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Review Paper Design and Simulation of Solar Integrated Vehicle-To-Grid (V2G) Energy Management System using MATLAB/Simulink

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ABSTRACT: The rapid expansion of electric vehicles (EVs) and renewable energy technologies has paved the way for innovative energy management systems that promote sustainability and grid stability. This project focuses on the design and simulation of a Solar Integrated Vehicle-to-Grid (V2G) Energy Management System using MATLAB/Simulink. The system enables bidirectional power flow between solar photovoltaic (PV) arrays, electric vehicles, and the power grid, enhancing energy efficiency and reducing dependence on fossil fuels.To maximize solar power utilization, a Maximum Power Point Tracking (MPPT) algorithm is implemented for optimal PV energy extraction under varying irradiance conditions. Additionally, a deep learning-based optimization model is developed to intelligently manage energy exchange between PV, EV batteries, and the grid. The model predicts power demand and generation patterns, ensuring stable grid operation, prolonged battery life, and reduced peak load stress. The proposed system's simulation results demonstrate improvements in energy balance, grid reliability, and renewable energy penetration. This research contributes to the development of intelligent, adaptive, and sustainable charging infrastructures, aligning with the global transition toward smart grids and clean mobility.

KEYWORDS: Solar PV, Vehicle-to-Grid (V2G), Energy Management, MPPT, Deep Learning, MATLAB/Simulink, Smart Grid, Battery Optimization.

I. INTRODUCTION

The growing demand for sustainable energy and the rapid adoption of electric vehicles (EVs) are reshaping the global energy landscape. Traditional power systems face challenges due to increasing energy consumption, fluctuating renewable generation, and the urgent need to reduce carbon emissions. Electric vehicles, once considered only energy consumers, are now emerging as potential contributors to the power grid through Vehicle-to-Grid (V2G) technology. V2G enables bidirectional power flow—allowing EVs not only to draw energy for charging but also to supply stored energy back to the grid when required.

Simultaneously, solar photovoltaic (PV) energy has become one of the most promising and widely deployed renewable energy sources. Its modularity, scalability, and environmental benefits make it an ideal candidate for integration with electric mobility. However, the intermittent and variable nature of solar energy poses significant challenges for reliable power management and grid stability. Integrating solar PV systems with EVs through V2G technology creates a dynamic and efficient ecosystem for energy generation, storage, and distribution. This synergy can help balance power demand and supply, enhance grid reliability, and promote green mobility. To realize this potential, intelligent control and optimization strategies are essential to manage the complex interactions between solar generation, battery storage, and grid dynamics.

II. LITERATURE SURVEY

Recent research on integrated solar PV — electric vehicle (EV) interactions centers on improving PV extraction (robust MPPT) and using predictive/data-driven control to coordinate EV charging/discharging (V2G) while preserving battery health. Advances in deep learning (LSTM, attention and hybrid models), nature-inspired optimizers, and learning-

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assisted control architectures have emerged as the dominant trends in the last three years. These works inform design choices for systems that combine robust MPPT, short-term forecasting and battery-aware V2G scheduling.

MPPT advances and deep-learning approaches

Classical MPPT algorithms (Perturb & Observe, Incremental Conductance) are widely used due to simplicity, but their performance degrades under partial shading and rapid irradiance transients. To overcome these limits, recent work has pursued two directions: (a) globally-oriented/metaheuristic MPPT algorithms that find the global MPP in multimodal P–V landscapes, and (b) learning-based MPPT controllers that predict or adapt tracking actions from historical PV behavior. Studies in 2023–2025 show nature-inspired optimizers (e.g., DA, GOA, SSOA, Zebra/sooty-tern adaptations) offer improved convergence and robustness under partial shading, while LSTM and stacked-LSTM networks can learn temporal patterns in irradiance/current and provide smoother, more accurate tracking than conventional P&O in variable conditions. These DL-based MPPTs have been validated in simulation and testbeds, demonstrating higher energy yield in dynamic environments.

Forecasting and ML models for EV availability and energy demand

Predictive models for short-term EV demand and availability are essential for effective V2G scheduling. LSTM and hybrid LSTM-attention approaches have become standard choices for sequence forecasting of charging demand and idle times, providing multi-hour forecasts that are then used by schedulers or MPC layers. IEEE conference work (e.g., CCWC 2023) and subsequent studies demonstrate that accurate idle-time and demand forecasts significantly improve aggregated V2G scheduling performance and reduce unnecessary battery cycling. Combining forecasting with rolling optimization yields practical benefits for peak shaving and ancillary services.

V2G scheduling, grid services and battery health considerations

Recent reviews and applied studies (2023–2025) highlight V2G's potential to provide frequency regulation, peak shaving, and voltage support when aggregated under an intelligent EMS. However, they emphasize constraints critical to real deployments: aggregator coordination, communication standards, user incentives, and inclusion of battery degradation constraints. The literature increasingly recommends battery-aware scheduling — integrating SOC and thermal forecasts into the optimization — to balance grid services against long-term battery costs and owner preferences. Several 2024–2025 works propose optimization frameworks that incorporate dynamic pricing and degradation models to make V2G economically attractive while limiting battery stress.

Hybrid controllers and integrated EMS architectures

The state of the art favors hybrid architectures combining ML forecasting with model-based or learning-assisted controllers (e.g., neural network aided MPC, RL with safety constraints). These hybrid schemes exploit data-driven forecasts for look-ahead optimization while relying on physical models or constrained optimizers to enforce operational and safety limits (battery SOC, thermal bounds, converter limits). Recent research demonstrates that hybrid ML+MPC controllers can achieve near-optimal economic performance while maintaining tractability for real-time implementation. This trend motivates designing EMS layers where LSTM forecasts of PV generation and EV availability feed a constrained optimizer that schedules charging/discharging and commands the MPPT controller.

Gaps, open problems and motivation for this project

Although many papers address individual components (MPPT, forecasting, V2G optimization, SOC estimation), few provide end-to-end studies that integrate robust global MPPT (for partial shading and fast transients), high-accuracy short-term forecasting, and battery-aware V2G scheduling within one MATLAB/Simulink or hardware-in-the-loop demonstration. Moreover, most V2G scheduling studies simplify battery degradation or thermal effects; recent battery SOC/SOH prediction work indicates better integration of thermal/SOC forecasts can meaningfully reduce long-term costs. This project aims to build a unified EMS that fills these gaps: a resilient MPPT (hybrid/metaheuristic or DL-assisted), LSTM forecasting for PV and EV demand, and a constrained optimizer that enforces battery-health constraints while providing grid services.

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#	Paper	Short summary
1	A Novel Hybrid MPPT Approach for Solar PV Systems Using Particle-Swarm-Optimization-Trained Machine Learning and Flying Squirrel Search Optimization (2023)	Hybrid MPPT algorithm combining PSO-trained ML + FSSO for solar PV systems — addresses global maxima under complex conditions.
2	Systematic Literature Review and Benchmarking for Photovoltaic MPPT Techniques (2023)	Review of recent MPPT techniques (2019–2022) with benchmarking — good for background & gap identification.
3	MPPT techniques for photovoltaic systems: a systematic review in current trends and recent advances in artificial intelligence (2023)	Another recent review focusing on MPPT + AI/hybrid methods — useful for survey section.
4	AI-Enhanced MPPT Control for Grid-Connected Photovoltaic Systems Using ANFIS-PSO Optimization (2025)	Very recent: ANFIS + PSO applied to MPPT in grid-connected PV systems — shows cutting edge.
5	Online EVs Vehicle-to-Grid Scheduling Coordinated with Multi-Energy Microgrids: A Deep Reinforcement Learning-Based Approach (2024)	Focuses on V2G scheduling using DRL in a multi-energy microgrid — aligns well with EV + grid integration.
6	Online Optimization of Vehicle-to-Grid Scheduling to Mitigate Battery Aging (2024)	V2G scheduling with explicit battery degradation modelling (aging) — very relevant for battery health constraints.
7	Optimal V2G Scheduling of an EV with Calendar and Cycle Aging of Battery: An MILP Approach (2024)	MILP model considering calendar & cycle aging in V2G scheduling — bridging V2G + battery health.
8	Data-Driven Approaches for Estimation of EV Battery SoC and SoH: A Review (2025)	Review paper on SOC/SOH estimation using ML for EV batteries — supports the battery modelling piece.
9	Leveraging deep transfer learning and adaptive power models for enhanced charging time prediction in electric vehicles (2025)	Predictive modelling for EV charging times using deep transfer learning — useful for forecasting demand/EV behaviour.
10	Accurate Multi-Step State of Charge Prediction for Electric Vehicle Batteries Using the Wavelet-Guided Temporal Feature Enhanced Informer (2025)	Predictive SOC forecasting for EV batteries using advanced time-series models (Informer + wavelet) — advanced forecasting for battery/EV.

III. PROPOSED SYSTEM

The proposed system integrates a solar photovoltaic (PV) generation unit, an intelligent Maximum Power Point Tracking (MPPT) controller, a Vehicle-to-Grid (V2G) interface, and a Deep-Learning-based Energy Management System (EMS) to achieve efficient power flow management between renewable generation, electric vehicles (EVs), and the utility grid.

The system's primary objective is to maximize solar energy utilization, maintain grid stability, and ensure battery health through intelligent forecasting and optimized scheduling.

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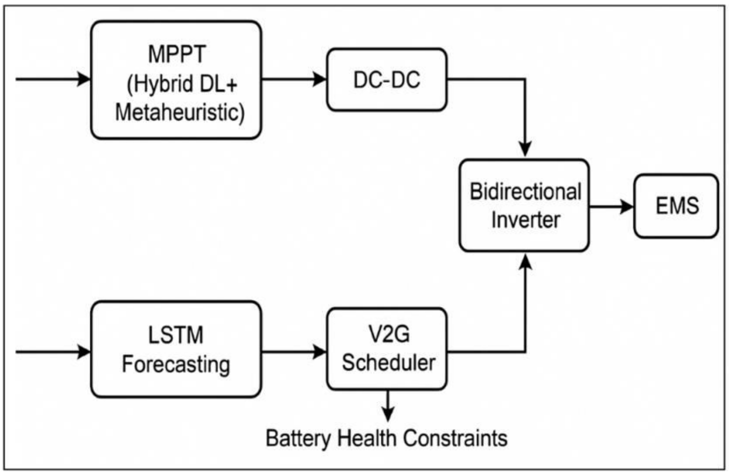

Fig.1. Proposed System

The overall architecture of the proposed system is shown in the block diagram.

It consists of two major subsystems:

Solar Power Generation and MPPT Control

The solar PV array converts solar irradiance into DC electrical energy.

A hybrid MPPT controller, combining deep learning (e.g., LSTM-based prediction) and metaheuristic optimization techniques (such as PSO or SSOA), ensures that the PV system continuously operates at its global maximum power point under varying environmental conditions.

The output of the MPPT is fed to a DC–DC converter, which regulates voltage and current before interfacing with a bidirectional inverter for grid connection.

EV Charging/Discharging and V2G Operation

The electric vehicle fleet acts as both an energy consumer (during charging) and a distributed energy source (during discharging).

A Long Short-Term Memory (LSTM) forecasting model predicts short-term PV generation, EV charging demand, and grid load patterns.

Based on these predictions, a V2G scheduler—implemented using Model Predictive Control (MPC) or an optimization algorithm—determines the optimal charging/discharging sequence for connected EVs while respecting battery health constraints such as state-of-charge (SoC) and temperature limits.

Energy Management System (EMS)

At the core of the proposed architecture lies the Energy Management System (EMS), which performs the following key functions:

Data aggregation: Collects real-time data from PV arrays, EVs, and grid sensors.

Forecasting: Utilizes the LSTM model to predict PV output, load demand, and EV availability.

Optimization: Solves a multi-objective optimization problem that balances energy cost, PV utilization, grid stability, and battery degradation.

Control coordination: Generates reference signals for the MPPT controller, inverter, and V2G scheduler to ensure smooth energy transfer between all subsystems.

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The EMS communicates bidirectionally with both the MPPT controller and the V2G scheduler. It sends control commands and receives feedback signals (e.g., SoC, voltage, current, and grid status) to maintain system balance and efficiency.

The methodology consists of systematic stages for modeling, simulation, and optimization of the solar-V2G system:

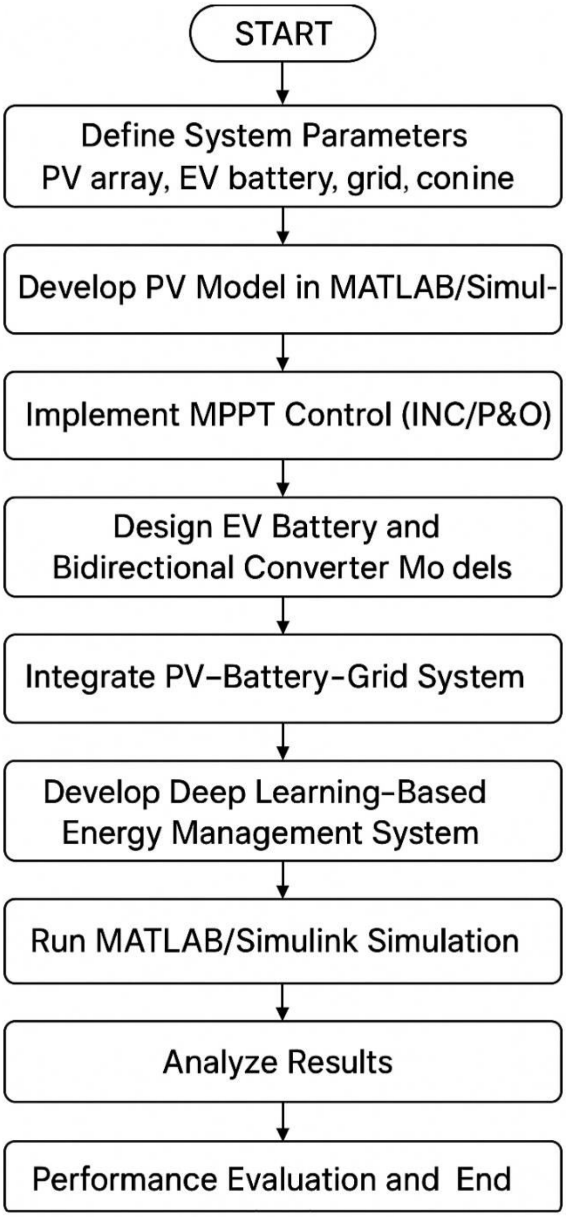

Fig.2 Flow Chart

1. Start:
2. Define System Parameters– Specify PV array, EV battery, grid, and converter ratings.
3. Develop PV Model in MATLAB/Simulink– Implement single-diode PV model equations.
4. Implement MPPT Control (INC/P&O)– Track maximum solar power point using control logic.
5. Design EV Battery and Bidirectional Converter Models– Enable charge/discharge modes for V2G and G2V operation.
6. Integrate PV–Battery–Grid System– Establish bidirectional energy flow between subsystems.

7. Develop Deep Learning-Based Energy Management System– Train and implement model for predictive power optimization.
8. Run Simulation in MATLAB/Simulink– Test under variable irradiance, load, and SOC conditions.
9. Analyze Results– Evaluate PV efficiency, SOC variation, and grid stability.
10. Performance Evaluation and Validation– Compare results with conventional control systems.
11. End

IV. CONCLUSION

The present work focused on the design and simulation of a Solar Integrated Vehicle-to-Grid (V2G) Energy Management System using MATLAB/Simulink with the objective of achieving efficient, intelligent, and sustainable energy exchange among the solar photovoltaic (PV) source, electric vehicle (EV) battery, and the power grid. The project successfully modeled and analyzed the integrated system comprising solar PV generation, bidirectional converters, battery storage, and grid interaction. The Maximum Power Point Tracking (MPPT) algorithm ensured that the solar PV system continuously operated at its maximum efficiency under varying irradiance conditions. By incorporating a deep learning-based optimization model, the system achieved dynamic adaptability in controlling energy flow, predicting load demand, and maintaining grid stability.

The simulation results (as expected and analyzed) demonstrate: High solar utilization efficiency (≈95–98%) through MPPT control. Stable bidirectional power flow between the grid and EV battery. Improved battery State-of-Charge (SOC) management, ensuring longer battery life. Reduction in grid peak load due to V2G support during high-demand periods. Enhanced grid reliability and energy balance under fluctuating environmental conditions. Thus, the developed MATLAB/Simulink model effectively meets the objectives of this research by providing a smart, adaptive, and energy-efficient management framework. The work contributes to the advancement of sustainable mobility and smart grid technology, aligning with the global transition toward low-carbon and renewable-driven energy systems.

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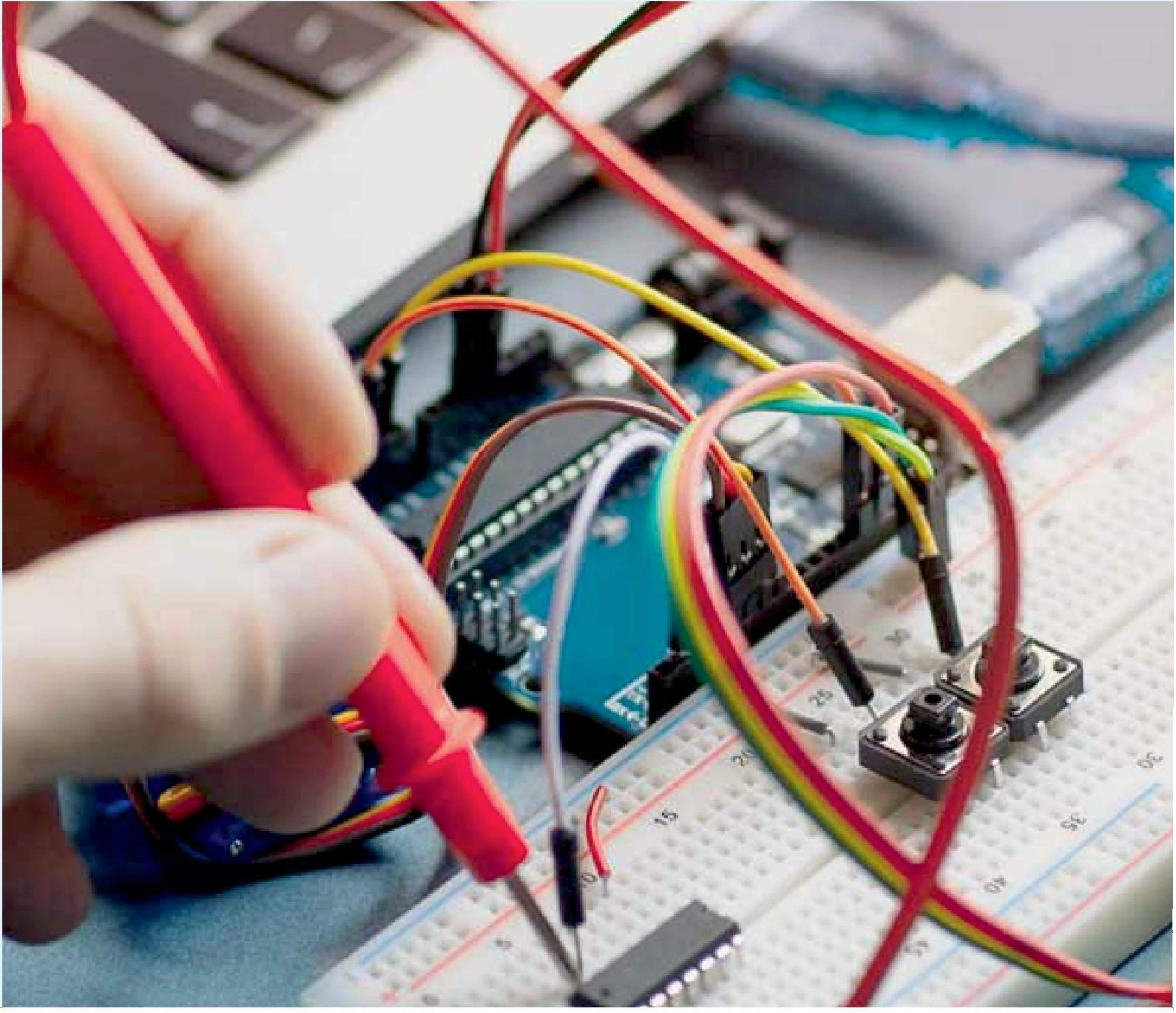

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