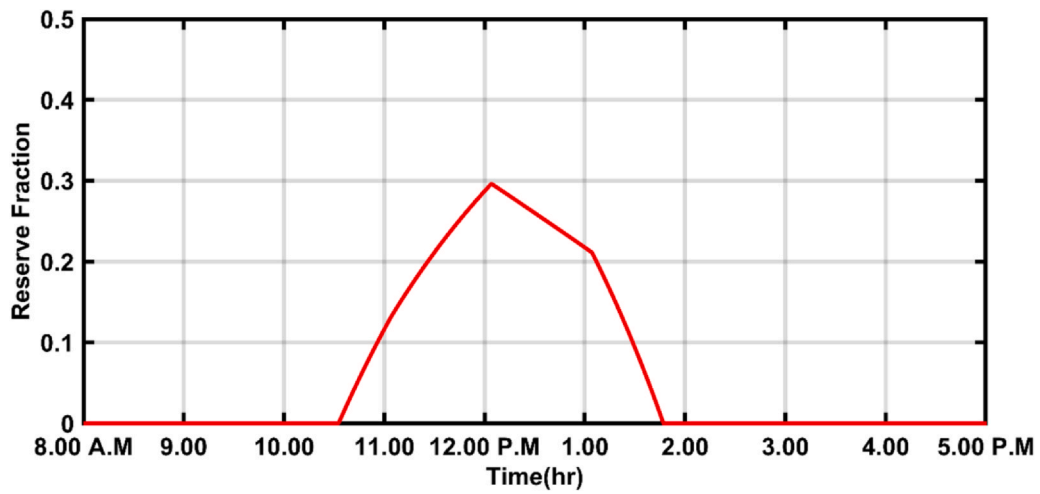


Fig. 12. Reserve Fraction Profile Computed by AI-APR System.

p.m.–5:00 p.m.), where load demand surpasses generation, creating a deficit period. Conversely, between 10:30 a.m. and 1:45 p.m., the surplus generation phase emerges, with PV output exceeding load demand. This surplus, if not properly managed, risks destabilizing the grid by inducing voltage or frequency deviations.

Fig. 9 depicts the voltage rise in the LT panel during the surplus period when no power regulation is applied. The voltage increases from approximately 420 V to 446 V between 10:30 a.m. and 1:30 p.m., resulting from continuous injection of surplus power into a lightly loaded network. This scenario illustrates overvoltage stress on the

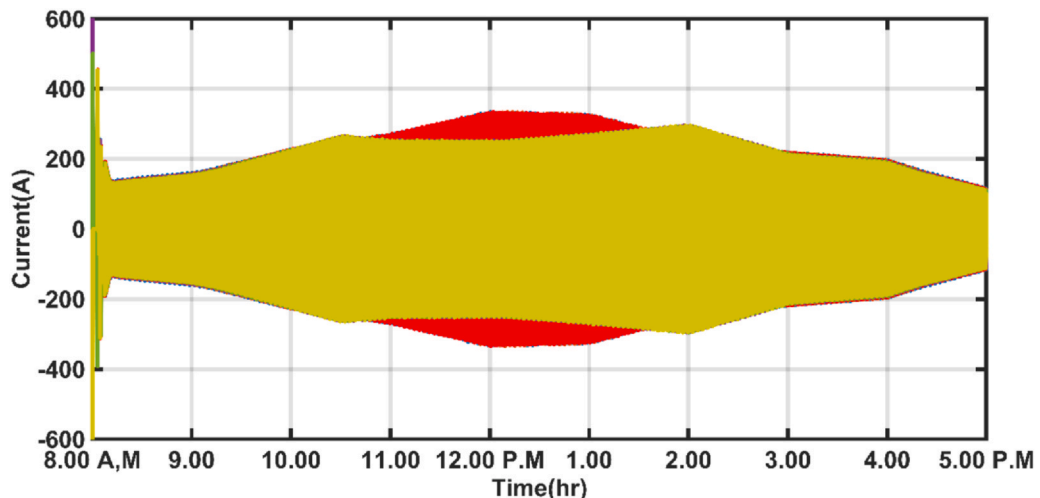


Fig. 13. Grid Current Profile Before and After APR Implementation.

Table 2

Key parameters for simulation analysis.

Solar panel specifications	Values
Total roof top system capacity	2 MW _p
Each building roof top system capacity	100 kW _p
Total number system connected into the grid	20
DC link voltage V _{dc}	560 V _{dc}
Phase	3
Grid voltage, V	415 V
Grid frequency, Hz	50
K _p value of PI controller	0.01
K _i Value PI controller	5

system, which can compromise grid compliance and damage legacy equipment.

Fig. 10 shows the frequency response under similar surplus conditions. In the absence of power regulation, the frequency drifts from 50.04 Hz to 50.17 Hz. This deviation reflects a lack of inertia in the system, where minor mismatches between generation and demand cause significant instability highlighting the need for adaptive regulation.

Fig. 11 demonstrates the impact of the AI-APR controller, where the PV output is regulated in accordance with the load profile. Using real-time reserve fraction computation [Eq. (2)] and power target adjustment [Eq. (3)], the system curtails generation during peak irradiance and avoids overproduction. This results in a flattened power curve, improving grid stability and minimizing voltage stress.

Fig. 12 presents the computed reserve fraction over the day. The reserve fraction increases significantly between 11:00 a.m. and 1:30 p.m., reaching a peak of 0.32 at solar noon. It remains zero during deficit hours, ensuring full utilization of available solar energy. This dynamic adjustment demonstrates the system's ability to optimize power delivery and minimize unnecessary curtailment.

Fig. 13 compares the grid current profile before and after deploying the AI-APR strategy. Without regulation, significant current fluctuations are observed during surplus hours. After applying APR, the current waveform is smoother, reflecting effective curtailment and better alignment with load demand. This validates the controller's real-time tracking performance using the adaptive PI mechanism [Eq.(5)], resulting in improved power quality and grid stability.

5.2. Hardware Implementation and Experimental Validation

To evaluate the practical performance of the proposed AI-Enhanced Adaptive Power Regulation (AI-APR) system, a 1 kWp grid-connected

rooftop solar PV prototype was developed and tested under laboratory conditions. As shown in Fig. 14, a programmable Chroma solar simulator was used to simulate varying irradiance and temperature profiles. The control strategy was implemented on a National Instruments myRIO embedded controller using LabVIEW, interfaced with a boost DC-DC converter and a single-phase SPWM inverter. Voltage and current were measured using LEM transducers, with gate signals for the converter isolated through HCPL drivers. A phase-locked loop (PLL) was used to synchronize the inverter with the 230 V, 50 Hz grid, ensuring stable operation under fluctuating conditions. The inverter output was connected to the grid via a single-phase autotransformer to provide electrical isolation and voltage compatibility. The system was tested under real grid-connected conditions, supplying typical household resistive-inductive (R-L) loads such as lighting and fans. No artificial or programmable loads were used, allowing all performance measurements particularly related to power curtailment and harmonic quality to reflect realistic, real-time operating scenarios. The key electrical and control parameters used in the hardware analysis are summarized in Table 3.

Fig. 15 shows the variation of the estimated maximum power ($\hat{P}_{mp}$) and the actual grid-injected power in the absence of reserve fraction control. The maximum power, estimated using the AI-based regression model, is represented by the blue curve, while the red curve depicts the injected power. In this configuration, the reserve fraction $R_f(t)$ is assumed to be zero for all conditions. As a result, the controller attempts to inject the entire estimated power into the grid without accounting for real-time demand. This leads to potential over-injection during periods of low load demand, highlighting the limitations of a non-adaptive control approach and underscoring the necessity of the reserve computation block in real-world rooftop PV scenarios.

Fig. 16 illustrates the system's performance with the reserve fraction computation enabled. The green curve represents the AI-estimated maximum power, while the brown curve shows the forecasted load demand. During the interval from 1 to 2 seconds, the irradiance is 980 W/m² and the temperature is 35 °C, yielding an estimated power of 905 W and a load of 710 W. The reserve fraction, computed as indicates that 21% of the power is curtailed. As the environmental conditions change, the reserve fraction dynamically adjusts—dropping to zero when generation matches demand (2–4.5 s) and rising to 0.11, 0.27, and 0.43 in response to increasing load-generation mismatches (4.5–8 s). This confirms the controller's ability to regulate power precisely according to real-time demand.

$$R_f(t) = \frac{\hat{P}_{mp}(t + \tau) - \hat{L}(t + \tau)}{\hat{P}_{mp}(t + \tau)} \approx \frac{905 - 710}{905} \approx 0.21 \quad (15)$$

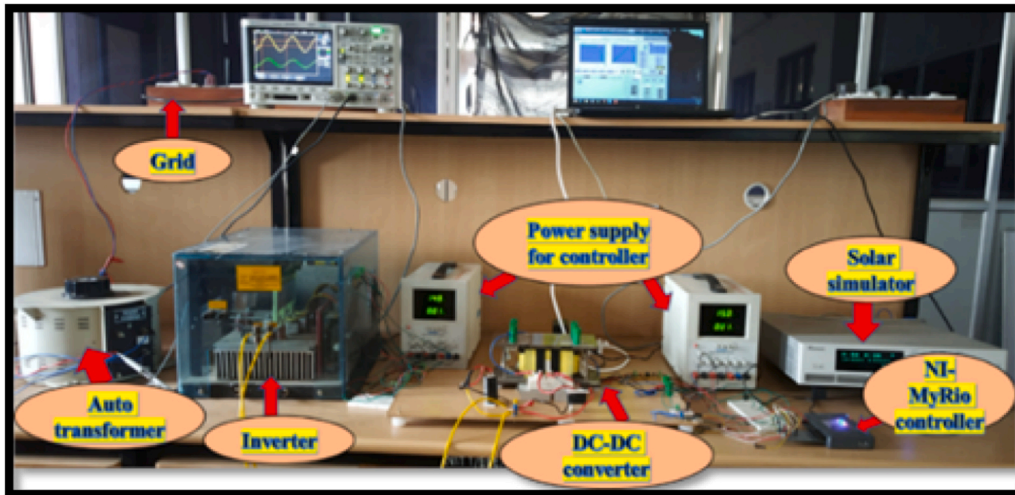


Fig. 14. Two-Stage Grid-Connected SPV System Controlled by NI myRIO Controller.

Table 3

Key parameters of the Two-Stage Grid-Connected SPV System.

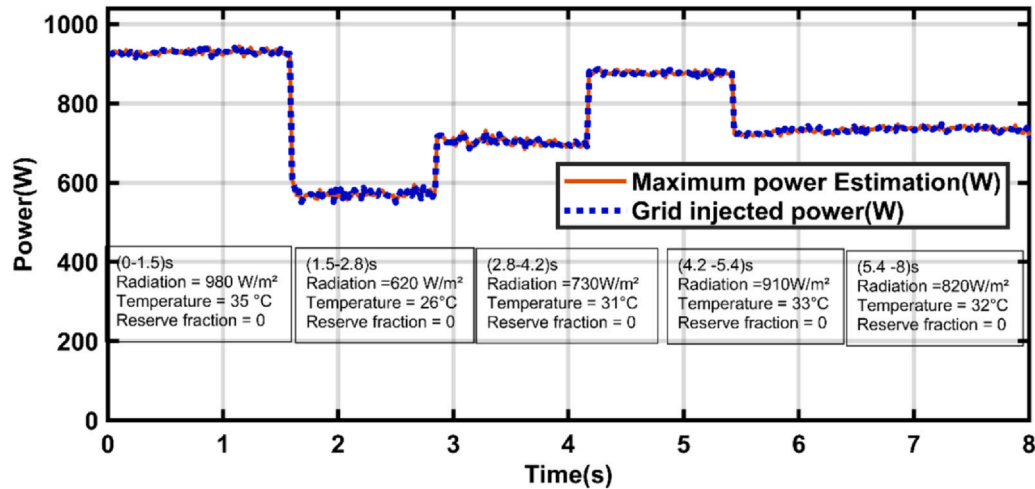
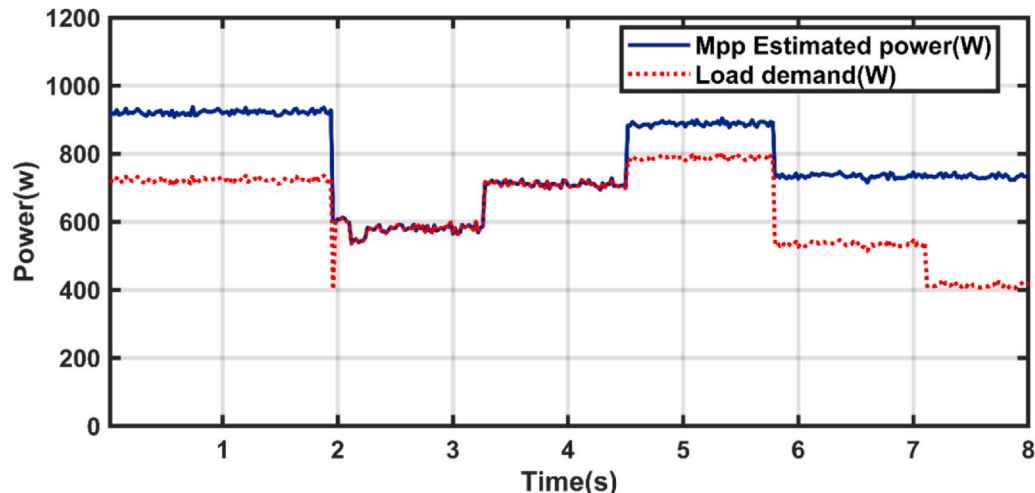
Solar panel specifications	Values
Phase	1
Grid Voltage, V	230
Grid frequency, Hz	50
Nominal Power	1 kW _p
Input capacitance of boost converter C_{pv}	470 μ F
Inductance of boost converter L_{dc}	500 μ H
Sampling frequency	20 kHz
DC link Voltage V _{dc}	325
Output capacitance boost converter C_{pv}	1175 μ F

Fig. 17 presents the reserve fraction $R_f(t)$ computed by the Reserve Fraction Computation (RFC) block over time. A stable reserve fraction of approximately 0.21 is observed during 1–2 seconds, corresponding to a surplus in generation. The fraction drops to zero between 2–4.5 seconds as load matches generation, and it increases step-wise to 0.11, 0.27, and finally 0.43 as the gap widens. These trends validate the effectiveness of the RFC algorithm in ensuring smooth and adaptive curtailment behavior under dynamically changing conditions.

Fig. 18 illustrates the variation in solar PV voltage and current when the energy generation falls short of the load demand. The reserve computation algorithm accurately calculates the reserve fraction

inputted to the APR controller. Additionally, the SPV right-hand side (RHS) algorithm shifts the actual solar PV operating voltage to the RHS of the maximum power point on the SPV characteristics curve. This adjustment enables us to achieve the highest level of reserve in Adaptive Power Regulation, enhancing converter stability at the peak reserve level. The dynamics of rapid variation occur when operating on the RHS side ensuring optimal power regulation.

Fig. 19 shows grid voltage and current waveforms at an irradiance of 450 W/m² and ambient temperature of 30 °C. With a reserve fraction of zero, the current is in phase and matches the voltage amplitude, indicating full power injection. When the reserve fraction is increased to 0.1, the current amplitude decreases proportionally, maintaining phase alignment and demonstrating effective curtailment without waveform distortion. Fig. 20 presents the total harmonic distortion (THD) of the grid-injected current, measured at 3.5% for a fundamental current of 1.08 A and frequency of 50.1 Hz well within the 5% limit specified by IEEE 519–2014 for low-voltage systems. Measurements were taken using a Fluke 435 Series II Power Quality Analyzer (IEC 61000–4–7 Class A), configured to capture harmonics up to the 50th order with a 10-second RMS averaging window. The measurement point was the Point of Common Coupling (PCC), located at the AC terminal of the inverter after the LC filter. A single-phase auto-transformer ensured electrical isolation and voltage matching. Grid impedance was approximately 0.5 Ω , and background harmonic distortion was under 1.5%, confirming that THD readings primarily reflect

**Fig. 15.** Grid Injection without Curtailment under Varying Conditions.**Fig. 16.** AI-Predicted Power Vs Load with Reserve Control.

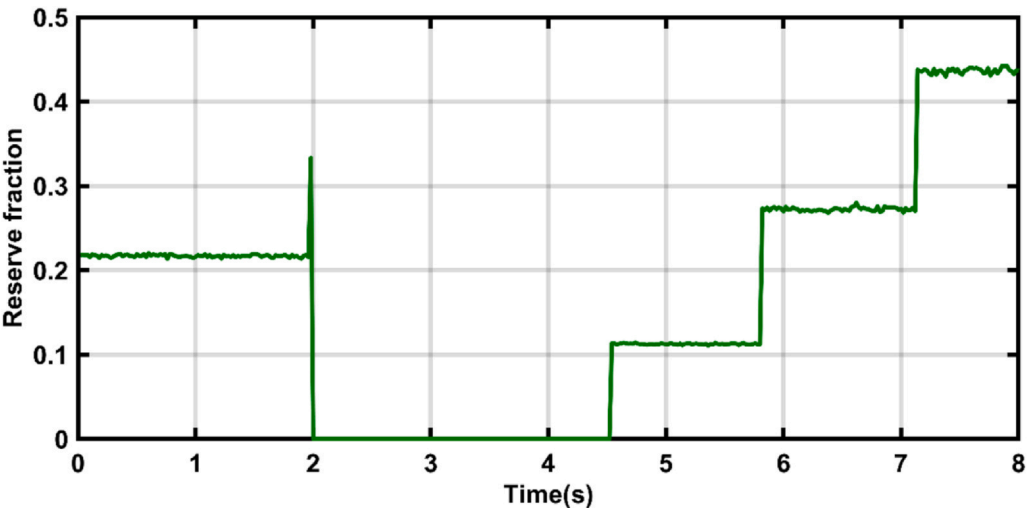


Fig. 17. Reserve Fraction Profile from RFC Algorithm.

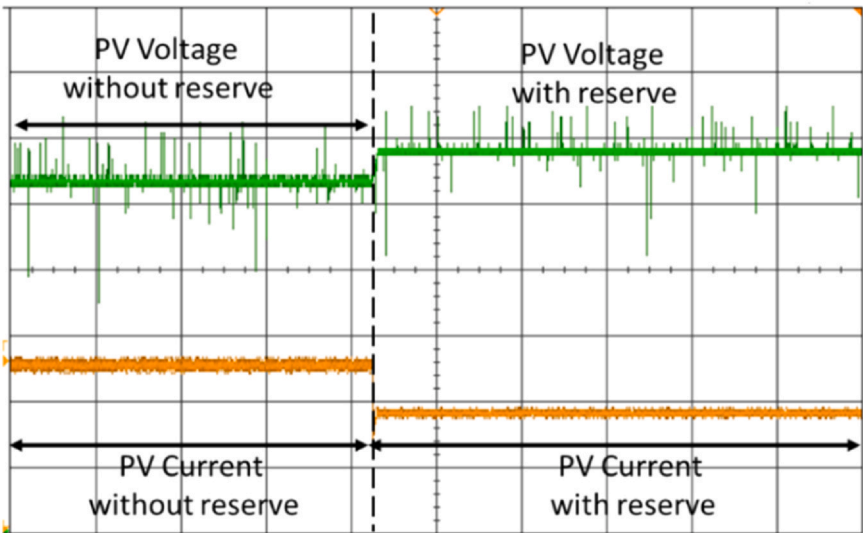


Fig. 18. PV voltage–current response in reserve mode.

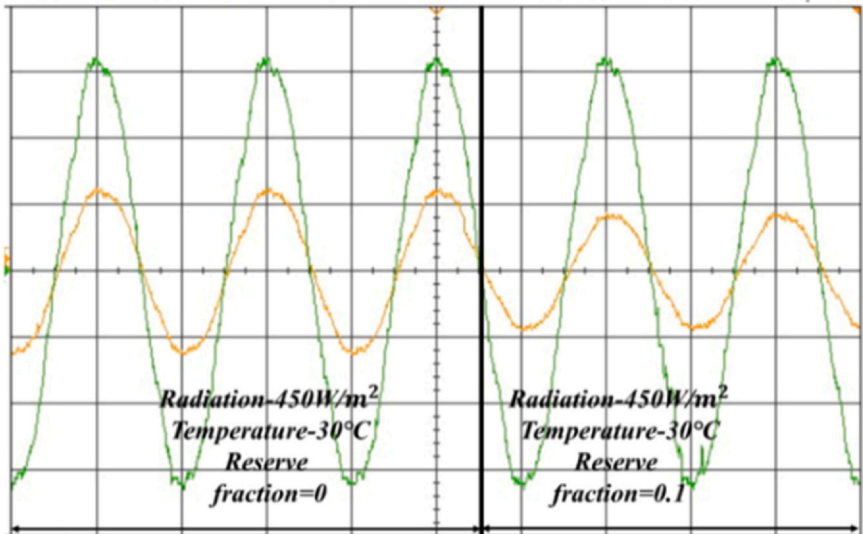


Fig. 19. Inverter output voltage and current with reserve activation.

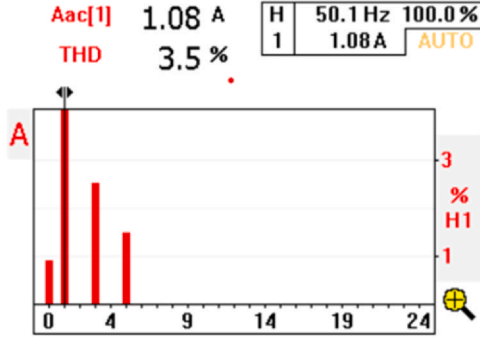


Fig. 20. Grid waveforms and THD under curtailment conditions.

the inverter's output. The harmonic spectrum showed dominant low-order components and minimal higher-order distortion, validating stable, compliant operation even under curtailment.

5.3. Stability Analysis of the Proposed AI-APR Scheme for Rooftop PV Systems

This section presents the stability analysis of the proposed Artificial Intelligence Assisted Adaptive Power Regulation (AI-APR) controller, implemented in a two-stage grid-connected rooftop solar photovoltaic (SPV) system. The AI-APR controller is integrated into the control loop of a DC-DC boost converter, which serves as the interface between the PV source and the inverter. Although the AI-APR framework is designed to be compatible with various converter topologies, the present analysis focuses solely on its implementation using a boost converter. The aim is to validate the dynamic stability of the control strategy under real-world operating conditions. All the parameters used for this stability analysis are sourced exclusively from the experimental setup. These parameters, including controller gains and converter components, are detailed in Table 3. No simulation results are referenced in this section. The controller's performance is assessed strictly using hardware-based evaluations.

The proposed AI-APR controller dynamically adjusts the duty cycle of the boost converter in real-time, based on the error between the PV-generated power and the desired power reference. The electrical network model representing the SPV system and its associated converter stage is illustrated in Fig. 21, while the control structure used for linearization and dynamic analysis is shown in Fig. 22. Moreover, it presents the internal closed-loop configuration of the AI-APR system, comprising the adaptive PI controller, power tracking error block, and a delay compensator to reflect real-time digital control behavior.

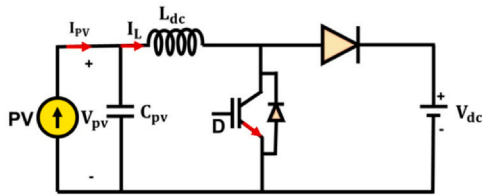


Fig. 21. Electrical Network Model of the SPV System Integrated with a Boost Converter.

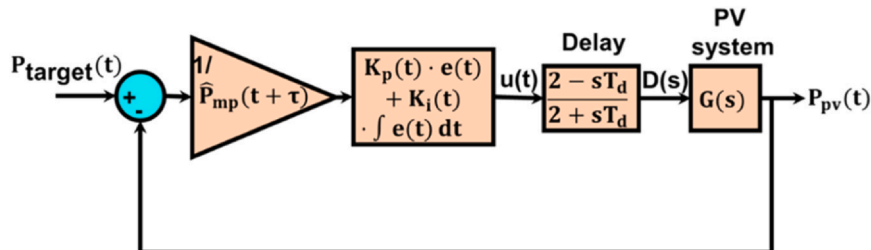


Fig. 22. Control block diagram of the proposed AI-enhanced adaptive power regulation (AI-APR) System.

ON state:

$$\begin{bmatrix} \frac{di_{Lm}}{dt} \\ \frac{dV_{pv}}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{L_m} \\ -\frac{1}{C_{dc}} & \frac{1}{R_{pv}C_{dc}} \end{bmatrix} \begin{bmatrix} i_{Lm} \\ V_{pv} \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} V_{dc} \quad (16)$$

OFF state:

$$\begin{bmatrix} \frac{di_{Lm}}{dt} \\ \frac{dV_{pv}}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{L_m} \\ -\frac{1}{C_{dc}} & \frac{1}{R_{pv}C_{dc}} \end{bmatrix} \begin{bmatrix} i_{Lm} \\ V_{pv} \end{bmatrix} + \begin{bmatrix} -\frac{1}{L_m} \\ 0 \end{bmatrix} V_{dc} \quad (17)$$

Small-signal perturbation:

$$\begin{bmatrix} \frac{d\hat{i}_L}{dt} \\ \frac{d\hat{V}_{pv}}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{L_m} \\ -\frac{1}{C_{dc}} & \frac{1}{R_{pv}C_{dc}} \end{bmatrix} \begin{bmatrix} \hat{i}_L \\ \hat{V}_{pv} \end{bmatrix} + \begin{bmatrix} -\frac{V_{dc}}{L_m} \\ 0 \end{bmatrix} \hat{d} \quad (18)$$

Output equation:

$$\hat{y} = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{i}_L \\ \hat{V}_{pv} \end{bmatrix} \quad (19)$$

Perturbed output power relation:

$$\Delta P_{pv} = I_{pv} + \frac{V_{pv}}{R_{pv}} \quad (20)$$

Natural frequency and damping:

$$\omega_0 = \frac{1}{\sqrt{L_{dc}C_{pv}}}, \quad \delta = -\frac{1}{2r_{pv}C_{pv}\omega_0} \quad (21)$$

Open-loop transfer function with delay compensation:

$$H(s) = \frac{K_0}{P_{mp0}} \cdot \frac{K_p(s) + K_i(t)}{s(s^2 + 2\delta\omega_0s + \omega_0^2)} \cdot \frac{2 - sT_d}{2 + sT_d} \quad (22)$$

Control signal (PI output):

$$u(t) = K_p(t) \cdot e(t) + K_i(t) \cdot \int e(t) dt \quad (23)$$

Error signal definition:

$$e(t) = P_{target}(t) - P_{pv}(t) \quad (24)$$

The gain values for the PI controller used in the experimental setup are $K_p = 0.01$ and $K_i = 5$, as listed in Table 3. These were initially selected using a modified Ziegler–Nichols tuning approach and fine-tuned under hardware conditions to ensure optimal performance. Fig. 23 and 26 present the experimental validation of the AI-APR controller under various reserve levels (100%, 80%, 60%, 40%, and 20%). In this each curve shows rapid convergence with minimal overshoot, confirming the controller's responsiveness under different curtailment conditions. Fig. 24 shows the Bode plots of the system, highlighting high phase margins (above 85°) across all conditions except full reserve (100%), where the phase margin drops to approximately 40° . This suggests the need for careful tuning at high reserve levels. These results confirm that the AI-APR controller, using experimentally validated parameters, provides stable, robust, and accurate power regulation suitable for real-time rooftop PV integration.

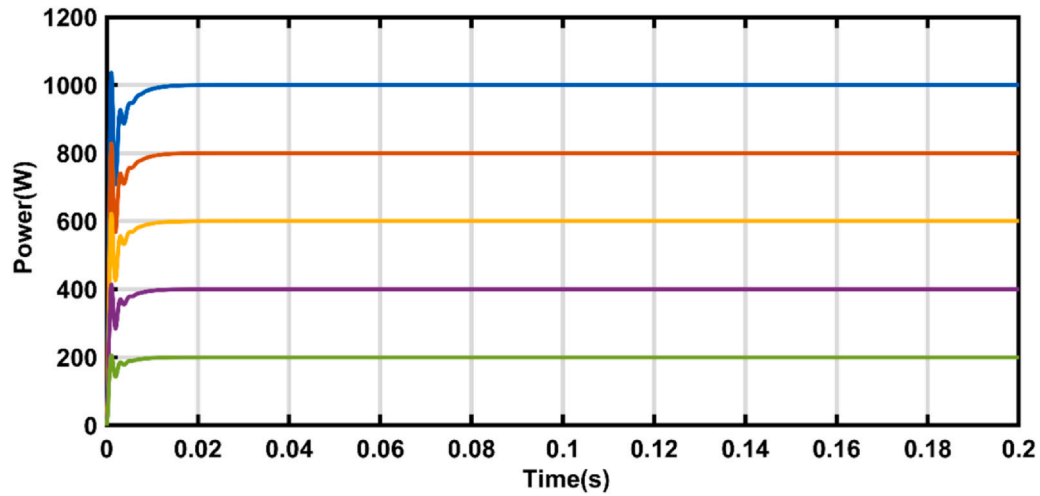


Fig. 23. Regulated Output Power Response under Various Reserve Levels Using AI-APR Scheme.

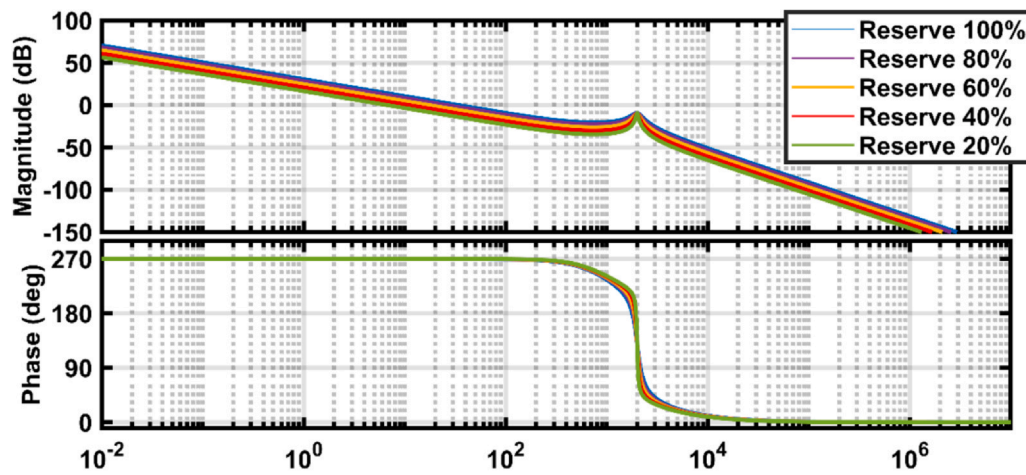


Fig. 24. Bode Plot of AI-APR-Controlled System under Varying Reserve Levels.

5.4. Seasonal applicability of the proposed AI-APR framework

The present study evaluates the proposed AI-APR framework using representative irradiance and temperature profiles corresponding to a typical operating day. Although this approach effectively demonstrates the dynamic response of the controller to varying environmental conditions, seasonal variations in solar resource availability were not explicitly simulated. In practical applications, solar irradiance and ambient temperature exhibit significant monthly and seasonal variations, which influence PV energy production and the frequency of power curtailment events. The proposed AI-APR framework is inherently adaptable to such variations because the AI-based estimator can be retrained using long-term site-specific operational data collected throughout the year. Consequently, the same control architecture can be deployed under different seasonal conditions without modification to the online control algorithm. Future work will include annual simulations and field validation using measured meteorological data to evaluate the long-term performance, robustness, and energy yield of the proposed framework under diverse climatic conditions.

6. Comprehensive Comparative Analysis of Proposed AI-APR with Conventional APR Methods

To rigorously evaluate the innovations and advancements of the proposed AI-driven Adaptive Power Regulation (AI-APR) method, this section presents a detailed comparative analysis through two distinct but complementary perspectives: (1) maximum power point (MPP)

estimation and tracking performance, and (2) detailed method features including control logic and computational characteristics, Table 4 provides an in-depth comparative analysis of MPP estimation and tracking performance, highlighting significant operational benefits of the proposed AI-APR method over previously validated conventional APR methods.

The AI-APR method demonstrates clear superiority in tracking accuracy, reduced error, faster response, and improved adaptability, crucial for robust real-time rooftop photovoltaic system management. A systematic comparison between the proposed AI-APR method and several conventional methods is summarized in Table 5. This analysis focuses on critical operational aspects, including the control side, RHS operation capability, MPP estimation approach, computational complexity, steady-state power oscillations, and load forecasting abilities.

The proposed AI-APR method clearly stands out with its hybrid AC/DC control strategy, predictive AI-based regression model for MPP estimation, and advanced forecasting via Quantum-behaved Particle Swarm Optimization (QPSO). Despite its higher computational complexity, it achieves significantly lower steady-state oscillations and robust adaptability to load variations.

Table 6 presents a qualitative comparison between the proposed controller and representative approaches reported in the literature. Conventional MPPT techniques, such as Perturb-and-Observe (P&O) and Incremental Conductance (INC), are primarily intended to maximize power extraction and do not explicitly address adaptive reserve power regulation. Analytical model-based approaches generally require photovoltaic model parameters and additional environmental measurements, increasing

Table 4
Comparative Analysis of MPP Estimation and Tracking Performance.

Performance Parameter	Proposed AI-APR Method	Simplified APR for Single-stage Micro-inverter[38]	Simplified APR for Two-stage System [37]
MPP Estimation Technique	AI-based polynomial regression	Simplified single-diode model (series/shunt resistances neglected initially)	Analytical simplified single-diode approximation
Inputs Required for MPP Estimation	V _{pv} , I _{pv} only	V _{pv} , I _{pv}	V _{pv} , I _{pv}
Tracking Accuracy (%)	≥ 95%	~ 92%	~ 91%
Tracking Error (%)	≤ 5%	~ 8%	~ 9%
Tracking Response Time (s)	~ 0.01	0.05–0.10	0.05–0.08
Steady-State Power Oscillations (%)	< 2%	3–5%	3–5%
Computational Complexity	Medium–High (AI computations)	Medium (Analytical simplification)	Medium (Analytical approximation)
Adaptability to Dynamic Conditions	Excellent (Predictive AI logic)	Moderate (Limited dynamic adaptation)	Moderate (Limited dynamic adaptation)
Reserve Power Capability	Predictive (AI-based forecasting)	Fixed reserve fraction	Fixed reserve fraction

computational complexity. Machine learning-based methods improve adaptability but often require larger computational resources and more complex training procedures. In contrast, the proposed controller employs a lightweight polynomial regression model to estimate the available maximum power using only PV voltage and current measurements. The estimated MPP is subsequently utilized within the adaptive power regulation framework to dynamically compute reserve power under varying environmental conditions. These characteristics make the proposed approach suitable for real-time embedded implementation in rooftop photovoltaic systems.

6.1. Limitations of the study and future scope

Although the proposed AI-based Adaptive Power Regulation (AI-APR) framework demonstrates promising performance for rooftop solar photovoltaic systems, several limitations should be acknowledged. First, the simulation and hardware validation were conducted using a representative 2 MWp institutional rooftop PV system, and the results

may vary for installations with different capacities, load characteristics, and network configurations. Second, the accuracy of the AI-based MPP estimator depends on the quality and representativeness of the training dataset. Significant changes in PV module characteristics due to ageing, partial shading, or environmental conditions may require periodic re-training of the regression model to maintain prediction accuracy. Third, the proposed controller was validated under predefined operating scenarios and has not yet been evaluated through long-term field deployment under diverse climatic conditions. In addition, battery energy storage systems, demand response mechanisms, and coordinated multi-inverter control were not considered in the present work.

Future research will focus on validating the proposed framework using large-scale field data collected from multiple geographical regions and climatic conditions. The use of advanced machine learning techniques, including deep neural networks and hybrid AI models, will also be investigated to improve prediction accuracy under highly dynamic operating conditions. Furthermore, integrating the AI-APR framework with battery energy storage systems, energy management

Table 5
Comparative Analysis of Method Features and Computational Characteristics.

Method	Control Side	MPP Estimation	RHS Operation	Control Logic	Computational Complexity	Power Oscillations (Steady State)	Load Forecasting
AI-APR (Proposed method)	AC + DC	AI regression	Yes	AI-predictive + reserve estimation	High	Low	Yes (QPISO-based)
Q–V / P–f Control[39]	AC	Not used	No	Voltage and frequency droop	Low	Medium	No
Droop + Virtual Impedance [40]	AC	None	No	Active/reactive droop with virtual impedance	Low	Medium	No
Decentralized Q Control[41]	AC	Sensor-based	No	Local Q-control based on grid voltage	Low	Medium	No
FPPT Algorithm [17]	DC	No MPP logic	No	Fixed power point tracking (no feedback)	Low	High	No
Multi-Mode Voltage Control [19]	DC	Voltage switching modes	Yes	Logic switching between operating points	Medium	High	No
Delta-Voltage Control [42]	DC	ΔDC-link estimation	Yes	ΔV-based dynamic control	Medium	Medium	No
Adaptive Voltage-Step MPPT[43]	Both	Adaptive voltage perturbation	Yes	Search-based adaptive voltage logic	Low	Low	No
Sensor less Reserved Power Control (Sangwongwanich et al., 2016)	DC	Sensorless MPPT	Yes	Constant power generation	Medium	Medium	No
Real-Time MPP Estimation via Curve Fitting [44]	DC	Real-time Curve fitting (Single diode model)	Yes	Single PI controller for power regulation	Medium	Low	No
Sensorless Photovoltaic Power Reserve Control[45]	DC	Lambert-W (sensorless real-time)	Yes	Linear reference from constant current region	Medium	Low	No
Binary Search FPPT[46]	DC	Binary Search Algorithm	Yes	Nonlinear binary search algorithm	Medium	Low	No
Secant Method FPPT [47]	DC	Secant Method	Yes	Iterative secant method	Medium	Low	No

Table 6

Qualitative comparison between the proposed controller and representative approaches.

Method	MPP Estimation	Reserve Power Regulation	Sensor Requirement	Computational Complexity	Real-Time Suitability
Perturb & Observe (P&O)	Iterative MPPT	No	Voltage, Current	Low	High
Incremental Conductance (INC)	Analytical MPPT	No	Voltage, Current	Medium	High
Analytical Sensorless Estimation	PV Model	Limited	Voltage, Current (+ PV Parameters)	High	Moderate
ANN/ML-Based Estimation	AI-Based	Limited	Multiple Inputs	High	Moderate
Proposed AI-Based APR Controller	Polynomial Regression	Yes	Voltage, Current	Low	High

systems, and smart grid communication infrastructure will enable more reliable, resilient, and intelligent operation of distributed rooftop PV installations.

7. Conclusion

This paper introduced a novel framework for enhancing grid stability in rooftop PV systems by combining a lightweight AI-based MPP estimation model with an adaptive power regulation (APR) strategy. By dynamically operating the inverter-based power conditioning unit in accordance with real-time building load demand, the system ensures that power injection aligns with local consumption, mitigating over-injection and grid disturbances. A second-order polynomial regression model, trained on PV voltage and current data, estimates the MPP without reliance on environmental sensors. The estimated MPP drives an RHS-based APR controller that shifts the PV operating point during surplus generation, enabling curtailment without abrupt inverter disconnections. Simulation studies for a 2 MW rooftop PV deployment across 20 buildings demonstrated effective voltage control (from 250 V to 231 V), frequency stability (within ± 0.2 Hz), and up to 21% curtailment. The system achieved $< 2\%$ power tracking error, ~ 0.01 s dynamic response, and $< 0.5\%$ steady-state oscillations. Experimental testing on a 1 kW rooftop prototype using NI myRIO validated real-time adaptability, maintaining IEEE 519-compliant THD at 4.76%. The proposed solution supports SDG 7 (Affordable and Clean Energy), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action) by promoting intelligent energy distribution and participatory grid interaction. Future work will focus on integrating predictive grid forecasting, enabling peer-to-peer energy trading frameworks, and applying coordinated multi-agent optimization for microgrid-level adaptability and resilience.

CRedit authorship contribution statement

J Ganesh Moorthy: Writing – original draft, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kalaiselvan Narasimman:** Writing – original draft, Validation, Software, Data curation, Conceptualization. **Arivoli Sundaramurthy:** Writing – review & editing, Validation, Software, Project administration, Formal analysis. **M Vijayakumar:** Visualization, Supervision, Resources, Methodology, Investigation.

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Data availability

The processed data supporting the findings of this study, including the irradiance profile, aggregated institutional load profile, MATLAB/Simulink model parameters, controller gains, AI-based polynomial-regression coefficients, and representative experimental waveform data, are available from the corresponding author upon reasonable request after publication. The raw institutional electrical load records are not publicly

shared because they contain site-specific operational information related to the campus electrical infrastructure. However, anonymized and aggregated datasets sufficient for scientific verification can be provided to qualified researchers for non-commercial academic use, subject to institutional permission and reasonable request to the corresponding author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used **OpenAI ChatGPT** to assist in **language refinement, grammar improvement, and formatting suggestions**. After using this tool, the author(s) thoroughly reviewed, verified, and edited the content to ensure accuracy, originality, and alignment with the intended scientific contribution. The author(s) take full responsibility for the content and integrity of the published article.

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