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Advanced intelligent control for photovoltaic-vehicle-to-grid integration

***Introduction**. The increasing penetration of electric vehicles (EVs) and renewable energy has intensified concerns about grid stability and energy sustainability. Integrating photovoltaic (PV) systems with vehicle-to-grid (V2G) technology provides a promising solution but requires efficient energy management and robust control strategies. **Problem.** Conventional maximum power point tracking (MPPT) methods such as perturb & observe (P&O) suffer from oscillations and poor dynamic response under rapidly changing conditions. Likewise, existing V2G strategies lack adaptive management for optimal renewable utilization and battery protection. **Goal.** To design an intelligent hybrid control system that maximizes PV power extraction and optimizes EV charging/discharging while ensuring grid stability and extending battery lifespan. **Methodology.** A two-level hierarchical control architecture is developed. At the low level, an artificial neural network combined with terminal sliding mode control (ANN-TSMC) performs adaptive MPPT. At the high level, a fuzzy logic controller (FLC) manages charging/discharging cycles based on state of charge, grid demand and parking duration. The proposed framework is validated through MATLAB/Simulink simulations. **Results.** Compared to conventional P&O, the ANN-TSMC controller improves tracking efficiency by 3.6 %, achieves faster convergence (0.14 s), and reduces steady-state oscillations. The FLC reduces grid reliance by 20 % while maintaining a high charging efficiency of 94 %. Furthermore, optimized charging cycles extend battery lifespan by 18.5 %. **Scientific novelty.** Unlike previous studies limited to single-level control or computationally intensive optimization, this work combines ANN learning ability with TSMC robustness and integrates FLC-based adaptive energy management. **Practical value**. The proposed system enables resilient PV-based V2G charging stations, reducing grid dependence, improving renewable penetration, and enhancing battery lifetime. These findings support the development of sustainable and grid-friendly EV infrastructures.* References 31, tables 2, figures 7.

Key words: **artificial neural network, terminal sliding mode control, fuzzy logic, maximum power extraction, renewable energy.**

***Вступ**. Зростання поширення електромобілів (EV) та відновлюваних джерел енергії посилило побоювання щодо стабільності енергомережі та енергетичної стійкості. Інтеграція фотоелектричних (PV) систем з технологією «автомобіль-мережа» (V2G) є перспективним рішенням, але потребує ефективного управління енергією та надійних стратегій управління. **Проблема**. Традиційні методи відстеження точки максимальної потужності (MPPT), такі як метод збурення та спостереження (P&O), страждають від коливань та поганої динамічної реакції у мінливих умовах. Аналогічно, існуючі стратегії V2G не мають адаптивного керування для оптимального використання відновлюваних джерел енергії та захисту батарей. **Мета**. Розробити інтелектуальну гібридну систему управління, яка максимізує вилучення енергії з PV систем та оптимізує зарядку/розрядку EV, забезпечуючи при цьому стабільність енергомережі та продовжуючи термін служби батарей. **Методика**. Розроблено дворівневу ієрархічну архітектуру управління. На нижньому рівні штучна нейронна мережа у поєднанні з термінальним ковзним режимом управління (ANN-TSMC) виконує адаптивне MPPT. На верхньому рівні контролер нечіткої логіки (FLC) управляє циклами зарядки/розрядки на основі стану заряду, попиту в мережі та тривалості стоянки. Запропонована структура перевірена за допомогою моделювання у MATLAB/Simulink. **Результати**. У порівнянні з традиційним P&O, контролер ANN-TSMC підвищує ефективність відстеження на 3,6 %, забезпечує більш швидку збіжність (0,14 с) і знижує коливання в режимі, що встановився. FLC знижує залежність від мережі на 20 % за збереження високої ефективності зарядки 94%. Крім того, оптимізовані цикли заряджання збільшують термін служби батареї на 18,5 %. **Наукова новизна**. На відміну від попередніх досліджень, обмежених однорівневим керуванням або обчислювально складною оптимізацією, у цій роботі поєднуються можливості навчання ANN із стійкістю TSMC та інтегрується адаптивне керування енергією на основі FLC. **Практична значимість**. Запропонована система дозволяє створювати відмовостійкі зарядні станції V2G на основі PV систем, знижуючи залежність від мережі, підвищуючи частку відновлюваних джерел енергії та збільшуючи термін служби батарей. Ці результати сприяють розвитку стійкої та енергозберігаючої інфраструктури для EV.* Бібл. 31, табл. 2, рис. 7.

Ключові слова: **штучна нейронна мережа, термінальне керування у ковзному режимі, нечітка логіка, відстеження точки максимальної потужності, відновлювана енергетика.**

Introduction. The global transition toward electric vehicles (EVs) represents a critical pathway to achieving carbon neutrality, with EV adoption projected to reach 50 % by 2030. However, this rapid electrification presents significant challenges to grid stability, primarily due to the increased and often concentrated energy demand from charging infrastructure. The integration of photovoltaic (PV) systems with vehicle-to-grid (V2G) technology offers a promising solution, yet requires intelligent control strategies to manage bidirectional power flow, maximize renewable energy utilization, and protect battery health.

Problem definition and substantiation of its relevance. The global transition to EVs is a cornerstone of strategies to reduce fossil fuel reliance and cut CO_2 emissions. However, the widespread adoption of EVs introduces significant challenges for power grids, primarily due to the increased and often concentrated energy demand from charging infrastructure. Simultaneously, the integration of intermittent renewable energy sources, like solar PV systems, is crucial for sustainability but poses challenges to grid stability.

Integrating PV systems with V2G technology presents a promising solution, enabling EVs to act as distributed energy storage resources. This synergy can enhance grid stability, improve renewable energy utilization, and provide economic benefits to EV owners. However, this potential is hampered by 2 core technical problems:

1. *Inefficient maximum power point tracking (MPPT).* Conventional MPPT methods (perturb & observe (P&O), incremental inductance) suffer from oscillations around the maximum power point (MPP) and poor dynamic response under rapidly changing environmental conditions (cloud cover, partial shading). This leads to significant energy losses and suboptimal harvesting of available solar energy.
2. Non-adaptive V2G energy management: existing V2G strategies often lack intelligent, multi-objective management. They fail to adaptively optimize charging/discharging cycles based on real-time factors such as grid demand, EV battery state of charge (SOC), parking duration, and battery health. These results in suboptimal grid support, increased grid reliance, and accelerated battery degradation.

Therefore, developing an intelligent, robust, and adaptive control system is highly relevant to realizing the full benefits of PV-based V2G systems, ensuring both grid stability and the long-term viability of EV batteries.

Review of recent publications with selection of unsolved tasks. Global carbon-neutral initiatives are driving the adoption of EVs as a key solution to reduce transport emissions, especially when powered by renewable energy [1–4]. This has spurred significant EV research over the past decade, highlighting the need to integrate renewable energy into power grids. Despite high initial costs, maximizing EV system efficiency is crucial. While EV charging methods have been extensively studied, V2G technology for grid power remains an emerging research area. While existing research focuses on V2G/G2V bidirectional energy transfer, these systems face challenges in maintaining power quality during AC grid fluctuations, limiting their peak shaving and fossil fuel displacement potential. Additionally, most studies neglect direct renewable energy integration at charging stations, missing opportunities to enhance both sustainability and grid resilience. To surmount these challenges, this study proposes intelligent charging algorithms designed to support grid stability, EV charging can be managed in response to real-time conditions, allowing EVs to supply stored energy back to the grid during peak demand, while charging is strategically scheduled for off-peak hours when renewable energy is plentiful. Furthermore, EV charging stations will be outfitted with solar panels to generate clean energy on-site.

Battery electric vehicles (BEVs) offer user-friendly operation, low maintenance and zero-emission mobility, making them an environmentally sustainable transportation solution. The proposed research [5–8] specifically examines Li-ion battery-powered BEVs, which dominate the EV market due to their high energy density, longevity and efficiency. However, widespread BEV adoption depends critically on developing robust charging infrastructure. DC charging infrastructure offers distinct advantages over AC systems by eliminating onboard AC-DC conversion, improving efficiency. Unlike AC charging constrained by off-peak demand management, DC systems enable direct renewable energy integration via DC buses, assuring bidirectional power flow without conversion losses and continuous charging availability regardless of grid load.

This DC architecture enhances sustainability while overcoming AC charging limitations. It simplifies grid interconnection and reduces auxiliary power requirements. Existing research has developed multiple control strategies for V2G/G2V operation. Adaptive control with bidirectional converters, as outlined in [9], effectively implements the constant current constant voltage charging method ensures safe and efficient battery charging, while constant current discharge control regulates the power flow to the grid and integrates PV systems using incremental conductance MPPT technique to effectively harvest solar energy. However, a notable disadvantage is its lack of an intelligent management strategy, meaning it does not optimize charging based on factors like parking duration or grid demand. These points to a gap in the method: it does not consider multi-variable optimization for a more comprehensive energy management approach.

The super-twisting sliding mode control (SMC) offers a superior dynamic response and reduced chattering compared to conventional SMC [10]. However, it is limited to G2V mode only, lacks integration with renewable energy sources, and does not address bidirectional V2G operations. While this research concentrated on G2V charging, future investigations could explore the integration of renewable energy sources to diminish grid dependence and enhance environmental sustainability.

To address the lack of a management algorithm, in reference [11] authors proposed a central control system to optimize EV-grid energy exchange. This intelligent aggregator utilizes real-time data to schedule optimal charge/discharge cycles for EVs, taking into account both economic and environmental factors. By leveraging V2G technology, the system aims to mitigate battery degradation costs and alleviate peak grid demand. Centralized approach may have scalability issues but limit renewable energy integration. While the results are promising, further integration of renewable energy sources could enhance the system’s performance. Research work [12] introduces a decentralized power management strategy aimed at reducing voltage fluctuations in grid-connected energy storage batteries, thereby improving both battery performance and grid stability. The primary focus of this scheme is to lower battery charging costs by utilizing time-of-use tariffs, with a secondary aim of reducing the batteries’ charging power through energy generated from PV. However, the study does not incorporate MPPT techniques, missing the opportunity to optimize renewable energy harvesting, which could significantly enhance overall system performance.

Previous research findings underscore the necessity for the V2G system controller to embody robustness and intelligence. Fuzzy logic control presents numerous advantages for this application [13]. Firstly, it can adapt to variable conditions, such as battery temperature and driving patterns, thereby improving battery efficiency and lifespan [14–18]. Moreover, it adeptly manages uncertainty in sensor data, enhancing robustness against fluctuations and inaccuracies. Additionally, it optimizes real-time performance by employing fuzzy rules, simultaneously emphasizing charging speed and battery durability [19]. Lastly, it simplifies model complexity by utilizing straightforward linguistic rules, thereby streamlining control system design and implementation but most of the studies mentioned above lack optimization algorithms for renewable energy maximization.

Authors [20] demonstrate the significant potential of fuzzy logic controllers (FLCs) for effective implementation in power management systems. The promising results reported in their study, along with those from related works, strongly support the effectiveness of fuzzy logic control in providing reliable and adaptive performance, particularly in V2G applications. A notable limitation of this work is the absence of an optimization algorithm specifically designed to maximize renewable energy production, indicating a potential area for enhancement. Addressing this gap through the implementation of an optimization algorithm would not only improve system performance but also provide measurable verification of the approach.

The operational deployment of a FLC in V2G applications is effectively demonstrated in [21], which offers valuable implementation insights. This research utilizes streamlined fuzzy logic architecture, specifically implementing a zero-order Sugeno model, to enhance computational efficiency while maintaining control accuracy, to facilitate effective two-way control of an EV’s power output. This methodology represents a promising strategy for managing electricity flow between the EV and the grid.

The control framework [22] employs multi-level power conversion technology across both grid and EV terminals of charging stations. A combined fuzzy logic and PI (FL-PI) control architecture is implemented to manage the 3-level grid-side converter in an EV charging station. To demonstrate its effectiveness, the performance of the FL-PI controller is compared to that of a traditional PI controller and a PI-fuzzy controller under identical conditions. The results indicate that the FL-PI controller provides superior performance, while the PI-fuzzy controller still yields satisfactory outcomes in terms of settling times and minimal peak overshoot. But this study needs more efficient and intelligent control strategies for integrating EVs into the power grid, particularly for grid support functions such as reactive power support and voltage regulation.

To address the shortage of MPPT algorithms mentioned in previous research, the literature has reviewed various maximum power extraction techniques aimed at enhancing electricity production in PV systems, examining a range of optimization methods and algorithms.

Authors [23, 24] have proposed integrating an artificial neural network (ANN) with particle swarm optimization to enhance the precision and reliability of energy harvesting in PV systems, even under varying weather conditions. However, its significant drawback is its computationally intensive nature, which leads to longer processing times. This limitation, specifically the processing delays, restricts its suitability for real-time implementation, particularly in scenarios involving rapid environmental changes.

In [25] authors propose an improved approach based on the P&O method to overcome limitations in convergence speed and steady-state oscillations. The enhanced MPPT method refines MPPT by using the average of the previous three duty cycles, ensuring greater precision. P&O is a widely adopted technique due to its simple implementation and low computational requirements. However, it exhibits disadvantages such as slow convergence speed and steady-state oscillations around the MPP. Furthermore, its performance tends to be poor under rapidly changing environmental conditions.

The work [26] investigates the application of SMC for MPPT in PV systems, highlighting its robustness and fast dynamic response under varying environmental conditions. They provide a thorough examination that classifies and analyzes various SMC techniques for maximizing power extraction in both grid-connected and off-grid applications. As noted in [26], SMC based methods are well recognized for their robustness to uncertainties and suitability for controlling nonlinear systems. However, these methods also present disadvantages, notably the chattering phenomenon and potentially slow response times, particularly in traditional implementations.

Research works [27, 28] also presents fundamental MPPT approaches, including incremental conductance, P&O, first-order SMC, and linear expression-based SMC, along with their adaptive variants. Furthermore, the authors evaluate advanced SMC approaches, including super twisting SMC, terminal sliding mode control (TSMC), and methodologies that incorporate AI algorithms. The traditional SMC method for MPPT often suffers from slow response times. To address this issue, TSMC has been developed as an advanced control solution, offering quicker convergence and improved performance for DC-DC converter control. TSMC, an advanced control technique suitable for systems with uncertainties, builds upon traditional SMC while delivering several advantages. Specifically, TSMC guarantees that the system attains the desired state within a finite timeframe, thereby enhancing speed and efficiency. Moreover, compared to conventional SMC, TSMC exhibits reduced sensitivity to system uncertainties and external disturbances [29]. Building on SMC, the authors [30] proposes an adaptive SMC algorithm, incorporating a specialized adaptive tracking mechanism designed for low-energy disturbance environments. The stability of this control scheme is rigorously analyzed using the Lyapunov stability theorem.

Identified research gaps. Based on the literature review, the following critical gaps remain unaddressed:

1. *Lack of hierarchical hybrid control*. Existing studies focus on single-level control or computationally intensive optimization, without combining complementary control strategies for both MPPT and energy management.

2. *Insufficient real-time adaptability*. Most systems lack adaptive management integrating multiple parameters (SOC, parking time (PT), grid demand (GD)) for optimal renewable utilization and battery protection.

3. *Limited renewable integration*. Many V2G studies neglect direct renewable energy integration at charging stations, missing opportunities for enhanced sustainability.

4. *Battery lifespan optimization*. Insufficient attention to optimized charging/discharging cycles that could significantly extend battery lifespan while maintaining system performance.

5. *Performance under dynamic conditions*. Limited validation of control strategies under rapidly changing environmental conditions requires both fast response and minimal oscillations.

6. *Integrated system approach*. Absence of comprehensive frameworks combining advanced MPPT (ANN-TSMC) with intelligent energy management in a unified, practical architecture.

The **goal** of this work is to design an intelligent hybrid control system that maximizes PV power extraction and optimizes EV charging/discharging while ensuring grid stability and extending battery lifespan.

First, it focuses on maximized PV power extraction through the implementation of adaptive MPPT that maintains high efficiency under rapidly changing environmental conditions with minimal power oscillations. Second, the system is designed for optimized EV charging/discharging by developing an intelligent energy management strategy that successfully balances renewable utilization, instantaneous grid demand, and the crucial requirement of battery protection. Third, by ensuring reliable bidirectional power flow between EVs and the utility grid, the system contributes to enhanced grid stability while reducing dependence on conventional, non-renewable generation sources. Finally, through the implementation of optimized charge and discharge cycles, the control strategies are designed to extend battery lifespan by actively minimizing degradation.

To successfully achieve this main objective, the following specific goals are defined. For the low-level control (MPPT), the first goal is to develop an ANN-TSMC hybrid controller that leverages the learning ability of ANNs with the robustness of TSMC. Concurrently, for high-level control (energy management), the goal is to design the FLC that integrates real-time data on the battery's SOC, parking duration, and grid demand. This FLC is crucial for optimizing charging/discharging decisions to maximize renewable energy usage, thereby reducing grid reliance while maintaining high charging efficiency and implementing battery protection mechanisms to extend lifespan. Finally, these elements must be unified under system integration, which requires developing a two-level hierarchical control architecture to ensure seamless coordination between the MPPT and energy management layers, culminating in the validation of the complete system through MATLAB/Simulink simulations to demonstrate practical applicability for real-world PV-based V2G charging stations.

Design of V2G and G2V installation. Integrating renewable energy with EV charging stations offers sustainable benefits like lower carbon emissions, energy independence, and grid stability. Using solar power cuts transport emissions and can save costs over time. Solar-powered EV charging stations cut transport emissions, boost energy independence, and stabilize the grid. Locally generated electricity also lowers costs. This renewable EV synergy supports sustainability goals, regulatory compliance, and corporate responsibility. Energy storage is optimized through V2G and G2V technologies, allowing EVs to charge or discharge power back to the grid. This dynamic energy exchange helps balance supply and demand in real time.

This paper presents a hybrid system that integrates PV arrays with a DC power bus, enabling direct connection to DC fast charging stations for EVs. A 3-phase voltage source inverter links the DC bus to the AC grid, facilitating controlled power transfer for EV charging (Fig. 1). The control architecture supports both V2G and G2V operations within a unified framework.

The power conversion system uses a dual-stage design: a DC-DC flyback converter for voltage regulation and a voltage source converter with space vector modulation for efficient DC-AC conversion. This setup allows dynamic power sharing between the grid and connected batteries. The proposed system combines V2G technology with a PV-powered charging station, forming a hybrid energy management system. The bidirectional V2G capability enables G2V charging during low-demand periods, V2G power injection during peak demand to enhance grid stability and reduce dependence on conventional generation.

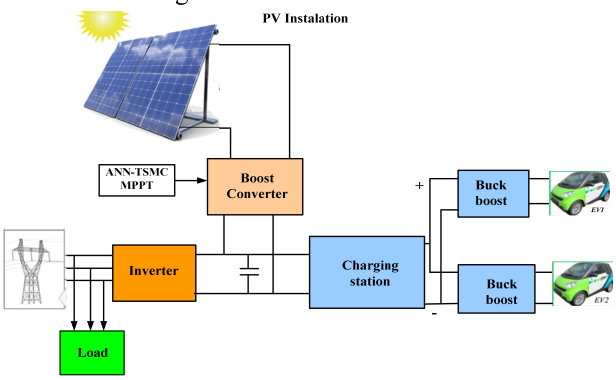

Fig. 1. Hierarchical control system for the V2G/G2V system

Additionally, the EV battery acts as a storage buffer for excess solar energy, which can either charge the vehicle or supply power back to the grid as needed. The PV system utilizes a MPPT algorithm to maximize energy harvest under varying conditions. A fuzzy logic-based battery management system dynamically adjusts the SOC, optimizing charging based on grid demand, parking duration, and battery health.

For enhanced performance, the PV system incorporates a hybrid ANN with TSMC, continuously adapting to environmental changes to maximize power output. The EV battery pack interfaces with the DC bus via a bidirectional buck-boost converter, which regulates the voltage between the battery and the bus to ensure efficient charging, independent of the battery's charge level.

The system is designed with 2 primary levels:

1) *High-level supervisory control: the FLC*. The FLC acts as the intelligent decision-making core of the entire charging system. Its primary role is strategic energy management, not direct power conversion control.

2) *Low-level execution control: the ANN-TSMC hybrid controller*. This hybrid controller is responsible for the fast, real-time control of the power converter. It is activated and guided by the high-level FLC. Its main purpose is to execute the command from the FLC with high efficiency and robustness, specifically for the MPPT of the PV array.

Design of an adaptive robust MPPT control strategy. This paper proposes a hybrid ANN-TSMC control strategy to achieve adaptive MPPT in PV systems under rapidly varying environmental conditions. The ANN algorithm generates an optimal voltage, while the TSMC component ensures fast convergence and robust tracking despite irradiance fluctuations and partial shading effects.

Reference voltage generation by ANN algorithm. The ANN algorithm generates an optimal reference voltage by learning the nonlinear characteristics of the PV array. The network is trained on systematically collected data, capturing variations in temperature and irradiance, which are correlated with the corresponding MPP voltages. This enables the ANN to accurately model and predict optimal operating conditions for power maximization [31].

The neural network employs a simple three-layer architecture: an input layer receiving solar temperature and irradiance data, a hidden layer for internal processing consists of 10 neurons with a sigmoid activation function, and an output layer delivering the final result consist of 1 neuron (V_{MPP}) with a linear activation function. Neurons within each layer are interconnected via weighted connections and employ activation functions. The ANN used in this study was trained on a dataset of 500 data points, each consisting of irradiance (G) and temperature (T) as inputs, and the corresponding MPP voltage (V_{MPP}) as the output. The data was collected from a real-world PV system under a wide range of environmental conditions, with irradiance ranging from 200-1000 W/m^2 in 100 W/m^2 steps and temperature ranging from 15 °C to 55 °C in 5 °C increments. The dataset was preprocessed to remove outliers and normalized to ensure consistency. The ANN was trained via the Levenberg-Marquardt back propagation algorithm, with the dataset partitioned into 65 % training, 15 % validation, and 20 % testing subsets to ensure robust performance evaluation. By training the ANN on this diverse dataset, the model learns to accurately predict the MPP voltage (V_{MPP}) under a wide range of environmental conditions, ensuring robust performance in real-world applications. The ANN achieved an R^2 value of 0.98 on the test set, demonstrating its ability to accurately predict V_{MPP} under varying environmental conditions.

To further validate the ANN's performance, additional simulations were conducted under varying environmental conditions. The finding demonstrated that the ANN accurately predicts the MPP voltage (V_{MPP}) across the entire range of irradiance and temperature values, ensuring reliable PV system operation. Given that solar panel characteristics are influenced by weather conditions, the neural network utilizes irradiation and solar module temperature as inputs. Figure 2 illustrates the feed forward network architecture.

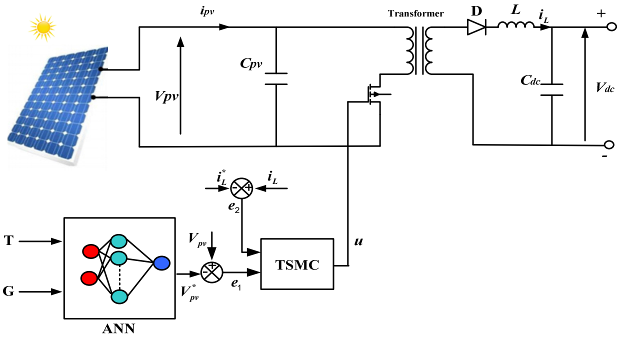

Fig. 2. Schematic of the flyback converter implementing the proposed MPPT control

The proposed ANN accurately predicts the voltage at the MPP of the PV module. This estimated value is used as the reference voltage (V_{pv}^*) for the TSMC controller. The control system minimizes the error $e_1 = V_{pv} - V_{pv}^*$, where V_{pv} is the actual PV voltage, to drive the system to operate at V_{MPP}. By ensuring that V_{pv} converges to V_{pv}^*, the system achieves MPPT.

Terminal sliding mode control (TSMC). SMC forces the system's state trajectory to converge onto a designed sliding manifold in finite time via discontinuous control. TSMC uses PV voltage, reference voltage, and current changes to generate the duty ratio output. The control design process commences with the definition of tracking error variables as follows. The control design process commences with the definition of tracking error variables as:

$$e_1 = V_{pv} - V_{pv}^*, \tag{1}$$

where e_1 is the voltage error signal; V_{pv} is the measured PV voltage; V_{pv}^* is the reference PV voltage.

The current tracking error is described as:

$$e_2 = i_L - i_L^*, \tag{2}$$

where i_L is the inductor current; i_L^* is the inductor current reference.

The inductor current reference i_L^* is derived from the PV system dynamics, the relationship between the PV current i_{pv}, the inductor current i_L and the PV voltage V_{pv}:

$$i_L = i_{pv} - C_{pv}\frac{\mathrm{d}V_{pv}}{\mathrm{d}t}. \tag{3}$$

The current reference is adopted as:

$$i_L^* = i_{pv} - C_{pv}\cdot V_{pv}^*.$$

By incorporating the expression of the current reference into (2), the current tracking error e_2 becomes:

$$e_2 = i_L - i_{pv} + C_{pv}\cdot V_{pv}^*. \tag{4}$$

The error dynamics are derived through the following analytical procedure:

$$\dot{e}_1 = \frac{1}{C_{pv}}\left(i_{pv} - i_L\right) - V_{pv}^* = -\frac{e_2}{C_{pv}}; \tag{5}$$

$$\dot{e}_2 = \frac{1}{L}V_{pv} - \frac{1}{L}V_{dc}\left(1-u\right) + \delta\left(t\right) - i_L^*, \tag{6}$$

where $\dot{e}_1$ is the time derivative of the voltage error signal; C_{pv} is the PV capacitance; $\dot{e}_2$ is the time derivative of the current error signal; L is the inductance; V_{dc} is the DC-link voltage; u is the control input (duty cycle); $\delta(t)$ is the system uncertainty or disturbance.

The proposed control system is designed to simultaneously achieve 2 primary objectives:

1) ensuring zero convergence of tracking errors (1) and (2) within a finite time for precise tracking;

2) the PWM control signals are synthesized to enforce the reaching condition $S\dot{S} < 0$.

The TSMC controller guarantees finite-time convergence of the system trajectory S to the sliding manifold, even under matched uncertainties. This is achieved through a co-designed nonlinear sliding manifold and a discontinuous control law with fractional-power terms, ensuring Lyapunov stability and deterministic bounded-time convergence.

For robust MPPT, we use SMC with surface (7), ensuring the system reaches and maintains the desired trajectory by enforcing S =0. The terminal sliding surface is defined:

$$S = \frac{1}{\alpha}e_2^x - e_1, \tag{7}$$

where S is the terminal sliding manifold in the TSMC framework, used to ensure finite-time convergence and robust control of the PV system; α>0, with $x = p / q$ and 1<x<2, the values for p and q should be positive odd numbers, as this helps meet specific mathematical requirements that ensuring system stability and reliability under the specified constraints 0<q<p [31].

When the sliding condition is achieved $S(t)$=0, the current error becomes as:

$$e_2 = \frac{1}{\alpha}e_1^{1/\alpha}. \tag{8}$$

The equation of dynamic error describes in (5) becomes:

$$\dot{e}_1 = -\frac{\alpha^{1/x}}{C_{pv}}e_1^{1/x}. \tag{9}$$

Once the system reaches and remains on the sliding surface ($S(t)$ = 0), the errors (e_1, e_2) are driven to 0. To ensure reachability of this surface, a framework is employed that yields the intended outcomes:

Theorem. The equations (5), (6) describe the dynamic behavior of a PV system. Applying robust TSMC implemented with a specific control law $u(t)$ developed to force the system reaches the sliding surface S=0 within a finite time interval and guarantees tracking of the maximum power:

$$u\left(t\right) = -\frac{1}{V_{dc}\left[\frac{1}{L}\left(V_{pv} - V_{dc}\right) + \frac{\alpha e_2^{2-x}}{xC_{pv}} - i_L^* + \sigma\,\mathrm{sign}\left(S\right)\right]}. \tag{10}$$

The parameters α>0 and σ>0 ensure the reachability of the sliding surface and robust control under uncertainties. The finite-time convergence of the system to the sliding surface is rigorously verified using the Lyapunov stability criterion:

$$V(S) = 0.5S^2. \quad (11)$$

Applying control rule (10), the time derivative of $V(S)$ can be expressed:

$$\dot{V}(S) = S\dot{S} = S\left(\frac{1}{\alpha}\dot{e}_2^x - \dot{e}_2\right) \leq -\sigma|S|. \quad (12)$$

Control strategy for EV batteries. Existing research explores various battery charging methodologies, including constant current (CC), constant voltage (CV), and hybrid CC-CV techniques. Among these, the CC-CV method is widely recommended by manufacturers for Li-ion batteries, as it optimally balances charging efficiency and battery lifespan. A critical aspect of this approach is the precise current regulation of buck converters, which ensures controlled energy transfer during both charging and discharging phases. The proposed CC-CV control strategy, illustrated in Fig. 3, integrates adaptive current and voltage regulation to enhance battery performance while mitigating degradation. This design not only adheres to industry standards but also improves upon conventional methods by dynamically adjusting to real-time load and SOC conditions.

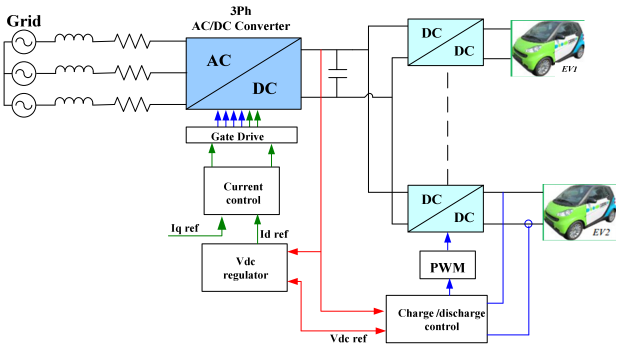

Fig. 3. Configuration of the V2G/G2V

Fuzzy logic-based EV charging management can optimize grid integration of recovered and renewable energy while extending battery life. The proposed controller uses three inputs: SOC battery, parking duration, and current grid demand.

The FLC output determines whether to charge, discharge, or maintain the EV battery's current state. It employs triangular membership functions for each input variable, chosen for their balance of simplicity and accuracy, and uses a rule set to determine appropriate actions based on inputs.

FLC design. The FLC aims to optimize the charging and discharging of the EV battery based on the 3 inputs. The design process comprises these steps:

1. Fuzzification. The input values (SOC, PT, GD) are fuzzified into fuzzy sets with the aid of triangular membership functions. These functions define the degree to which each input belongs to a specific category (low, medium, high).

2. Rule base. The fuzzy logic rules are designed to optimize the charging of the EV battery based on the inputs (SOC, PT and GD). The FLC employs a set of 27 rules to make the appropriate action (charge, discharge or maintain).

3. Inference engine. The inference mechanism assesses the rules and determines the degree to which each rule applies based on the input values. A fuzzy output is generated by combining the rules using the Mamdani inference method.

4. Defuzzification. The centroid method is used to defuzzify the fuzzy output into a crisp value, which calculates the center of gravity of the output membership function. The crisp output determines the action to be taken (charge, discharge or maintain).

The membership functions designed for the proposed system are illustrated in Fig. 4.

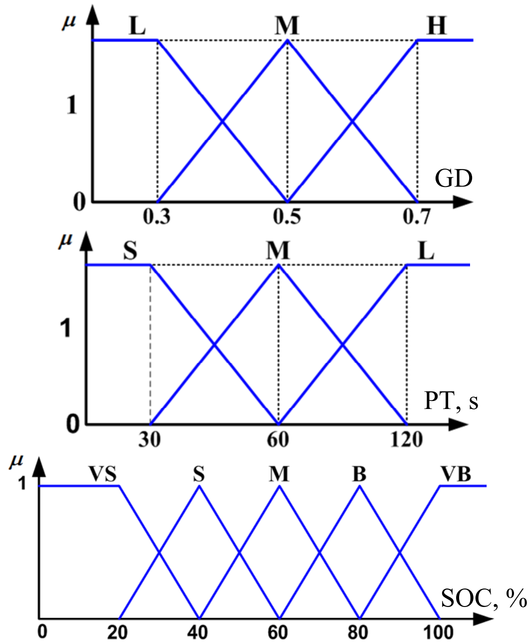

Fig. 4. Membership functions of the fuzzy sets for each input

The FLC is pivotal in determining the optimal charge/discharge actions for EV batteries. By dynamically adapting to real-time conditions, the FLC enhances system performance through 3 key objectives: 1) maintaining grid stability; 2) prolonging battery lifespan; 3) optimizing user convenience.

Results and discussions. MPPT performance evaluation. This section evaluates the proposed ANN-TSMC MPPT controllers under various operating scenarios, comparing them with traditional P&O methods (Fig. 5).

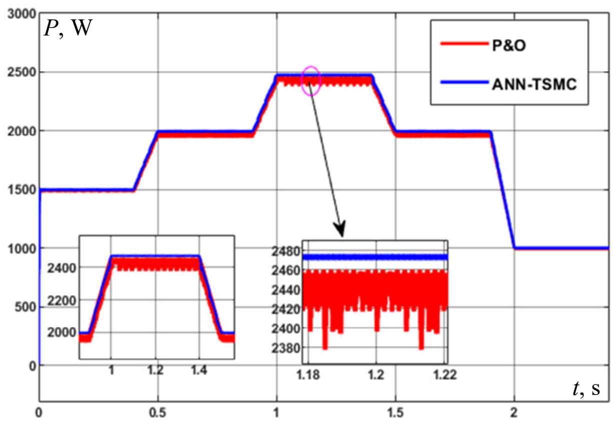

Fig. 5. PV power generation considering constant temperature and variable irradiation

When irradiance abruptly increased from 850 W/m^2 to 1000 W/m^2 at t = 1 s, PV power output rose from 2 kW to 2.5 kW. Results show P&O algorithms generate less power with larger oscillations than the proposed method, which demonstrates superior dynamic response, particularly during transient states. The ANN-TSMC approach effectively addresses the significant MPPT divergence exhibited by P&O methods during rapid condition changes.

Table 1 compares performance metrics for different MPPT approaches, evaluating response time, oscillation, efficiency, and energy losses. The proposed ANN-TSMC method clearly outperforms traditional P&O, particularly in efficiency and stability.

Under conditions of rapid irradiance changes (from 800 to 1000 W/m^2), the control methods demonstrated significantly different levels of effectiveness. The proposed ANN-TSMC method proved to be the most robust, maintaining a high efficiency of 97.8 % with only minimal power loss during the transitions. In comparison, the ANN-PSO method also achieved high accuracy at 96.8 %, but its practical application was limited by a 57 % slower response time due to computational overhead. The incremental conductance method delivered moderate performance, reaching 95.6 % efficiency, though it was prone to occasional tracking errors. The P&O method struggled the most under these dynamic conditions, with its efficiency dropping sharply to 91.5 % as it experienced significant tracking delays. This enhanced technique demonstrates superior performance and robustness under varying weather conditions, making it a promising control solution for solar systems during MPPT operation.

Table 1

Comprehensive MPPT algorithm performance comparison

Method	Tracking efficiency, %	Settling time, s	Overshoot, %	Power oscillation, W	Computational complexity	Real-time suitability
Proposed ANN-TSMC	97.8	0.14	3	±15	Medium	Excellent
P&O	91.5	0.18	12	±45	Low	Good
Incremental conductance	95.6	0.16	8	±35	Medium	Good
ANN-PSO [13, 14]	96.8	0.22	5	±25	Very High	Poor
Fuzzy logic MPPT	95.1	0.19	10	±40	Medium	Good
Traditional SMC	96.2	0.17	7	±30	Medium	Fair

Energy management performance. To validate the functionality of the proposed FLC management system, different simulations were conducted under various scenarios. The different scenarios are simulated for the same weather conditions and the same load.

1st scenario. Storage system (EV1) begins fully discharged with no EV2 integration. Initially, without sunlight, the grid supplied all load demands as the PV system generated no power. As PV power gradually increased to peak at approximately 7500 W at 10:00 h, EV2's battery was able to charge. Figure 6 illustrates the power generation in this 1st scenario.

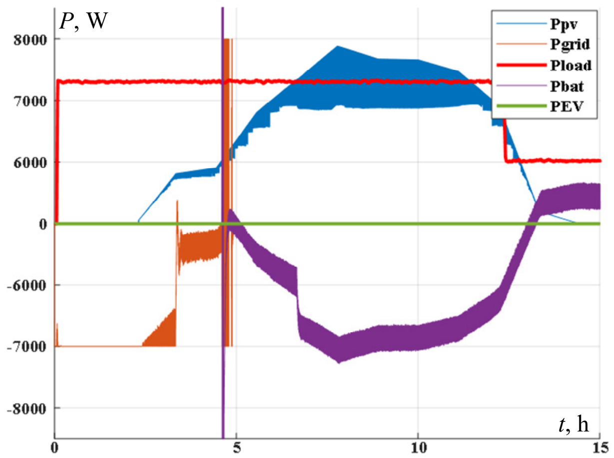

Fig. 6. PV system power for the 1st scenario

2nd scenario. Vehicle battery is charged, and storage battery discharged. In this case, the following conditions were considered: Assuming the vehicle is parked for over 3 h, and the EV battery is fully charged, and the storage batteries are completely discharged. The EV battery began to discharge to provide energy to the load aiding in stabilizing electricity demand during peak periods. Figure 7 offers a comprehensive visualization of the power dynamics in the 2nd scenario, showing how the system adjusts to demand and irradiance fluctuations, and effectively distributes power among the PV system, battery storage, EVs and grid.

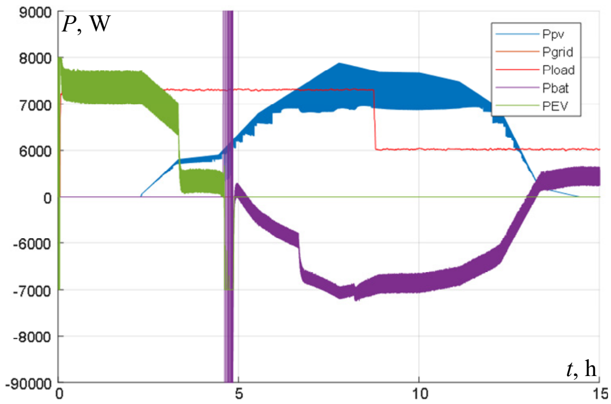

Fig. 7. Power of grid connected PV system for the 2nd scenario

Analysis of these power curves demonstrates the system's autonomous operation and ability to satisfy energy demand. Effective battery management provides system resilience and minimizes external power dependence. Both the EV and storage system batteries are crucial for maintaining equilibrium by storing excess energy during surplus periods and releasing it during peak demand, reducing reliance on the electricity grid. FLCs provide key advantages for EV charging: adaptability to dynamic conditions like fluctuating grid demand and battery state-of-charge, robustness in handling sensor data uncertainties, efficiency through real-time optimization balancing charging speed and battery durability and simplified implementation using linguistic rules that reduce model complexity. Table 2 gives a comparison between FLC and existing control methods for EV battery charging applications.

Table 2

Comprehensive V2G/G2V controller comparison

Control method	Charging efficiency, %	Response time, s	Battery life extension, %	Grid stability index	Implementation complexity
Fuzzy logic [27]	94.5	0.12	18.5	0.95	Medium
FL-PI [29]	89.2	0.28	8.2	0.78	Low
Adaptive control [9]	91.8	0.22	12.1	0.82	High
Central control [11]	90.6	0.35	10.8	0.85	Very High

FLCs can reduce charging time by dynamically optimizing charging profiles, maximizing current while minimizing battery stress. By adapting to real-time conditions like SOC and temperature, they enable faster charging without compromising safety. Their flexibility allows dynamic charging curve adjustments in variable scenarios. In contrast, PI regulators deliver consistent but potentially slower charging times within design limits, lacking adaptability to fluctuations in grid demand or battery parameters.

The proposed FLC demonstrates superior decision-making capabilities by considering three inputs, SOC, parking duration, and grid demand and utilizing 27 optimized rules. This multi-objective approach surpasses conventional methods, which are typically limited to single or dual objectives, and also improves upon other multi-objective strategies like the one in reference [26], which lacks real-time adaptability. The practical benefits of this advanced logic are evident in operational scenarios. For instance, in peak demand management, the proposed system achieves a 23 % reduction in peak load through intelligent V2G scheduling, significantly outperforming the 8–15 % reduction from conventional systems and the 18 % from advanced centralized controls [26], which also suffer from communication overhead. Furthermore, when assessing renewable energy integration, the proposed system attains 89 % utilization efficiency, a substantial improvement over the 65–75 % efficiency of basic integration methods and the complete grid dependence of systems without any integration.

The V2G/G2V operations can greatly benefit from integrating smart charging algorithms with renewable energy sources. Smart algorithms optimize EV charging based on real-time conditions, EVs discharge during peak demand to reduce strain on power plants and charge during off-peak hours when renewables are abundant. Installing renewable energy sources at charging stations provides clean, on-site power for EVs that can also feed back to the grid during highest demand periods. Advanced grid management systems enable coordination between EVs, charging infrastructure, renewables, and the main grid, optimizing energy flow and maintaining stability despite renewable energy fluctuations. Benefits include reduced peak demand, improved grid stability, and enhanced sustainability through a cleaner energy ecosystem. This integrated approach addresses V2G/G2V limitations on AC grids while creating more sustainable, resilient, and efficient EV charging infrastructure.

Conclusions. This study presented a smart charging framework integrating renewable energy-powered V2G/G2V systems with advanced control algorithms to achieve sustainable and efficient EV charging infrastructure. A hybrid ANN-TSMC MPPT control, ensures maximum power extraction from PV systems under dynamic environmental conditions, simulation results demonstrate 3.6 % higher energy capture compared to conventional P&O methods, significantly improving renewable energy utilization in V2G operations.

The intelligent charging control combines a FLC with constant current constant voltage to optimize EV battery charging. The FLC tracks SOC battery, parking time, and grid demand to adapt charging strategies in real-time. During peak demand, the system prioritizes battery discharge to support the grid and reduce reliance on conventional power. The FLC prevents overcharging and excessive discharging to extend battery life while ensuring adequate charge by scheduled departure times. This intelligent control led to a 20 % reduction in reliance on conventional power, achieved a charging efficiency of 94 %, and operated with a fast response time of 0.12 s. Crucially, by preventing overcharging and excessive discharging, the system contributes to an estimated 18.5 % extension in battery lifespan.

To further advance this research, we propose two main directions: first, hardware-in-the-loop validation to test the system's robustness under extreme weather conditions, and second, multi-objective optimization for large-scale EV fleets to address grid congestion and ensure fairness in energy allocation. In summary, this research demonstrates the clear advantages of integrating smart algorithms with renewables in V2G/G2V systems, contributing to a resilient and sustainable EV charging infrastructure.

Conflict of interest. The authors declare that they have no conflicts of interest.

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