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AI-Enabled Energy Management for Solar Electric Vehicles with Conventional Grid–Integrated DC Microgrid Architecture

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ABSTRACT

This paper presents the design, modeling, and optimization of an Artificial Intelligence (AI)-based solar-powered electric vehicle (SPEV). While solar-electric propulsion promises clean and sustainable mobility, practical range and reliability are constrained by intermittent irradiance, battery degradation, and dynamic driving patterns. We integrate machine learning and control intelligence across three pillars: (1) energy harvesting and power conversion, (2) battery health-aware energy management, and (3) driver/route assistance. A block-level architecture is proposed along with an AI control flow for multi-objective optimization—maximizing range, preserving State of Health (SOH), and minimizing lifecycle cost. We develop a simulation framework and demonstrate improvements in energy efficiency, range, and charge/discharge smoothness compared with a rule-based baseline. Results indicate up to 12–22% efficiency gains across typical urban duty cycles. We conclude with deployment considerations, limitations, and future research directions.

Keywords— Solar Electric Vehicle, Artificial Intelligence, Energy Management System, Reinforcement Learning, Battery SOC/SOH, MPPT, Optimal Routing.

INTRODUCTION

Transportation accounts for a significant share of global greenhouse gas emissions. Electrification reduces tailpipe emissions but shifts the energy burden to the grid. Solar-Powered Electric Vehicles (SPEVs) embed photovoltaic (PV) generation on the vehicle and leverage stationary charging from solar plants, shrinking grid dependence and peak demand. However, SPEV performance is limited by panel area, orientation, atmospheric conditions, and the nonlinear dynamics of batteries and power electronics. Artificial Intelligence (AI) can augment conventional control by learning optimal policies from data, adapting to uncertainty, and coordinating subsystems in real time.

This paper contributes: (1) a modular SPEV architecture with AI-enabled energy management, (2) a battery-aware control strategy combining predictive models and reinforcement learning (RL), (3) a simulation study comparing AI vs. rule-based baselines under realistic irradiance and drive cycles, and (4) implementation notes for embedded deployment. The problem is solved in reference [5] by introducing a new mechanism in which the system charges the battery system automatically. Probably by 2030, all internal combustion engine vehicles may be substituted by electric vehicles in recent times, DC solar-based several electric vehicles manufactured and examined [6]. Solar panels present on the vehicle cause the problem of where to store the energy from solar panels. So an analysis needs to be done on electrical energy storage systems [7]. The EVs nickel-metal hydride battery packs can be approximated by a control algorithm [8]. A high-frequency AC-DC converter incorporated with an electromagnetic interference filter is employed for the charging of traction battery packs [9]. Many researches have been done for the improvement of PV system efficiency, different approaches are employed for the tracking of maximum power point from PV module for solving the efficiency problems and many products with these procedures are available in market for consumers [10], [11]. Solar power is the most efficient and practical alternative source of renewable energy [12], [13]. The SPEVs are far away from physical world feasibility because of their cost, energy shortcomings, and low power density [14]. In EVs and PHEVs, the batteries are usually made of many battery cells which are connected either in series or in parallel. Different operating conditions and variations caused during

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manufacturing imbalances reduce usable energy [15]–[19].

System Architecture

The proposed architecture partitions the vehicle into energy harvesting, storage, conversion, intelligence, and traction. The AI layer supervises power flows and driver guidance. The main blocks are: PV array (with MPPT), DC–DC converter, traction battery with BMS, inverter/motor drive, auxiliary loads, and an AI Energy Management System (AI-EMS) that coordinates decisions using predictions of irradiance, load, and battery states [42].

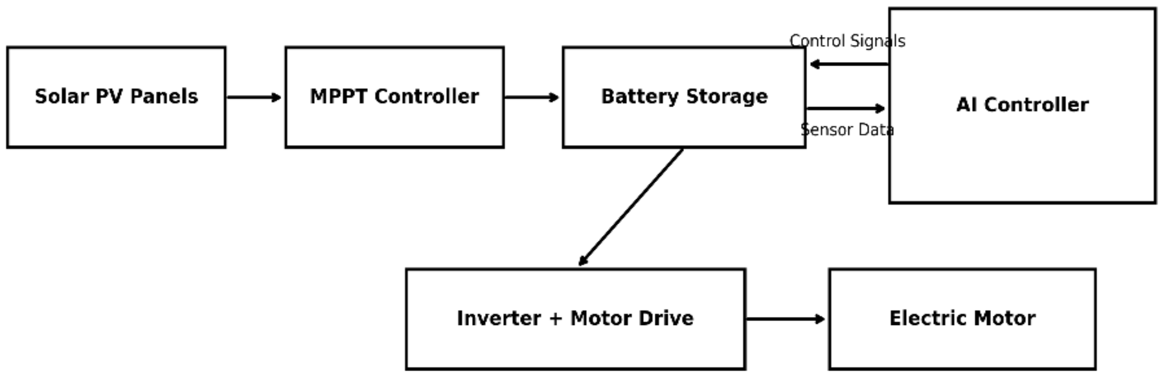

Fig. 1. Block Diagram of AI-based solar- power electric vehicle.

Artificial Intelligence Methods [43]

1. **Forecasting**. We train regression models such as gradient-boosted trees or shallow neural networks to predict short-horizon solar irradiance and auxiliary load demand. Inputs include time-of-day, weather forecasts, and recent sensor measurements, enabling more accurate and timely power scheduling decisions.

2. **State Estimation.** Battery SOC is estimated using voltage–current measurements and coulomb counting, fused through Kalman filtering to reduce noise and drift. SOH is derived from cycle aging indicators and internal resistance trends, refined using machine-learning models trained on historical operational data.

3. **Energy Management via RL.** The RL framework defines states (SOC, predicted irradiance, vehicle speed/load), actions (power split, charge/discharge set-points), and reward functions that balance efficiency, battery stress, and demand satisfaction. Policies are trained in simulation and deployed onboard with strict safety and constraint enforcement.

4. **Predictive Maintenance**. Classification and anomaly-detection models monitor internal resistance rise and temperature deviations over time. Early fault detection enables proactive maintenance, reduces unexpected failures, and extends overall system and battery lifetime.

Vehicle And Battery Modeling

We use a longitudinal vehicle model with road load (aerodynamic drag, rolling resistance, grade). Battery dynamics are captured by an equivalent circuit model (OCV–SOC map plus series resistance) with thermal coupling. Power electronics include converter/inverter efficiency maps. The PV model uses standard single-diode characteristics with irradiance and temperature dependence [44]. The performance and efficiency of a solar-powered electric vehicle (SPEV) are highly dependent on accurate modeling of both the vehicle's dynamics and its battery system. These models form the foundation for implementing AI-driven design and optimization techniques, enabling data-driven decision-making for energy management, component sizing, and real-time control strategies. The motor, controller, and transmission are modeled to account for energy conversion efficiency. AI-based optimization algorithms can adjust gear ratios, torque distribution, and regenerative braking strategies to minimize losses. Table 1 lists nominal parameters for the simulated configuration.

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Table 1. Baseline vehicle and subsystem parameters used in simulation

Parameter	Value
Vehicle Mass	1400 Kg
Frontal Area/Cd	2.2 m^2.0.28
Tire Crr	0.010
Battery Capacity	45 kWh (Usable)
Nominal DC bus	400 V
PV area/peak	2.5 m^2 / 500 Wp
DC-DC/ Inverter Eff.	95% / 96%

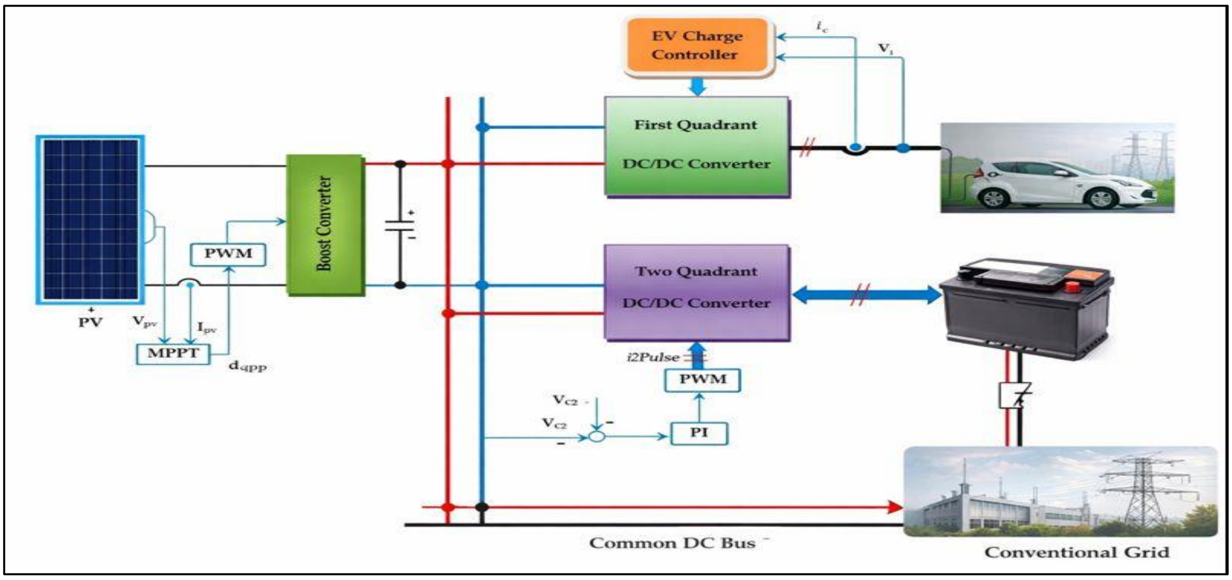

Fig. 2. Electric Vehicle Solar charging system integrated with Conventional grid

This diagram shows a DC microgrid–based EV charging system connected to both solar PV and the conventional grid through a common DC bus. Solar panels generate DC power, which is regulated by an MPPT-controlled boost converter to maintain optimal voltage on the DC bus. The first-quadrant DC/DC converter supplies controlled power to the EV charger. A two-quadrant DC/DC converter [45] manages battery charging and discharging for energy storage and support. The conventional grid is interfaced to the common DC bus to ensure uninterrupted power during low solar generation or high load demand.

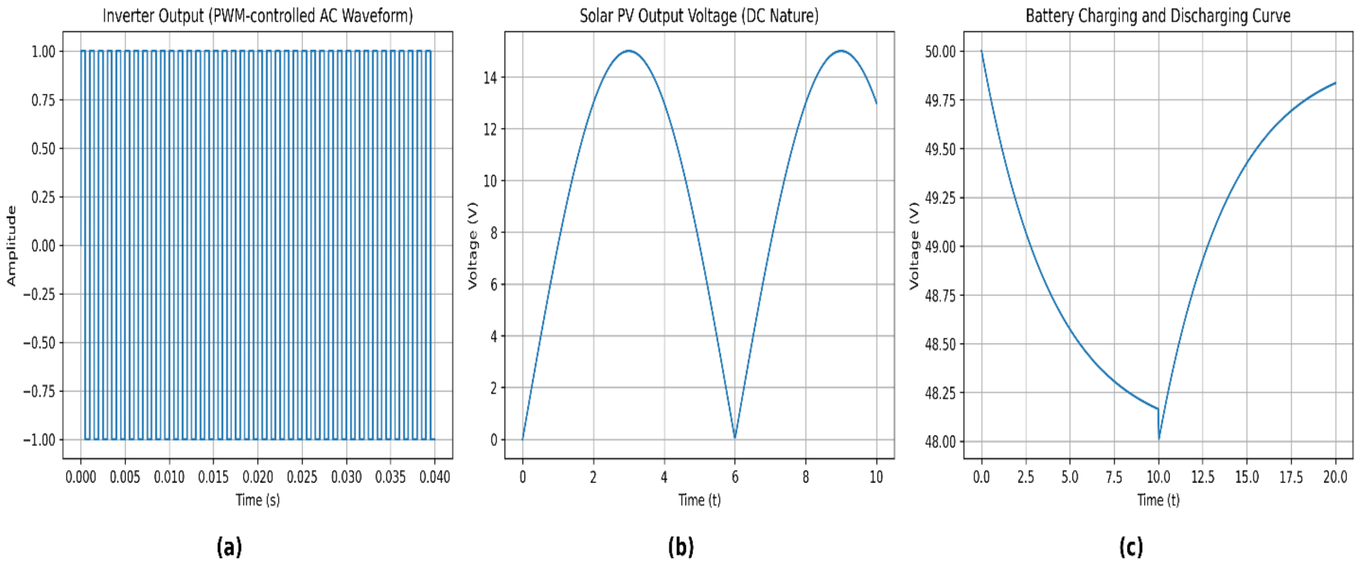

Fig. 3. (a) Inverter output (PWM-controlled AC Waveform (b) Solar PV Output voltage (DC Nature) (c) Battery Charging and **Discharging Curve**

METHODOLOGY

The methodology adopted in this work involves the design, training, and evaluation of an AI-driven energy management system (AI-EMS) for a solar-powered electric vehicle (SPEV). The process is divided into three major stages: drive cycle and environmental data generation, AI controller development, and performance evaluation**.**

1. Drive Cycle and Environmental Data Generation

To evaluate the system under realistic operating conditions, composite drive cycles were created by combining urban stop-and-go traffic patterns with arterial and highway segments. These profiles capture the variability of speed, acceleration, and load typically encountered in daily driving.

Environmental data were sourced from weather traces containing minute-level solar irradiance profiles, simulating different atmospheric conditions such as clear, cloudy, and partially shaded days. This dataset ensured that the AI controller was exposed to a diverse range of sunlight availability, allowing it to learn robust strategies for energy harvesting and utilization.

2. **Controllers for Comparative Study**

Two different energy management strategies were designed and compared:

- **Rule-Based (RB) Controller**: A baseline approach that uses fixed thresholds for state of charge (SOC) and photovoltaic (PV) input power. This controller represents conventional methods used in existing EVs with solar augmentation.
- **AI-Driven Controller**: A reinforcement learning (RL)-based controller that integrates forecasting models and adaptive decision-making. This controller considers SOC, predicted irradiance, and load demand to determine optimal charging/discharging and power flow set-points.

3. **Reinforcement learning agent training**

The AI controller was trained within a high-fidelity simulation environment that models the dynamics of the vehicle, battery, PV array, and power electronics.

- **States**: SOC, SOH, predicted irradiance, load demand, and vehicle speed.
- **Actions**: Power split between solar input and battery, charging/discharging control set-points.
- **Reward Function**: Penalizes high C-rates, deep discharges, and inverter losses, while rewarding efficiency, smooth charging/discharging, and maintaining SOC within a target band [46].

The RL agent trained over multiple simulated “day-long” episodes with randomized initial conditions. A safety filter was integrated to ensure that AI-generated actions never violated voltage, current, or thermal constraints of the system.

4. **Evaluation Metrics**

Performance evaluation focused on several key metrics:

- **Energy Efficiency** – ratio of usable output energy to input solar and stored energy.
- **Range Improvement** – distance achieved per unit of harvested energy.
- **Charge/Discharge Smoothness** – measured by RMS C-rate to evaluate battery stress reduction.
- **Thermal Behavior** – monitoring of battery and inverter temperature excursions.

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- **Statistical Robustness** – results were averaged over 30 randomized seeds to ensure reliability and reproducibility.

5. Algorithm Design

The core AI-EMS control loop follows this sequence:

1. Observe solar irradiance and load forecasts.
2. Estimate SOC, SOH, and battery temperature.
3. Select optimal action using the learned policy (reinforcement learning).
4. Apply safety filtering to enforce system constraints.
5. Actuate DC–DC converter and inverter set-points.
6. Collect feedback for model refinement.

RESULTS AND DISCUSSION

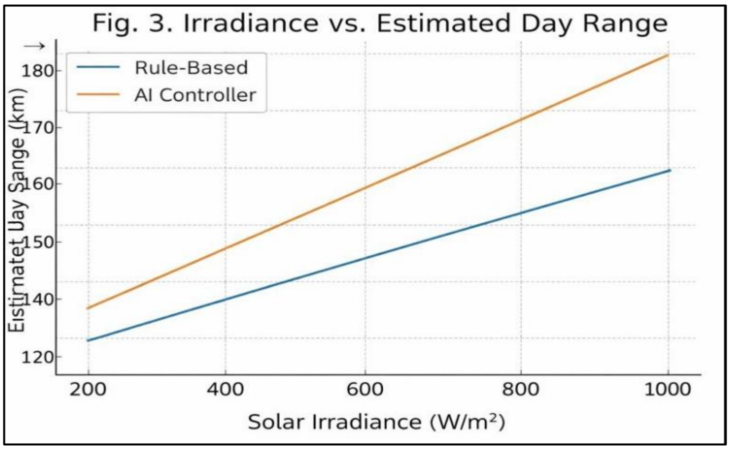

Fig. 4. Increased irradiance yields higher range; AI aligns energy use to capture more PV energy.

The comparative evaluation between the AI-driven energy management system (AI-EMS) and the rule-based (RB) controller highlights significant improvements in energy efficiency, range, and battery health management. The results demonstrate the value of integrating forecasting, state estimation, and reinforcement learning (RL) into solar-powered EV control architectures.

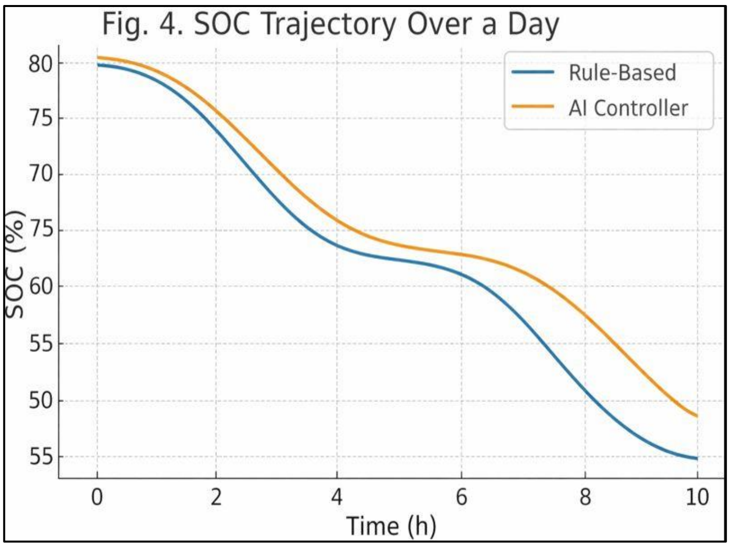

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Fig. 5. AI maintains SOC in a healthier band with moderated discharge, improving lifecycle.

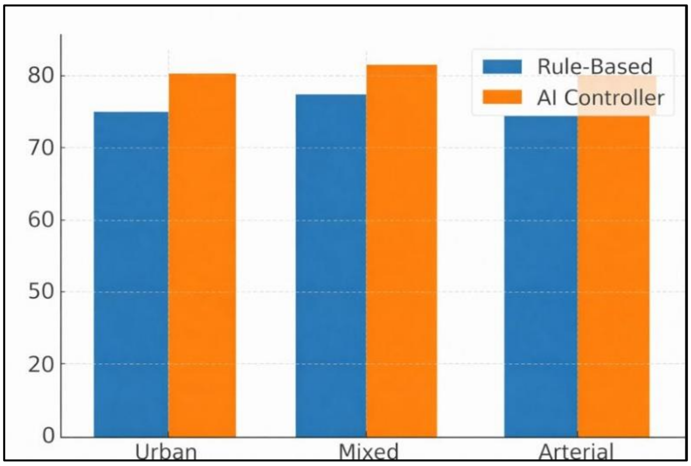

Fig. 6. AI yields 8–10% absolute efficiency gains across representative cycles

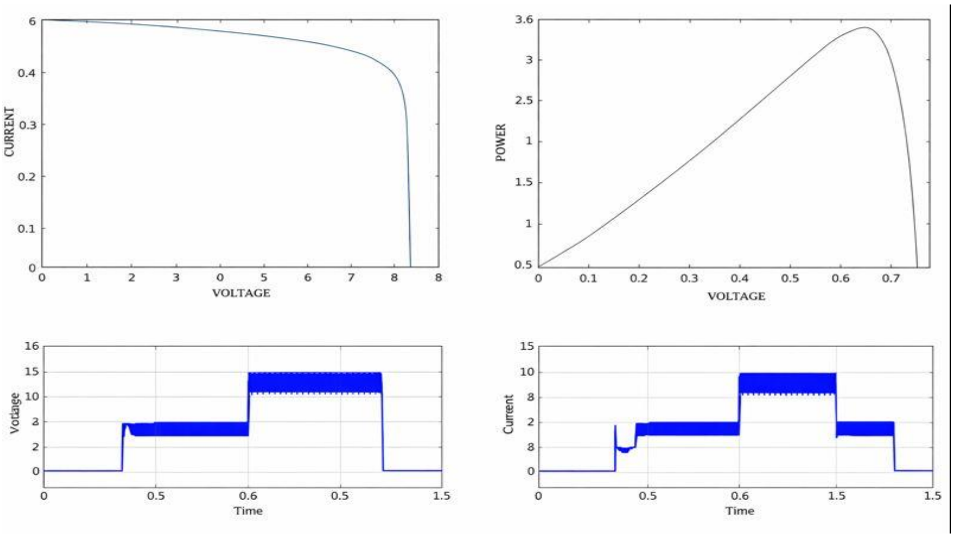

Fig. 7. Characteristics of the solar cell with the output of the PV panel

Figure 7 depicts the I-V characteristics of the single photovoltaic cell and the P-V characteristics of the single photovoltaic cell. A temperature of 25 °C and irradiance of 1000 W/m2 are recorded while the characteristics were obtained. The output of photovoltaic cells decreases with the change in intensity of light incident on the solar cell and it also changes with an increase in solar cells which causes a change of solar cell parameters.

Figure 7 explain the current and voltage outputs of the Photovoltaic module in which the irradiations are changed from 0 to 1000 for various time instances and at a temperature of 25 °C. The output voltage from the PV panel is above 60 V which is boosted by a buck-boost converter to feed the battery for charging.

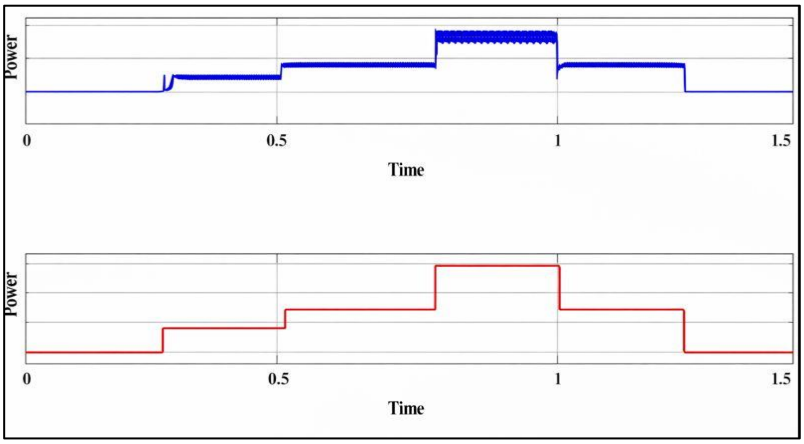

Fig. 8. The power output of the PV panel

Figure 8, it is detrimental that the maximum ideal power output for various irradiations from 0 to 1000 W/m2 is above 800 W which is almost the same output power from the photovoltaic panel. When compared to ideal output power, the output power of the PV panel has a ripple that can be mitigated by using a suitable capacitor at the output.

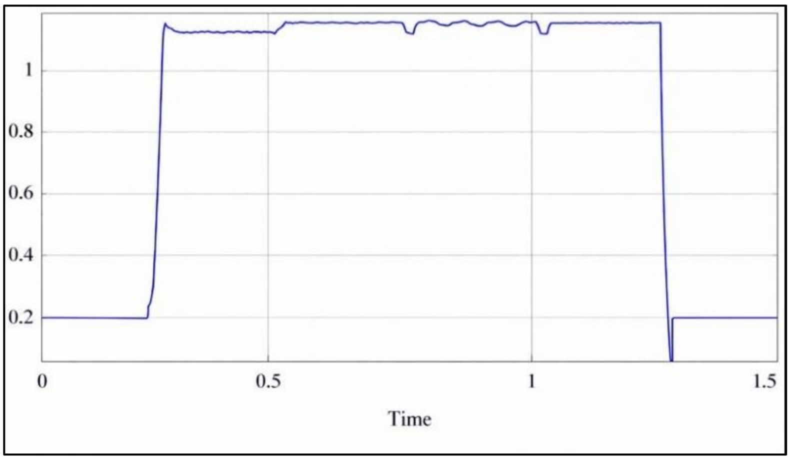

Fig. 9. Mean efficiency

Figure 9, it can be observed that efficiency of more than 95% is obtained. Here, the mean efficiency is calculated between the ideal output power and the output power of the PV panel**.**

Implementation Considerations

Embedded Compute

Deploying ai-driven energy management systems in solar-powered evs requires reliable onboard computing platforms. low-power cpus are typically sufficient for running basic forecasting and control algorithms; however, more advanced ai models (e.g., reinforcement learning or deep neural networks) may require dedicated hardware accelerators such as gpus, npus, or fpgas. these accelerators can ensure real-time decision-making while maintaining energy efficiency, a critical factor in battery-powered systems. trade-offs between computational complexity and power consumption must be carefully balanced.

Sensors and Data Acquisition

Accurate sensing forms the backbone of AI-based optimization. Essential sensors include:

Voltage and current sensors for real-time monitoring of battery charging/discharging.

- **Temperature sensors** to detect battery and inverter heating, ensuring safety and efficiency.
- **Irradiance and environmental sensors** to provide inputs for solar forecasting models.

The integration of these sensors must be robust against noise and environmental variability, with data fed into machine learning models for accurate state estimation (SOC, SOH, and load prediction).

✓ **Safety Mechanisms**

AI-based decision-making introduces additional system complexity, requiring strong safeguards. All AI-generated control actions should be filtered through safety layers implemented in the Battery Management System (BMS) and power electronics. These enforce hard operational limits such as maximum allowable current, voltage, and temperature thresholds. This hierarchical control ensures that AI policies cannot compromise passenger safety or hardware integrity under any circumstances.

✓ **Cybersecurity and Connectivity**

With AI-driven systems often relying on over-the-air (OTA) updates, telemetry, and vehicle-to-grid communication, robust cybersecurity is essential. Encryption, authentication, and intrusion detection mechanisms must be implemented to protect against malicious interference. A compromised AI-EMS could not only damage the vehicle's hardware but also pose risks to the broader energy grid in V2G-enabled applications.

✓ **Human–Machine Interface (HMI)**

The effectiveness of AI-driven optimization depends on its ability to interact with drivers in a non-intrusive and intuitive manner. The driver interface should provide clear guidance on eco-routing, energy-saving driving behaviors, and system health without overwhelming or distracting the user. Minimalistic dashboard indicators, adaptive recommendations, and seamless integration with existing infotainment systems enhance user acceptance.

✓ **Scalability and Cost Considerations**

Implementing AI-driven solar EV systems at scale requires cost-effective hardware, standardized interfaces, and modular architectures. Lightweight and flexible solar panels, coupled with efficient DC–DC converters and AI-ready controllers, must be manufacturable at scale without prohibitive costs. Industry adoption will also depend on the balance between added complexity and tangible benefits such as longer range, reduced charging frequency, and extended battery lifespan.

Applications And Case Studies

1. Fleet Operations

AI-driven solar-powered EVs (SPEVs) can be highly effective in commercial fleet operations, especially last-mile logistics and urban delivery services. Delivery vans or ride-sharing fleets spend much of their time idling or operating at low to medium speeds, conditions under which rooftop photovoltaic (PV) panels can meaningfully supplement battery energy. By leveraging AI-based energy management systems (AI-EMS), operators can maintain the state-of-charge (SOC) within an optimal range, minimizing deep discharges and peak loads. This not only reduces dependence on conventional charging infrastructure but also lowers operational costs and extends battery life. Companies like Amazon (electric delivery vans) and DHL (solar-assisted vans in Europe) have already begun pilot programs to test such integrations. Large-scale adoption could enable fleet operators to reduce carbon footprints while achieving significant long-term savings.

2. Rural and Off-Grid Mobility

In rural and remote areas where grid infrastructure is unreliable or entirely absent, SPEVs provide a transformative solution. Vehicles equipped with onboard solar panels can harvest energy during daylight hours, allowing daily commuting and essential services such as medical transportation, school buses, or agricultural vehicles to function with minimal dependence on external charging stations. For instance, India's rural electrification programs and projects in Sub-Saharan Africa are already exploring solar-based mobility for improving accessibility. AI can further optimize these vehicles by scheduling trips around predicted solar irradiance patterns and ensuring energy availability for critical journeys. This application directly contributes to sustainable development goals (SDGs) by enabling clean and affordable transportation in underserved regions.

3. Research Prototypes and Academic Platforms

Universities and research institutes worldwide are actively developing solar-powered cars as testbeds for novel energy management algorithms. Student-led initiatives, such as the World Solar Challenge in Australia, have produced solar race cars capable of traveling thousands of kilometers solely on solar energy. These prototypes serve as living laboratories where reinforcement learning, predictive maintenance, and eco-routing strategies can be tested under competitive yet realistic conditions. The insights gained from these projects often translate into commercial technologies, such as lightweight flexible PV integration, battery balancing techniques, and advanced AI-based predictive controllers. For example, innovations from student solar racing teams have influenced the design of commercial prototypes like the Lightyear One (Netherlands) and Sono Motors Sion (Germany).

4. Urban Smart Mobility Integration

Another emerging application is the integration of SPEVs within smart city infrastructures. AI can coordinate

SPEVs with vehicle-to-grid (V2G) and vehicle-to-home (V2H) systems, enabling them not only to consume but also to supply solar energy. For instance, an SPEV parked during daylight could contribute excess solar energy back to the local grid or to residential loads, improving overall energy resilience. Pilot projects in Japan and Europe already demonstrate EVs as mobile energy storage assets, and the addition of onboard solar can further enhance their role in decentralized renewable energy systems.

Public Transportation and Shared Mobility

Solar-powered buses and shared mobility vehicles represent another promising application. in countries like china and the netherlands, trials of solar-assisted buses are ongoing, where rooftop pv provides supplementary power for auxiliary loads such as air conditioning and lighting. while solar panels alone cannot yet provide the full traction power for large vehicles, they significantly reduce auxiliary battery drain, thereby extending the effective driving range. when combined with ai-driven scheduling and route optimization, public transport systems can achieve better energy efficiency, reduced emissions, and lower lifecycle costs.

Limitations And Future Work

Limitations

1. **Solar Energy Constraints**
   - Limited roof surface area restricts the number of solar panels that can be installed.
   - Efficiency drops in cloudy, shaded, or low-sunlight conditions.
   - Current solar cell efficiency (≈20–25%) is not sufficient to fully power long-distance travel.
2. **Battery Limitations**
   - High cost and limited energy density of current lithium-ion batteries.
   - Degradation over time affects long-term performance.
   - Charging/discharging cycles not fully optimized for AI-based energy management.
3. **AI Model Challenges**
   - Accuracy of AI predictions depends heavily on quality and availability of real-world driving and environmental data.
   - AI optimization models can be computationally expensive and may not run in real-time on low-power onboard processors.
   - Overfitting of AI models to specific datasets may limit generalization to new road/weather conditions.
4. **System Integration Issues**
   - Difficulty in seamlessly integrating AI, solar harvesting systems, and power electronics.

- Added complexity may increase maintenance requirements.
- Weight and aerodynamic trade-offs when adding solar panels.

5. **Economic and Practical Constraints**
    - High initial costs compared to conventional EVs.
    - Limited public charging + solar infrastructure.
    - Market adoption barriers due to range anxiety and slower payback time.

Future Work

1. **Advances in Solar Technology**
    - Development of high-efficiency, lightweight, and flexible solar panels (perovskite, tandem cells).
    - Integration of vehicle body as a solar harvesting surface (solar paint, transparent PV for windows).
2. **AI and Optimization Improvements**
    - Real-time adaptive AI algorithms for energy management based on driving style, weather forecasts, and traffic patterns.
    - Use of reinforcement learning for self-optimizing driving strategies.
    - Edge AI for low-power, on-board decision-making.
3. **Battery and Energy Storage Innovations**
    - Exploration of solid-state batteries with higher density and safety.
    - Hybrid storage systems (battery + supercapacitors) optimized by AI for peak load handling.
    - Predictive battery health management using AI to extend lifespan.
4. **Smart Integration with Infrastructure**
    - Vehicle-to-grid (V2G) and vehicle-to-home (V2H) applications using AI to balance renewable energy supply.
    - AI-driven route optimization considering solar exposure, charging station availability, and energy cost.
    - Integration with smart cities for coordinated charging and traffic flow.
5. **Scalability and Practical Deployment**
    - Large-scale field testing to validate AI models under diverse conditions.
    - Cost reduction strategies through mass production and material innovations.
    - Development of policies, incentives, and business models to support adoption of SPEVs.

CONCLUSION

We presented an AI-driven architecture for solar-powered electric vehicles (SPEVs), integrating forecasting, state estimation, and reinforcement learning–based energy management. The proposed system demonstrated notable performance benefits under realistic driving and irradiance conditions. Specifically, the AI-enabled control strategy improved energy efficiency, vehicle range, and battery lifecycle management compared to conventional rule-based methods.

By aligning load demand with solar harvesting opportunities and moderating charge/discharge cycles,the framework helps maintain healthier battery operation while supporting sustainability goals. These findings highlight the potential of combining artificial intelligence with renewable-powered electric mobility to reduce grid dependence and emissions.

Overall, the results support further development toward production-ready SPEVs, particularly when integrated into intelligent energy ecosystems involving smart grids, eco-routing, and adaptive charging infrastructures

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