International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 2, Mar-Apr 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

AI-Enabled Adaptive Solar Energy Management System for Portable Charging Devices: A Proposed System Architecture

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Abstract:

Portable electronic devices have become indispensable in modern life, yet conventional solar chargers remain limited by static charging circuits, poor adaptability to changing environmental conditions, and inadequate battery protection mechanisms. This paper proposes a conceptual system architecture for an AI-Enabled Adaptive Solar Energy Management System designed for portable charging devices. The proposed architecture integrates three core functional pillars: an AI-based Maximum Power Point Tracking (MPPT) module for adaptive solar energy harvesting, an Intelligent Battery Management System (BMS) for predictive health monitoring, and a Smart Power Distribution module for dynamic multi-device energy allocation. The design draws upon and synthesizes established techniques from the photovoltaic systems, machine learning, and power electronics literature. This work does not present experimental validation or prototype implementation; rather, it contributes a coherent, literature-grounded architectural framework that is technically feasible and aligned with the patent disclosure for this invention. The proposed system is expected to improve solar energy utilization, extend battery lifespan, and enable reliable off-grid power delivery for a range of practical applications including outdoor activities, emergency response, and rural electrification.

Keywords — *Adaptive Solar Charging, Artificial Intelligence, Battery Management System, Maximum Power Point Tracking, Photovoltaic Systems, Portable Power Electronics, Smart Power Distribution.*

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I. INTRODUCTION

The rapid proliferation of portable electronic devices—smartphones, tablets, wearable sensors, and GPS navigation systems—has created a sustained and growing demand for reliable off-grid power solutions. Traditional portable power banks, which depend exclusively on grid electricity for recharging, are fundamentally unsuitable for remote areas, extended outdoor activities, or emergency situations where conventional power infrastructure is unavailable [1].

Solar-powered portable chargers represent a compelling alternative by harnessing freely available renewable energy. However, the current state of commercially available solar chargers reveals significant limitations. Most devices rely on basic photovoltaic panels with fixed charging circuits that cannot adapt to variations in sunlight intensity, ambient temperature, or load demand. As documented in the literature, basic solar power banks typically achieve solar conversion efficiencies of only 10–15% and require 8–12 hours of favorable sunlight exposure for partial charging [2]. Even commercially advanced models offering 18–22% panel efficiency continue to lack intelligent, adaptive energy management capabilities.

The core problem is therefore not merely hardware efficiency—it is the absence of intelligence. Existing devices cannot predict solar energy availability, cannot dynamically protect battery health, and cannot intelligently allocate power among multiple connected devices. These limitations collectively reduce reliability, shorten battery lifespan, and diminish user utility in precisely the scenarios where dependable off-grid charging is most critical.

This paper proposes a conceptual system architecture that addresses these limitations by integrating artificial intelligence with solar energy harvesting and battery management in a compact portable form factor. The proposed design is grounded in a synthesis of existing, well-validated techniques from the academic literature and is directly aligned with the patent disclosure for this invention. The primary objective of this paper is to define the architectural components, describe their intended interactions, and discuss the expected performance characteristics based on prior work—not to present novel algorithms, experimental results, or implementation data.

The remainder of this paper is structured as follows: Section II reviews relevant literature on MPPT methods, battery management, and power distribution. Section III presents the proposed system architecture. Section IV discusses the conceptual AI-based energy management design. Section V offers a literature-based comparative analysis. Section VI presents practical applications. Section VII addresses limitations and future work. Section VIII concludes the paper.

II. CONTRIBUTIONS OF THIS WORK

In the interest of academic clarity, the contributions of this paper are explicitly defined as follows:

- This paper proposes a system architecture for an AI-enabled adaptive solar energy management system for portable charging devices. It does not present a novel machine learning algorithm, a novel circuit topology, or breakthrough performance claims.
- The architecture integrates existing, literature-validated techniques—specifically AI-based MPPT, intelligent Battery Management Systems, and smart power distribution—into a unified, coherent design framework suitable for portable off-grid charging applications.
- The paper provides a conceptual and analytical framework that bridges the academic literature on photovoltaic systems, machine learning, and power electronics with the specific design requirements of portable solar charging devices.
- This work has not been experimentally validated. No physical prototype has been constructed. All performance expectations cited in this paper are grounded in prior literature, and are clearly attributed as such.

This work therefore constitutes a design and analysis contribution in the tradition of conceptual system architecture papers, intended to provide a rigorous technical foundation for future prototype development and experimental validation.

III. LITERATURE REVIEW

A. Maximum Power Point Tracking (MPPT) Methods

The fundamental challenge in photovoltaic energy harvesting is continuously locating the operating point that maximizes instantaneous power output. The power output of a PV array is governed by a non-linear, environment-dependent P-V curve. Traditional MPPT algorithms—primarily Perturb and Observe (P&O) and Incremental Conductance (IncCond)—have been widely deployed due to their simplicity and low computational requirements. However, extensive research has documented their significant limitations under Partial Shading Conditions (PSCs), where the P-V curve exhibits multiple local maxima. Under these conditions, P&O and IncCond algorithms are prone to convergence at Local Maximum Power Points (LMPPs) rather than the Global Maximum Power Point (GMPP), resulting in substantial energy losses [3].

To address this, the research community has explored metaheuristic optimization techniques including Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO). While these approaches can escape local maxima, they introduce convergence delays and computational overhead that may be excessive for resource-constrained portable devices [4].

More recent literature demonstrates that Artificial Neural Network (ANN)-based MPPT algorithms can map environmental inputs—irradiance and temperature—directly to the reference GMPP voltage, bypassing iterative search entirely. Studies indicate that ANN-based MPPT can achieve sub-10 millisecond response times with zero steady-state oscillation, and prior studies have reported annual energy yield improvements of approximately 14% over traditional P&O methods under variable irradiance conditions [5]. Deep Reinforcement Learning (DRL)-based MPPT has also been proposed, offering the additional advantage of online adaptability to novel shading patterns without requiring pre-labeled training datasets [6].

B. Battery Management Systems and State Estimation

The Battery Management System (BMS) is the critical safety and monitoring layer of any portable energy storage device. Beyond basic over-voltage and over-temperature protection, advanced BMS architectures are required to accurately estimate the State of Charge (SOC) and State of Health (SOH) of lithium-ion cells. SOH estimation is particularly challenging because it requires tracking capacity fade over hundreds of charging cycles under variable temperature and current conditions [7].

Traditional BMS designs rely on Equivalent Circuit Models (ECMs) or coulomb counting techniques. These approaches are computationally light but suffer from cumulative estimation drift, particularly under the irregular, solar-driven charging profiles characteristic of portable devices [8]. Data-driven machine learning models—notably Long Short-Term Memory (LSTM) networks—have demonstrated improved accuracy in capturing temporal degradation dynamics. However, purely data-driven models lack physical interpretability and can produce physically impossible predictions when exposed to out-of-distribution conditions [9].

Physics-Informed Neural Networks (PINNs) represent a promising advancement in this area. PINNs incorporate the governing physical equations of battery electrochemistry—such as Fick's law of diffusion and empirical capacity fade models—directly into the neural network's loss function as a regularization term. Prior studies have reported that PINN-based SOH estimators can restrict mean absolute percentage error to below 1%, significantly outperforming purely data-driven alternatives, while ensuring that predictions remain physically plausible [10].

C. Power Distribution Systems

The delivery of energy from a portable storage device to multiple end-user electronics has traditionally been governed by static hardware routing. Conventional multi-port chargers divide available power based on fixed circuit parameters, without accounting for the actual demand profiles of connected devices. This leads to power stranding on low-demand ports and throttling of high-demand devices [11].

The introduction of the USB Power Delivery (USB PD) specification—and the subsequent USB PD 3.1 Extended Power Range (EPR) update—has enabled dynamic, negotiated power allocation between source and sink devices. Under USB PD, connected devices communicate their precise power requirements, allowing the source to allocate power intelligently. The USB PD 3.1 EPR specification supports delivered power up to 240W, enabling high-performance laptops and field equipment to be powered from portable sources [12].

Research on AI-driven multi-port power management in GaN-based chargers has demonstrated that intelligent allocation algorithms can significantly reduce thermal stress and improve per-device charging efficiency compared to static routing schemes [13]. These findings motivate the integration of dynamic power distribution intelligence into the proposed portable solar charging architecture.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed AI-Enabled Adaptive Solar Energy Management System is organized as a pipeline of functional modules, each performing a distinct role in the energy flow from solar input to device output. Figure 1 (see patent IDF, Figure 1) illustrates the overall system block diagram. The following subsections describe each module and its design rationale.

A. Photovoltaic Solar Panel

The primary energy source is a high-efficiency photovoltaic panel integrated into the portable device housing. The panel captures incident solar radiation and converts it into direct current (DC) electrical energy. The selection of panel technology—monocrystalline silicon or emerging perovskite-silicon hybrid cells—is a design consideration that affects the achievable open-circuit voltage, short-circuit current, and fill factor across the operational temperature range. The PV panel is connected to the downstream electronics through a DC bus that serves as the input to the adaptive energy optimization circuit.

B. Environmental Sensor Module

A dedicated sensor array continuously monitors the environmental and electrical conditions relevant to energy management decisions. This module includes light intensity sensors (photodiodes or ambient light sensors) for estimating solar irradiance, temperature sensors (NTC thermistors) for monitoring both ambient temperature and panel surface temperature, and electrical transducers for measuring PV output voltage and current. The data from this module is streamed in real-time to the AI Energy Management Controller, providing the input signals required for intelligent decision-making.

C. AI Energy Management Controller

The AI Energy Management Controller is the central intelligence layer of the proposed system. It is envisioned as an embedded microcontroller or system-on-chip with sufficient computational resources to execute lightweight machine learning inference workloads—consistent with the TinyML paradigm documented in recent literature [14]. The controller receives sensor data from the Environmental Sensor Module and battery status information from the BMS, and produces control outputs that regulate the Adaptive Solar Optimization Circuit and the Smart Power Distribution Module.

D. Adaptive Solar Optimization Circuit

This module implements the Maximum Power Point Tracking function in hardware, executing control signals generated by the AI controller. It incorporates a DC-DC converter topology—such as a buck-boost converter—capable of dynamically adjusting its duty cycle to match the operating point of the PV array to the GMPP as identified by the AI controller. The circuit is responsible for voltage and current regulation, ensuring stable and efficient energy transfer from the PV panel to the battery storage unit.

E. Battery Management System (BMS)

The BMS module continuously monitors the health and safety parameters of the lithium-ion energy storage unit. It measures cell voltage, charging and discharging current, and internal temperature at multiple points, comparing these measurements against configurable safety thresholds. The BMS implements protective functions including over-voltage cutoff, under-voltage protection, over-current limiting, and thermal shutdown. In addition to these reactive safety functions, the proposed BMS architecture incorporates an AI-based predictive layer that estimates SOC and SOH from the monitored parameters, enabling proactive charge cycle management and early warning of thermal or degradation risks.

F. Energy Storage Unit

The energy storage unit consists of a lithium-ion battery pack with capacity suitable for the intended portable application. The battery serves as the primary energy reservoir, storing excess harvested solar energy and supplying power to connected devices when solar generation is insufficient or unavailable. The BMS interfaces directly with the battery to ensure safe charge and discharge operation throughout the battery's cycle life.

G. Smart Power Distribution Module

The Smart Power Distribution Module manages the delivery of stored energy to connected end-user devices through USB and USB Type-C output interfaces. Rather than using static power routing, this module implements a dynamic allocation strategy that identifies the power requirements of each connected device—through USB Power Delivery protocol negotiation—and distributes the available power pool accordingly. Priority logic can be configured to favor critical devices, devices with low battery states, or high-demand devices requiring immediate power, depending on user settings and system conditions.

H. System Operating Phases

The proposed system is designed to operate through the following sequential and continuous phases:

- Phase 1 — Solar Harvesting: The PV panel converts incident sunlight into DC electrical energy, with output dependent on irradiance and temperature conditions.
- Phase 2 — Environmental Monitoring: The sensor module continuously streams irradiance, temperature, and electrical measurements to the AI controller.
- Phase 3 — AI Analysis: The embedded AI controller processes sensor data and battery status to estimate available solar energy and determine optimal charging parameters.
- Phase 4 — Adaptive Optimization: The AI controller adjusts the duty cycle of the DC-DC converter to track the GMPP and maximize energy transfer.
- Phase 5 — Intelligent Battery Charging: Optimized energy is transferred to the battery under BMS supervision, with real-time monitoring of voltage, current, and temperature.
- Phase 6 — Smart Power Distribution: When devices are connected, the AI controller negotiates power requirements and allocates the available energy pool dynamically.
- Phase 7 — Continuous Feedback: The AI controller continuously monitors system performance and adjusts energy distribution to maintain stable, efficient operation.

V. AI-BASED ENERGY MANAGEMENT (CONCEPTUAL DESIGN)

This section describes how artificial intelligence is intended to be applied within the proposed architecture. It is emphasized that the AI models described here are design options grounded in the existing literature—they have not been trained, implemented, or evaluated within the scope of this work.

A. AI-Based MPPT Design Options

Two AI methodologies are identified as candidate approaches for the MPPT function, each with distinct trade-offs that make them suitable for different deployment scenarios.

The first approach is an Artificial Neural Network (ANN)-based MPPT model. In this design, a multi-layer perceptron trained offline on a dataset of P-V curves under diverse irradiance and temperature conditions would learn a direct mapping from environmental inputs to the optimal reference voltage. This approach is expected to offer very fast inference (sub-10 ms) and zero steady-state oscillation during operation. Its primary limitation is that its accuracy is bounded by the diversity of its offline training data; shading patterns not represented in the training set may lead to suboptimal predictions. As documented in prior literature, ANN-based MPPT has demonstrated improved energy extraction compared to P&O methods in variable irradiance environments [5].

The second approach is a Deep Reinforcement Learning (DRL)-based MPPT agent. A DRL agent—formulated as a Markov Decision Process with state inputs of PV voltage, current, and power, and actions corresponding to incremental duty cycle adjustments—would learn an optimal MPPT policy through continuous online interaction with the PV system. The reward signal is proportional to the change in output power. This approach offers adaptive online learning capability, meaning it can self-improve under novel shading patterns without requiring retraining. Prior research indicates that DRL-based MPPT is particularly robust to parameter drift and sensor noise [6].

The proposed system architecture is designed to accommodate either approach. For a first implementation, an ANN-based MPPT is recommended given its lower computational requirements and deterministic inference behavior, with DRL considered as a future enhancement for online adaptation.

B. AI-Based Battery Health Management

The BMS AI layer is proposed to implement a Physics-Informed Neural Network (PINN) for SOC and SOH estimation. The rationale for selecting PINNs over purely data-driven models is grounded in the literature: standard LSTM networks, while accurate within their training distribution, can generate physically impossible predictions (such as increasing SOH values) when exposed to out-of-distribution operating conditions. PINNs address this by incorporating electrochemical constraints—such as capacity monotonicity and diffusion dynamics—into the neural network loss function, ensuring that all predictions remain physically consistent [10].

In the proposed system, the PINN-based estimator would receive continuous streams of voltage, current, and temperature measurements from the BMS sensor array and produce real-time SOC and SOH estimates. These estimates would inform the AI controller's charge cycle management decisions, such as reducing maximum charging voltage during high-temperature conditions or alerting the user when battery degradation reaches a threshold warranting inspection.

C. Smart Power Allocation Logic

The power distribution AI is designed to operate as an embedded Device Policy Manager that continuously monitors the connected device landscape and the available power pool. Using the USB Power Delivery protocol, the controller receives declared power requirements from each connected device. The allocation algorithm then solves a real-time optimization problem to distribute the total available power—from solar generation and battery—to maximize total charging throughput while respecting per-port power limits and thermal safety constraints.

For example, if a laptop, a smartphone, and a wearable device are connected simultaneously, the controller allocates power proportionally to their stated requirements, dynamically re-allocating freed capacity when a device reaches full charge or reduces its demand. If the AI thermal monitoring module detects that the GaN switching circuits are approaching their thermal limit, the algorithm gracefully throttles lower-priority ports rather than executing a hard safety shutdown.

VI. COMPARATIVE ANALYSIS (LITERATURE-BASED)

This section presents comparative analyses of the key architectural choices made in the proposed system, based on evidence from prior studies. The data presented in the following tables is sourced from the cited literature; no original measurements have been conducted in this work.

TABLE I: Comparative Analysis of MPPT Algorithms (Literature-Based)

Algorithm	***Tracking Eff. (%)***	***Response Time***	***Partial Shading***	***Notes***
P&O	*88–92*	*> 50 ms*	*Poor (LMPP trap)*	*Low cost, widely deployed [3]*
Incremental Conductance	*90–94*	*40–50 ms*	*Poor (LMPP trap)*	*Slightly better than P&O [3]*
ANN-Based	*98–99*	*< 10 ms*	*Excellent (GMPP)*	*Requires offline dataset; fast inference [5]*
DRL-Based	*98–99*	*10–20 ms*	*Excellent (Adaptive)*	*Online learning; robust to drift [6]*

Note: All efficiency and response values in Table I are drawn from prior literature and represent the expected performance of each approach under the cited experimental conditions. They do not represent measurements obtained in this work.

TABLE II: Comparative Analysis of BMS State Estimation Methods (Literature-Based)

Method	***Est. RMSE (%)***	***Phys. Validity***	***Data Needs***	***Notes***
Coulomb Counting / ECM	*> 2.0*	*High (model-based)*	*Low*	*Prone to cumulative drift [8]*
LSTM (Pure DL)	*1.5–2.0*	*Low (black-box)*	*High*	*May violate physics OOD [9]*
PINN-Based	*0.85–1.1*	*Very High (PDE-constrained)*	*Moderate*	*Prior studies report ~40% error reduction [10]*

Note: Values in Table II are drawn from prior literature [8][9][10] and do not reflect measurements from this work.

TABLE III: Comparison of Existing Solar Portable Chargers vs. Proposed Architecture

Feature	**Basic Solar Charger**	**MPPT Solar Charger**	**Proposed AI Architecture**

MPPT Method	None / Fixed circuit	P&O or IncCond	ANN or DRL (adaptive)
Battery Management	Basic threshold protection	Standard BMS	AI-based predictive BMS (PINN)
Multi-Device Power Allocation	Static / None	Static	Dynamic AI-driven allocation
Environmental Adaptation	None	Partial (hardware-limited)	Continuous sensor-driven adaptation
Output Interface	USB-A	USB-A / USB-C	USB + Type-C with PD protocol

VII. APPLICATIONS AND USE CASES

The proposed system architecture is designed for broad applicability across scenarios where reliable off-grid power is required. Based on the patent disclosure and analysis of the target use environment, the following application domains are identified:

- Outdoor and Adventure Activities: Trekking, hiking, camping, and extended travel are contexts where access to grid power is unavailable for extended periods. The proposed system's ability to harvest solar energy adaptively and charge multiple devices simultaneously addresses the power needs of such users.
- Emergency Response and Disaster Relief: During natural disasters or grid outages, emergency responders and affected individuals require reliable charging for communication devices. The system's off-grid design and intelligent energy management make it a suitable tool for these high-stakes scenarios.
- Rural and Remote Electrification: In areas with unstable or absent electricity supply, the proposed system can serve as a primary portable power source for smartphones, GPS units, and other essential electronics, contributing to energy access goals.
- Field Research and Environmental Monitoring: Field researchers, ecological monitoring teams, and rescue operations that deploy portable electronic instruments in remote locations require sustained, self-sufficient power sources. The proposed architecture is well-suited to such professional applications.
- Daily Mobile and Commuter Use: The system also addresses the needs of everyday commuters and mobile professionals who require convenient, sustainable charging without dependence on wall sockets.

The environmental benefits of the proposed system include promotion of renewable energy adoption, reduction of dependence on fossil-fuel-based grid electricity, extension of battery lifespan through intelligent charge management (thereby reducing electronic waste), and support for clean energy goals at the individual device level.

VIII. LIMITATIONS, SCOPE, AND FUTURE WORK

A. Scope and Limitations of This Work

The following explicit limitations apply to this paper:

- No physical prototype has been constructed. The proposed architecture exists at the conceptual design stage.
- No experimental validation has been conducted. Performance characteristics attributed to the proposed system are based on prior literature concerning the individual component technologies (ANN/DRL MPPT, PINN BMS, USB PD).
- No novel machine learning algorithms are proposed or claimed. The AI methods described (ANN, DRL, PINN) are established techniques applied in a new integration context.
- Compliance with regulatory standards such as IEEE 2686-2024 is not verified. The architecture

can be designed to target compliance with relevant standards; verification would require prototype testing.

- The system's performance under real-world environmental variability—including dust accumulation on panels, extreme temperatures, or highly dynamic shading—has not been evaluated.

B. Future Research Directions

Future work on this proposed architecture should proceed along the following directions:

- Prototype Development: A hardware prototype integrating commercial photovoltaic panels, environmental sensors, a microcontroller-based AI module, and a BMS should be developed to validate the architectural design in practice.
- Experimental Validation: Controlled testing under diverse environmental conditions—varying irradiance levels, temperatures, partial shading patterns, and multi-device load profiles—is required to quantify the actual performance of the system.
- AI Model Training and Evaluation: Suitable training datasets for the ANN/DRL MPPT and PINN BMS models should be assembled and the models trained, with performance metrics (tracking efficiency, SOH estimation error) compared against the literature benchmarks cited in this paper.
- Federated Learning Extension: As a longer-term extension, federated learning could be explored to enable a network of deployed devices to collaboratively refine their AI models while preserving user data privacy. This is framed as a future extension, not a core system component, as it requires significant deployed infrastructure to be meaningful.
- Miniaturization and Form Factor Optimization: Engineering challenges related to integrating high-efficiency solar panels, AI processing hardware, and intelligent BMS electronics into a compact, durable, and cost-effective portable device require dedicated design and materials research.

IX. CONCLUSION

This paper has proposed a conceptual system architecture for an AI-Enabled Adaptive Solar Energy Management System for portable charging devices. The architecture integrates three functional pillars—AI-based adaptive MPPT for efficient solar energy harvesting, an intelligent predictive Battery Management System, and a dynamic multi-device power distribution module—into a coherent design framework grounded in the existing academic literature.

The proposed system addresses the well-documented limitations of conventional portable solar chargers: static charging circuits, poor adaptability to environmental variation, inadequate battery protection, and inflexible power distribution. By incorporating machine learning intelligence at the MPPT and BMS levels, the architecture is expected—based on prior literature—to offer significantly improved solar energy utilization, extended battery lifespan, and more reliable off-grid power delivery for a range of practical applications.

This work does not claim experimental validation, novel algorithm development, or regulatory certification. It contributes an architecturally coherent, literature-grounded design framework that is aligned with the patent disclosure for this invention and provides a rigorous foundation for future prototype development and empirical evaluation. The proposed system represents a technically feasible pathway toward smarter, more sustainable portable energy technology.

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