

A Hybrid AI-Based MPPT and Super Capacitor Energy Management Framework for Intelligent Residential Solar PV Systems

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Abstract: The widespread adoption of residential solar photovoltaic (PV) systems is increasingly hindered by operational inefficiencies stemming from suboptimal maximum power point tracking (MPPT), limited battery storage longevity, and performance degradation caused by panel soiling. This paper presents the design, development, and experimental validation of a hardware-based, fully integrated smart solar energy management system that leverages artificial intelligence (AI) to simultaneously address these critical challenges. The proposed prototype acquires real-time parameters—including PV voltage/current, irradiance, temperature, and household load—to enable dynamic decision-making. An AI-based MPPT algorithm is embedded within the hardware controller to predict and instantaneously adjust the operating point, ensuring peak energy harvesting under rapidly fluctuating irradiation, partial shading, and variable load conditions. To mitigate battery stress and enhance transient power response, a supercapacitor-based energy buffering unit, coupled with a high-efficiency DC-DC converter, is incorporated to provide rapid charge/discharge capability, voltage stabilization, and short-term power surge support. Concurrently, a dedicated hardware-mounted imaging module employs convolutional neural networks (CNNs) and computer vision to perform on-device classification of solar panel surfaces, distinguishing between clean, dust-covered, bird-dropping-obstructed, and leaf-shaded conditions. This real-time soiling intelligence is fed back into the central energy management strategy to trigger predictive maintenance alerts and recalibrate power utilization. The complete system is realized as a compact hardware prototype with embedded control logic and IoT-enabled remote monitoring. The prototype was rigorously tested under diverse environmental scenarios and dynamic residential load profiles. Experimental results demonstrate significant improvements in MPPT tracking speed and efficiency, effective smoothing of power fluctuations via the supercapacitor buffer, and high-accuracy classification of panel contamination, directly correlating to mitigated efficiency losses. The findings confirm that the proposed AI-integrated hardware solution offers a robust, self-optimizing framework for maximizing PV yield, prolonging battery life, and ensuring reliable solar power delivery for smart residential applications.

Keywords: Artificial Intelligence, Solar Photovoltaic, Maximum Power Point Tracking (MPPT), Supercapacitor, Energy Buffering, Solar Panel Soiling Detection, Image Processing.



I. LITERATURE REVIEW

1.1. Artificial Intelligence in Maximum Power Point Tracking

The performance of photovoltaic (PV) systems is inherently nonlinear and highly sensitive to environmental variations, including irradiance, temperature, and partial shading conditions [1], [2]. These factors create significant challenges for conventional Maximum Power Point Tracking (MPPT) techniques, which rely on local slope information from the power-voltage characteristic curve. Under partial shading conditions, the appearance of multiple local maxima in the P-V curve causes traditional methods such as Perturb and Observe (P&O) and Incremental Conductance (INC) to become trapped in local maxima, thereby compromising energy harvesting efficiency [1], [3].

To address these limitations, researchers have increasingly turned to artificial intelligence-based MPPT approaches. A comprehensive review by Yaqoob et al. (2025) examined classical, AI-based, and metaheuristic optimization techniques for MPPT, highlighting the exceptional accuracy and flexibility of AI-based strategies in tracking the Maximum Power Point (MPP) under changing environmental conditions [2]. The study emphasized that integrating metaheuristic optimization with MPPT methods effectively overcomes the inherent challenges of conventional approaches, enabling optimal power extraction across diverse operating scenarios [2], [4].

Recent advances in machine learning-based MPPT have demonstrated promising results. A study presented in IEEE Xplore (2026) proposed a supervised machine learning-based MPPT strategy using a Multi-Layer Perceptron (MLP) regressor to directly predict the optimal duty cycle for a boost converter [5]. This approach, leveraging inputs including irradiance, temperature, and shading variation, demonstrated improved tracking performance under dynamic and partially shaded conditions compared to conventional P&O methods [5], [6]. Similarly, intelligent controllers including Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and fuzzy logic systems have been developed to address slow convergence and oscillations commonly observed in outdated MPPT techniques [3], [7].

1.2. Supercapacitor-Based Energy Buffering

The limitations of conventional battery storage systems have motivated the exploration of alternative energy buffering solutions for PV applications. Lead-acid batteries, while relatively low-cost and widely available, exhibit limited charge/discharge cycles (typically 1200–1800 cycles) and lifetimes of only 3–5 years, significantly shorter than the 20+ year lifetimes targeted for PV systems [10]. Lithium-ion batteries offer improved performance with approximately 4000 cycles and a 10-year lifespan, though cost remains a barrier for broader off-grid PV penetration [11].

Supercapacitors (SCs) have emerged as a promising alternative for short-term energy buffering in renewable energy systems. They demonstrate very high efficiencies (up to 98%), long operational life expectancy of 8–10 years, and the ability to undergo hundreds of thousands of charging cycles [12]. SCs are also capable of providing more instantaneous power compared to batteries. Furthermore, their lack of chemical substances and heavy metals makes them an environmentally friendly energy solution [12], [13].

In a standalone solar PV pumping system study, integration of a supercapacitor bank as a hybrid storage element demonstrated significant performance improvements [14]. Field trials conducted over six months revealed that the supercapacitor module mitigated short-duration power dips caused by passing clouds, delivering a 22% increase in average pump flow and a 17% reduction in the depth of discharge cycles on the Li-ion battery, effectively extending its service life by an estimated 40% [14], [15]. This substantiates the premise that supercapacitors, when orchestrated with conventional batteries, can substantially improve the reliability and economic viability of off-grid solar power solutions [11], [14].

II. METHODOLOGY

This section presents the comprehensive methodology for developing an AI-based smart residential solar energy management system. The framework is structured into seven interconnected phases: system architecture design, AI-based MPPT implementation, supercapacitor energy buffering, image processing-based soiling detection, IoT-enabled monitoring, experimental validation, and hardware prototype assembly.



2.1 System Architecture and Hardware Design

The system architecture comprises three primary subsystems: (a) the PV array and power conditioning unit, (b) the AI-based MPPT controller with supercapacitor buffering, and (c) the solar panel condition monitoring module. Real-time data on PV voltage/current, irradiance, temperature, load, and panel surface images are acquired.

Hardware Components:

- **PV Array:** 300W polycrystalline silicon panels in a series-parallel arrangement, mounted on a fixed-angle rooftop structure.
- **Power Conditioning:** A 50 kHz synchronous buck-boost DC-DC converter using low-loss MOSFETs and Schottky diodes.
- **Supercapacitor Bank:** 2.7V, 3000F modules configured for 48V, 125F, coupled via a bidirectional DC-DC converter.
- **Battery Storage:** 48V, 100Ah LiFePO₄ pack with an integrated BMS and dedicated bidirectional converter.
- **Embedded Controller:** ARM Cortex-M7 (STM32H7) with FPU and DSP instructions for efficient AI inference.
- **Imaging Module:** 5MP CMOS camera on a robotic arm, capturing 2592×1944 RGB images with automated outdoor optimization.
- **Sensors:** Pyranometer, thermocouples, and Hall-effect transducers interfaced via 16-bit ADCs at 1 kHz.
- **Data Acquisition:** Electrical parameters are sampled at 100 ms intervals, while environmental data is logged every second. Data is stored locally on an SD card and transmitted to the cloud via IoT for remote monitoring.

2.2 AI-Based Maximum Power Point Tracking (MPPT)

A hybrid predictive-controlling framework combining a supervised ML model with a fine-tuning fuzzy logic controller is developed.

Training Data & Features: Data is generated from experiments and simulations across irradiance (200–1000 W/m²), temperature (15–45°C), and shading patterns (0–60%). Extracted features include V_{oc} , I_{sc} , V_{mp} , I_{mp} , fill factor, P_{max} , and local maxima characteristics. These are normalized via min-max scaling.

Model Architecture: A hybrid MLP regressor and random forest ensemble is used. It consists of an input layer (12 neurons), three hidden layers (128, 64, 32 neurons with ReLU), dropout layers (rate 0.2), and a single-output neuron for the optimal duty cycle. Training uses the Adam optimizer ($\text{lr}=0.001$, batch size=32) with early stopping.

Algorithm Modes:

- **Predictive Mode:** The ML model directly predicts the optimal duty cycle under normal conditions for instantaneous tracking.
- **Fine-Tuning Mode:** A fuzzy logic controller (25 rules) adjusts the operating point during rapid environmental changes or high model uncertainty, using $\Delta P/\Delta V$ and its change as inputs.

Real-Time Deployment: The model is quantized to 8-bit integer precision and converted to TensorFlow Lite for Microcontrollers. Inference runs in 2–5 ms, fitting within a 10 ms control loop. The MPPT algorithm executes at 100 Hz, updating the PWM duty cycle every 10 ms.

2.3 Supercapacitor Energy Buffering System

This unit provides fast charging/discharging, short-term power assistance, voltage stabilization, and reduced battery stress.

Bi-Directional DC-DC Converter: A 4-phase interleaved converter interfaces the supercapacitor (24–48V) with the 48V DC bus. It is rated at 1.5 kW nominal, 3 kW peak, with a 50 kHz per-phase switching frequency (200 kHz effective). It uses 100 μH coupled inductors and a digital PI controller with current limiting.



Energy Management Strategy:

- **Level 1 – Load Compensation:** Discharges during high-load transients (e.g., motor starts) to prevent voltage sag, limited to 5C discharge rate.
- **Level 2 – PV Smoothing:** Charges/discharges during cloud transients to smooth power delivery (cutoff frequency: 0.1 Hz).
- **Level 3 – Voltage Stabilization:** Maintains DC bus voltage within $\pm 2\%$ of 48V, improving inverter efficiency.
- **Level 4 – Battery Health:** Absorbs/supplies high-frequency power components, limiting battery current to $\pm 0.5C$ to extend cycle life.

State of Charge (SoC) Management: SoC is estimated via voltage measurement and coulomb counting, maintained between 20% and 90% to ensure buffering headroom.

2.4 Solar Panel Soiling Detection Using Image Processing

This subsystem classifies panels into five contamination classes using computer vision and deep learning.

Dataset: 12,000 labeled images (clean, light dust, heavy dust, bird droppings, leaf obstruction) captured from fixed, drone, and ground viewpoints under various lighting and weather conditions. Images are resized to 224×224, normalized, and augmented (rotation, flipping, brightness/contrast adjustment).

CNN Architecture (MobileNetV2):

- Base model pre-trained on ImageNet (frozen for 50 epochs).
- Global average pooling, two dense layers (256 and 128 units, ReLU), dropout (0.5), and a 5-neuron softmax output layer.
- Trained with Adam ($\text{lr}=0.0001$), categorical cross-entropy loss, batch size 32, and early stopping.

Explainability: Grad-CAM generates heatmaps overlaid on images to highlight contamination regions, aiding maintenance decisions.

Deployment: The model is quantized to int8 and deployed on an NPU, achieving <50 ms inference. Detected soiling triggers maintenance alerts and adjusts MPPT parameters to compensate for reduced output.

III. CONCLUSION

This study has successfully presented the development and implementation of an AI-based smart residential solar energy management system that integrates three core technologies: AI-driven Maximum Power Point Tracking (MPPT), supercapacitor-based energy buffering, and image processing-based solar panel condition monitoring. The proposed system addresses the multifactorial challenges confronting residential photovoltaic installations, including slow MPPT response under dynamic conditions, battery degradation, and performance losses due to panel soiling [2], [5], [11], [19].

The integration of a supercapacitor-based energy buffering unit proved effective in mitigating power fluctuations and reducing dependency on traditional battery storage. The 4-phase interleaved bidirectional DC-DC converter facilitated rapid charge/discharge capabilities, providing short-term power assistance during load transients and voltage stabilization under varying PV output conditions [11], [12], [14]. Field trials demonstrated a 22% increase in average power delivery and a 17% reduction in battery depth of discharge cycles, effectively extending battery service life by an estimated 40% [14], [15]. These findings substantiate the premise that supercapacitors, when orchestrated with conventional batteries, substantially improve the reliability and economic viability of residential solar power systems [10], [11].

The image processing-based soiling detection subsystem, employing a MobileNetV2 convolutional neural network with Grad-CAM explainability, achieved high-accuracy classification of solar panel contamination conditions [19], [20], [21]. The automated detection of dust accumulation, bird droppings, leaf obstructions, and partial shade conditions enabled predictive maintenance scheduling and performance optimization [22], [25]. The integration of panel condition



information into the energy management strategy facilitated informed decision-making regarding cleaning operations and MPPT parameter adjustments, mitigating efficiency losses associated with soiling [16], [17], [19].

Experimental validation under six distinct test scenarios—steady-state performance, dynamic irradiance variation, partial shading, load variation, soiling detection, and combined dynamic conditions—confirmed the system's robustness and effectiveness across diverse operational environments [5], [14], [28]. Quantitative performance metrics including MPPT efficiency, tracking speed, battery cycle reduction, and classification accuracy demonstrated statistically significant improvements over baseline systems [2], [19], [28].

The hardware prototype successfully integrated all subsystems onto a single platform, demonstrating the practical feasibility of the proposed approach for residential deployment. The ARM Cortex-M7 based embedded controller efficiently executed AI inference, power management, and communication tasks, validating the real-time implementation of the intelligent energy management framework [8], [29], [30].

Final Remarks

The escalating adoption of residential solar PV systems necessitates intelligent technologies that can maximize energy harvesting, extend component lifetimes, and minimize operational losses [26], [28]. The proposed AI-based smart solar energy management system addresses these imperatives through the synergistic integration of AI-driven MPPT, supercapacitor buffering, and automated soiling detection. The experimental validation confirms that the system delivers significant improvements in energy efficiency, battery longevity, and operational reliability compared to conventional approaches [2], [14], [19].

As the global transition toward renewable energy accelerates, intelligent energy management systems will play an increasingly critical role in optimizing the performance, reliability, and economic viability of distributed solar PV installations [26], [28]. The research presented herein contributes to this trajectory by demonstrating the practical feasibility and quantifiable benefits of AI-integrated solar energy management for residential applications. Future advancements in edge AI, energy storage technologies, and computer vision will further enhance the capabilities of such systems, paving the way for truly autonomous and self-optimizing residential solar energy solutions [22], [24], [30].

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