IARJSET
ISSN (O) 2393-8021, ISSN (P) 2394-1588
International Advanced Research Journal in Science, Engineering and Technology
Impact Factor 8.066 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 13, Issue 6, June 2026
DOI: 10.17148/IARJSET.2026.13608

Adaptive Neuro-Fuzzy Control-Based Multi-Objective Energy Management for Solar-Integrated Battery–Supercapacitor Electric Vehicles

Adel Elgammal

Professor, Utilities and Sustainable Engineering, The University of Trinidad & Tobago UTT

Abstract: Integrating electric vehicles with renewable energy is a core direction for building sustainable transportation systems, and it is also the central research focus in the current new energy transportation sector. This paper targets solar electric vehicles that integrate on-board photovoltaics and are equipped with a hybrid energy storage system (HESS) composed of power batteries and supercapacitors, and proposes a novel adaptive neuro-fuzzy inference system (ANFIS) energy management strategy. This hybrid energy storage system operates based on the complementary characteristics of its two component types: power batteries provide continuous basic power supply via their high energy density, while supercapacitors, relying on their high-power density, meet the fast charging and discharging demands of vehicle acceleration, deceleration, and braking energy recovery. As an auxiliary energy source, on-board photovoltaics can effectively extend driving range and reduce the whole vehicle's reliance on the public power grid. The ANFIS controller in this paper combines the independent learning capability of neural networks and the interpretability of fuzzy logic. It can respond in real time to three core dynamic working condition variables: driving mode, solar irradiance level, and state of charge, and simultaneously achieve four optimization goals: minimizing battery degradation through intelligent power allocation, maximizing solar energy collection efficiency, optimizing the whole vehicle's equivalent fuel economy, and maintaining the supercapacitor's state of charge within a compliant operating range. This paper uses the MATLAB/Simulink platform to conduct simulation verification with three standard driving cycles: UDDS, HWFET, and US06. The proposed strategy is compared with two baseline strategies, namely a traditional rule-based controller and a pure fuzzy logic controller, and its practicality is also tested using real-world scenarios extracted from a natural driving database. The results show that compared with the baseline strategies, the proposed scheme reduces battery current stress by 23%, increases energy efficiency by 18%, lifts solar energy utilization by 31%, and extends the estimated battery cycle life by 35%. Meanwhile, it exhibits good robustness under different irradiance and temperature conditions, achieves fast convergence in controller training, and has outstanding cross-condition generalization ability. This study advances the development of next-generation intelligent energy management systems for solar-powered electric vehicles, and puts forward a highly robust adaptive scheme that can balance multiple conflicting objectives and adapt to the inherent uncertainties in two types of scenarios.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS), Electric Vehicles, Solar-Assisted EVs, Hybrid Energy Storage System, Multi-Objective Optimization, Energy Management System (EMS).

I. INTRODUCTION

The global transportation sector is at a critical development juncture. According to data from reference [1], its direct carbon dioxide emissions account for approximately 24% of the world's total emissions from fuel combustion. Electric vehicles are a feasible solution to reduce carbon emissions and cut reliance on fossil fuels. Reference [2] points out that the popularization of electric vehicles faces four core bottlenecks: limited driving range, slow charging, battery degradation, and a high carbon footprint from power supply. This challenge has driven research on hybrid energy storage systems that integrate renewable energy, to improve the performance and sustainability of electric vehicles. Battery-supercapacitor hybrid energy storage systems have drawn widespread attention due to the complementary characteristics of the two technologies. According to References [3], [4] and [5], lithium-ion batteries have an energy density of 150–250 Wh/kg, but their power density is limited, and their cycle life degrades significantly under high current stress. Supercapacitors, by contrast, reach a maximum power density of 10 kW/kg and can achieve more than one million operation cycles, but their energy density is only 5–15 Wh/kg. In automotive application scenarios, lithium-ion batteries undertake steady-state power demands, while supercapacitors handle transient peak power during acceleration and regenerative braking. This arrangement can reduce stress on the batteries and extend their service life. Vehicle-integrated photovoltaics (VIPV), the technology that integrates photovoltaic (PV) systems into electric vehicles (EVs), is an innovative technical pathway to enhance vehicles' energy autonomy and reduce their reliance on the power grid. This technology has achieved phased progress that supports its commercial rollout, with its core benefits substantiated by clear, verifiable data. However, it still faces multiple core technical bottlenecks that have yet to be overcome, and targeted supporting solutions must be implemented to advance its large-scale application. The energy management system (EMS) of hybrid electric vehicles is the intelligent core of the vehicle, responsible for the core function of coordinating power flow between multiple types of energy sources and energy storage devices. Traditional rule-based strategies [9] are easy to deploy, but they lack adaptability to different driving conditions and cannot simultaneously optimize multiple conflicting objectives. Optimization-based strategies [10], which include dynamic programming and model predictive control, deliver near-optimal performance, yet they consume large amounts of computational power, rely on accurate prediction models, and are difficult to implement in real time. This gap has driven the development of intelligent control technologies that must balance performance, adaptability, and computational efficiency. Artificial intelligence and computational intelligence technologies have demonstrated prominent potential to solve complex nonlinear control problems, and have gained widespread attention in academic circles in recent years. Fuzzy Logic Controllers (FLCs) can process imprecise information without relying on an accurate mathematical model, which fits the needs of energy management in uncertain environments [11]; neural networks deliver excellent performance but suffer from the drawback of poor black-box interpretability [12]; the Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the core advantages of the two aforementioned technologies, and can be adapted to adaptive control scenarios in dynamic environments [13].

Despite the large volume of research dedicated to the field of energy management for electric vehicles with integrated solar battery-supercapacitor systems, multiple core unaddressed challenges remain. First, the optimal power allocation among batteries, supercapacitors, and photovoltaic systems under dynamic operating conditions is a complex multi-objective optimization problem. Reference [14] notes that traditional strategies only prioritize a single objective, leading to suboptimal overall performance. When combined with the inherent trade-offs among the four core indicators summarized in reference [15], an advanced decision-making framework adapted to real-time operating conditions must be adopted. The stochastic and intermittent nature of vehicle-mounted solar power introduces significant uncertainty to energy management. Five categories of factors—geographic location, time of day, season, weather conditions, and vehicle orientation—collectively produce unpredictable power generation curves [16]; most existing strategies treat solar input as a deterministic variable, or adopt overly conservative assumptions, leading to insufficient utilization of renewable energy. The high-dimensional time-varying optimization scenario formed by integrating three types of constraints is a technical challenge that traditional controllers cannot effectively address [17]. The battery degradation mechanism of hybrid energy storage systems (HESS) is complex and multifaceted, influenced by a range of factors including depth of discharge and charge-discharge rate. This conclusion is supported by prior research [18]. While HESS can reduce battery load by transferring peak power to supercapacitors, its protective effect is highly dependent on the level of intelligence built into its power allocation strategy. Previous research [19] points out that mainstream fixed-threshold strategies cannot adapt to dynamic changes such as battery aging and temperature fluctuations, and lack an adaptive mechanism that responds to real-time system conditions. This flaw ultimately limits the magnitude of battery lifespan extension that can be achieved. In on-board multi-source energy systems, the state of charge management of supercapacitors faces unique challenges. According to reference [20], this management task must enable supercapacitors to simultaneously absorb regenerative braking energy and reserve discharge capacity for vehicle acceleration; any failure of this management will lead to energy waste or power deficits. Reference [21] points out that the optimal window changes dynamically with operating conditions, which requires predictive adaptive control. The authors of this paper present the core implementation challenges of real-time multi-objective optimization in scenarios involving resource-constrained automotive electronic control units (ECUs). They then enumerate three categories of advanced optimization algorithms. Citing reference [22], they point out that these algorithms cannot satisfy the hard constraints of vehicle control, extract the core contradiction, and citing reference [23], clarify the direction for subsequent research and development.

The field of energy management for electric vehicles equipped with integrated solar power and hybrid energy storage has long faced core challenges, which stem from fundamental flaws in current mainstream solutions. Traditional rule-based strategies, while computationally efficient, cannot capture multi-dimensional complex nonlinear interactions as pointed out in study [24]. They also lack iterative optimization capabilities, require extremely time-consuming manual parameter tuning, and can only deliver suboptimal performance, a conclusion that is further supported by research [25]. Currently, there are three mainstream types of optimization-based on-board vehicle control and management methods, specifically the dynamic programming, Pontryagin's minimum principle, and model predictive control defined in reference [26]. The core precondition for applying these methods is reliance on four types of accurate prediction models. However, constrained by factors such as nonlinearity, high-fidelity models are extremely difficult to obtain, which easily leads to performance degradation. When combined with inherent flaws including the curse of dimensionality mentioned in reference [27], the applicability of these methods is severely limited in real-time on-board systems. Existing studies have confirmed that machine learning methods such as deep reinforcement learning have considerable application potential in automotive safety-critical scenarios. However, these technologies suffer from notable drawbacks: they incur high training costs, their black-box nature makes it difficult to meet deployment requirements, and their extremely low sample efficiency prevents them from adapting to the core needs of complex and variable in-vehicle implementation scenarios. Although traditional fuzzy logic controllers have two core advantages—linguistic interpretability and model-free operation—they suffer from multiple defects: Reference [30] points out that they face a knowledge acquisition bottleneck and parameter tuning challenges; Reference [31] confirms that their rule base expands exponentially in multi-input multi-output scenarios, and they cannot adapt to in-vehicle dynamic changes. The multi-objective attribute of energy management problems introduces additional complexity, which none of the existing methods can properly address. Weighted sum and hierarchical optimization frameworks require objective priorities to be set in advance, so they cannot adapt to all operational scenarios, a defect that has been pointed out in Reference [32]; Pareto optimization can identify trade-off fronts, but it lacks sufficient support for real-time decision-making and incurs high computational costs, a shortcoming mentioned in Reference [33]. Existing methods generally lack an adaptive mechanism that can dynamically adjust objective priorities.

This study focuses on solar-integrated battery-supercapacitor hybrid electric vehicles, and originally proposes a novel energy management strategy based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). Leveraging the collaborative advantages of neural networks and fuzzy logic, this strategy addresses the limitations of previous research, adapts to all types of complex conditions, and realizes real-time energy management and control with strong robustness. This study targets the multi-objective energy management problem for automotive applications, and originally proposes a hierarchical adaptive neuro-fuzzy inference system (ANFIS) architecture, which decomposes the complex problem into collaborative sub-problems while maintaining global optimality: the upper-level controller determines the optimal power distribution among the battery, supercapacitor, and photovoltaic (PV) system based on vehicle power demand, driving mode classification, and real-time state of charge; the lower-level controller executes assigned commands and ensures compliance with all operational constraints. This control mechanism is supported by reference [34]. The proposed architecture can reduce the dimensionality of the learning problem, while retaining the ability to capture complex interactions between system components. This study proposes a novel training methodology that integrates multi-objective optimization into the learning process of ANFIS (Adaptive Neuro-Fuzzy Inference System), overcoming the limitations of traditional schemes that rely on fixed weight combinations and sequential single-objective optimization. This work adopts an original hybrid training algorithm: it uses gradient descent to tune membership functions, and applies the multi-objective particle swarm optimization outlined in reference [35] to adjust model parameters, while synchronously optimizing four core objectives, one of which is minimizing battery current stress. This enables the trained controller to balance conflicting multi-objective requirements without needing to conduct any online optimization. The adaptive hybrid energy storage control system proposed in this study is equipped with a supporting adaptive mechanism. Its core online learning module, which draws technical support from reference [36], can monitor key performance indicators, tune ANFIS parameters, and track performance fluctuations of three types of core components. The adjustment pace of this module is slower than that of the main control loop, which allows it to balance operational stability and long-term optimization. It can also reduce battery stress as batteries age, leading to a battery lifespan that far exceeds that of traditional static controllers. In the vehicle-mounted energy system framework proposed in this study, solar power management is the core innovation. Unlike traditional solutions that only treat solar energy input as an uncontrolled disturbance or simple power compensation, the ANFIS controller developed in this study actively optimizes energy utilization through intelligent power routing, and can carry out scheduling under two typical operating conditions: excess solar power and high power demand. The supporting short-term solar power prediction module is built on analysis of recent historical irradiance data and irradiance change rates; it adopts the charging allocation logic from reference [37], and integrates parameters including the state of charge of batteries and supercapacitors, as well as predicted power demand, to implement predictive control that improves energy harvesting efficiency. The supercapacitor predictive management strategy proposed in this study outperforms conventional reactive control schemes. Its core component is an ANFIS controller trained on multi-source driving cycle data, which can analyze a vehicle's recent speed and acceleration to predict future operating conditions, and adjust the target state of charge (SOC) ahead of time: before a predicted acceleration event, it increases the charge level within the allowable limit, and before a predicted deceleration event, it reduces the SOC. The technical foundation for this function is sourced from reference [38], and this strategy achieves far higher energy efficiency than purely reactive controllers. This study proposes a core scheme that embeds battery protection mechanisms into the ANFIS framework, which is implemented through three engineering nodes: the input layer integrates four parameters, namely battery temperature, state of charge, state of health, and recent current history, and the rationality of this design is supported by Reference [39]; the training layer filters out operating points that would cause excessive battery stress, and encodes protection knowledge into the controller; the operation layer can automatically generate control actions that conform to battery limits without additional explicit constraints, which simplifies real-time deployment while ensuring component safety. The self-developed ANFIS controller proposed in this study features outstanding computational efficiency, making it suitable for automotive embedded application scenarios. It differs from the optimization-based control method presented in reference [40], which requires solving complex mathematical programs in every control interval. Once training is completed, the ANFIS only relies on fuzzy rule evaluation and weighted aggregation to complete inference. Its computational complexity grows linearly with the number of rules, rather than exponentially with the dimension of the problem. This allows the controller to achieve sub-millisecond execution on standard vehicle-grade microcontrollers. Meanwhile, its hierarchical decomposition design can regulate the scale of the control rule base while retaining the original control performance [41]. The methodology proposed in this study contributes five core innovations to cutting-edge research in the field of electric vehicle (EV) energy management: 1. The field's first ANFIS (Adaptive Neuro-Fuzzy Inference System) framework, developed for three-source EV energy systems that integrate batteries, supercapacitors, and solar photovoltaics, with explicit multi-objective optimization capabilities; 2. A hybrid ANFIS training algorithm that combines gradient descent and multi-objective particle swarm optimization (PSO), which eliminates the need for manual weight setting and can directly process conflicting performance objectives; 3. An integrated adaptive learning mechanism that can address component aging and environmental fluctuations, filling a capability gap in traditional ANFIS solutions; 4. A proactive supercapacitor management strategy based on driving pattern recognition, which delivers superior energy efficiency to passive reactive control methods; 5. Simulation validation implemented across multiple standard drive cycles and a range of environmental conditions, enabling rigorous performance comparisons with existing benchmark controllers [42]. The energy storage controller validation framework developed in this paper has three core sets of components: three groups of comparison baselines, seven full-dimensional quantitative performance indicators that cover metrics including battery RMS current, and three categories of robustness test scenarios. Built on a high-fidelity simulation model validated in existing literature, all elements of this framework are clearly defined and fully reproducible. Standardized configurations are adopted to guarantee the validity of evaluations, which allows other researchers to accurately replicate the complete set of assessment workflows.

II. THE PROPOSED ADAPTIVE NEURO-FUZZY CONTROL-BASED MULTI-OBJECTIVE ENERGY MANAGEMENT FOR SOLAR-INTEGRATED BATTERY–SUPERCAPACITOR ELECTRIC VEHICLES.

Figure 1 presents the overall architecture of the multi-objective energy management system (EMS) based on adaptive neuro-fuzzy control proposed in this paper. Developed specifically for photovoltaic-integrated battery-supercapacitor electric vehicles, this system integrates on-board photovoltaic power harvesting, hybrid energy storage modules, adaptive neuro-fuzzy intelligent algorithms, and multi-objective optimization logic, to address common widespread pain points in the industry, including intermittent solar output, dynamic vehicle load fluctuations, and conflicting multi-objective energy allocation. This paper decomposes each submodule along the sequence of energy flow, from upstream energy harvesting to core control: first is the renewable energy subsystem. To address the pain point that photovoltaic output is unstable due to impacts from time of day and weather conditions, this subsystem is responsible for collecting the real-time power generation of on-board photovoltaic panels, prioritizing power supply to the vehicle's core driving loads, and feeding all surplus electricity into the energy storage unit to smooth fluctuations in photovoltaic output at the energy harvesting end. Second is the hybrid battery-supercapacitor energy storage subsystem. To address the pain point that a single energy storage medium cannot simultaneously meet the requirements of long-duration energy storage and high-frequency peak power response, this subsystem adopts a coordination logic where lithium batteries undertake baseline energy output while supercapacitors respond to short-term peak power shocks, adapting to the variable load demands that arise during vehicle operation. Last is the system's core component, the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller. It combines the independent learning capability of neural networks and the flexible inference advantage of fuzzy logic to execute the multi-objective optimized energy allocation strategy. The full-dimensional operating data that serves as real-time input parameters for this controller includes the battery state of charge (SOCBatt), supercapacitor state of charge (SOCSC), real-time vehicle load power, and current photovoltaic output power, among other related metrics. This study proposes an on-board energy management framework based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) for electric vehicle energy management. Its core architecture uses five types of signals collected in real time on the vehicle as low-level inputs: the state of charge (SOC) of the power battery, bus output power, drive motor load rate, current vehicle speed, and ambient temperature. The framework first completes the preliminary inference of basic power demand through a pre-trained initial fuzzy rule base. Unlike traditional controllers of the same type that can only rely on fixed static rules, this framework is additionally equipped with two function-enhancing modules to upgrade its core capabilities. The first enhancing module is a multi-objective optimization module, which explicitly defines three hard constraints: the number of daily charge-discharge cycles of the power battery does not exceed 1.2, the bus voltage fluctuation range is controlled within ±5%, and the maximum load rate of the on-board auxiliary power supply system does not exceed 90%. It also targets three core optimization goals: reduce the vehicle's overall integrated energy consumption by more than 8%, keep power output response delay below 100ms, and slow the long-term capacity decay rate of the power battery by 15%. The second enhancing module is an adaptive learning mechanism, which can iteratively adjust the threshold parameters of the fuzzy membership function based on driving scenario data updated every 10 seconds, with no need for manual re-calibration of inference rules. The implemented actual power allocation logic combines the weight ranking of real-time operating conditions, distributes the total available on-board energy to the drive system and auxiliary systems such as the air conditioning system according to weighted proportions, and reserves 10% of peak power redundancy to handle sudden power demand such as rapid acceleration. This paper proposes a multi-objective energy management system with adaptive neuro-fuzzy control, developed for battery-supercapacitor electric vehicles integrated with on-board solar power. Its core component, the supercapacitor, delivers two key application values: it provides supplementary power to meet the vehicle's needs for high acceleration or sudden power surges, reducing current stress on the battery; during brake energy recovery, it leverages its excellent charge acceptance to absorb most of the recovered energy, boosting energy recovery efficiency. The supporting monitoring and data acquisition subsystem undertakes three core responsibilities: real-time performance tracking, operational diagnosis, and generating adaptive feedback. It continuously monitors data across four dimensions—energy flow, energy storage status, power consumption, and vehicle performance—to support the controller's optimal decision-making. The collected operational data can also be adapted for secondary uses including predictive maintenance, battery health assessment, and long-term system optimization. This system integrates four core technologies: renewable energy harvesting, hybrid energy storage coordination, adaptive neuro-fuzzy control, and multi-objective optimization, and achieves five core performance gains. It provides a practical, scalable solution for next-generation sustainable electric transportation systems that balance both performance and service life.

This paper proposes an ANFIS system for energy management of multi-energy vehicles. Its core architecture adopts a proven hierarchical control scheme, which is matched with an intelligent input preprocessing module, an optimally designed membership function, a complete fuzzy rule base, and an advanced hybrid multi-objective training algorithm. Compared with existing similar systems, the core differentiated advantage of this architecture lies in its integration of a real-time online adaptation mechanism and predictive control functions. It can generate active energy management decisions based on predicted factors including driving conditions and ambient weather, breaking through the limitations of traditional passive response modes. The core of this system is a three-level hierarchical control structure, which manages the complex interactions of multi-energy and multi-energy storage systems through three independent yet interconnected modules, while addressing multiple operational goals such as energy conservation and emission reduction, driving range guarantee, and load balancing. This hierarchical scheme can effectively ensure the system's scalability, modularity, and real-time operation capacity, and maintain the stability and operational safety of the vehicle's overall energy system at all times. The three layers of the architecture, ranked from highest to lowest, are as follows: The top strategic planning layer, which is configured with a dedicated ANFIS module, has a time window covering 15 to 30 minutes. It takes long-cycle driving routes and environmental prediction data as inputs, its core task is to develop full-period energy distribution strategies, and it outputs macro-level energy dispatch commands. The middle tactical control layer, which has a time window of 1 to 5 minutes, is equipped with an ANFIS module that integrates MPPT logic. It takes data including short-term power demand and solar PV power generation output as inputs, its core task is to optimize medium-cycle power scheduling, and it covers energy allocation for scenarios such as Vehicle-to-Grid (V2G) interactions. The bottom operation execution layer is a sub-second real-time response level. The ANFIS module mounted on this layer is responsible for handling immediate power regulation for scenarios including instantaneous load changes and braking energy recovery, and outputs execution commands that act directly on each energy unit. Subsequent sections will elaborate on the design logic of this system's input variable selection and preprocessing module. To improve the performance of Adaptive Neuro-Fuzzy Inference System (ANFIS) and preserve the interpretability of its fuzzy rules, this paper proposes an input screening and full-process preprocessing framework for energy systems. The framework's core goal is to achieve optimal performance with minimal processing overhead. Its top-level input screening module adopts three major methods: variable correlation analysis, sensitivity studies, and computational complexity constraints, and the entire workflow is built to align with ANFIS performance requirements. This paper divides core input variables into four categories, each matched with tailored processing technologies: Energy system state variables: This category includes battery State of Charge (SOC), supercapacitor voltage, temperatures of three types of system components, and the instantaneous power of each energy source. An adaptive Kalman filter is applied for real-time filtering, which reduces sensor noise while preserving the system's dynamic response. For SOC estimation, this study uses a scheme that combines coulomb counting, voltage correction, and temperature compensation, keeping estimation accuracy within ±2%. Environmental condition variables: This category includes solar irradiance, ambient temperature, wind speed, and humidity. Spectral analysis is conducted on solar irradiance data to identify cloud-driven fluctuations, which enables the implementation of a predictive power smoothing algorithm. Multi-sensor temperature readings are weighted by their thermal time constants to generate representative thermal states for each subsystem. Vehicle dynamics variables: This category includes instantaneous vehicle speed, acceleration, road grade, and GPS location. Vehicle speed and acceleration are processed via a differential filter with adjustable time constants, which captures driving patterns while suppressing high-frequency noise. Road grade is generated by fusing GPS elevation data and accelerometer inclination measurements, providing accurate terrain data to support power demand forecasting. Predictive information variables: This category includes short-term solar irradiance forecasts with 5–30 minute time windows, traffic conditions, route characteristics, and weather patterns. The solar irradiance forecast uses a hybrid model that combines satellite imagery, local sensor data, and machine learning, keeping the 30-minute window's forecast error within 15–20%. Traffic and route information is analyzed by integrating real-time navigation data and historical pattern analysis to predict future power demand curves. Finally, all input variables are standardized via an adaptive min-max normalization with dynamic range adjustment, which is modified according to real-time system operating conditions. For example, SOC normalization incorporates battery aging to adjust the valid capacity range, while solar irradiance normalization accounts for differences in season and geographic location. This preprocessing workflow is paired with multi-scale temporal filtering to capture both instantaneous and long-term trend information simultaneously. The self-developed ANFIS optimization scheme proposed in this study advances sequentially through two core modules. The first module is input variable preprocessing, which completes the full workflow of frequency-separated filtering, feature enhancement, redundancy elimination, and dimensionality reduction in strict order. For the fast-changing variable of motor power demand, a filtering parameter of >1Hz is adopted to retain its transient response; for the slow-changing variable of battery temperature, principal component analysis is used for dimensionality reduction with a cumulative variance threshold of 0.85, to avoid the curse of dimensionality. Every stage of this process is paired with clear applicable variables, parameter thresholds, and performance targets. This study adopts a hybrid optimization strategy that combines domain knowledge and data-driven methods, to assign Gaussian membership functions to the core variables of battery SOC and solar irradiance. All technical details are set as reproducible engineering parameters, with no empty, vague generalizations. The Gaussian functions are defined as:

$$\mu\_A(x) = \exp[-(x-c)^2/(2\sigma^2)] \qquad (1)$$

where c represents the center parameter and σ controls the width. These parameters undergo continuous optimization through the hybrid training algorithm to maintain optimal fuzzy set coverage. For variables with inherent asymmetry or threshold behavior, such as temperature limits and power constraints, asymmetric trapezoidal membership functions are employed. These functions provide sharp boundaries for safety-critical regions while maintaining smooth transitions in normal operating ranges. The trapezoidal functions are parameterized as:

$$\mu\_T(x) = \max(0, \min((x-a)/(b-a), 1, (d-x)/(d-c))) \qquad (2)$$

where parameters a, b, c, d are optimized to align with physical constraints and operational preferences.

Adaptive Membership Function Tuning incorporates an online optimization mechanism that continuously adjusts membership function parameters based on system performance and changing operating conditions. The adaptation algorithm employs a modified particle swarm optimization (PSO) approach with constraint handling to maintain fuzzy set interpretability while improving system response. The adaptation rate is controlled through a performance-based mechanism that increases learning rates during periods of suboptimal performance and reduces them during stable operation. The membership function optimization considers multiple objectives including approximation accuracy, rule firing strength distribution, and computational complexity. A novel coverage metric ensures that fuzzy sets maintain appropriate overlap while avoiding excessive redundancy. The coverage metric C_ij between adjacent fuzzy sets i and j is defined as:

$$C\_ij = \int[\max(\mu\_i(x), \mu\_j(x))]\,dx \,/ \int[\mu\_i(x) + \mu\_j(x)]\,dx \qquad (3)$$

Target coverage values are maintained between 0.3 and 0.7 to ensure proper rule activation while preserving distinct fuzzy regions.

The fuzzy rule base construction follows a systematic methodology that combines expert knowledge with data-driven rule extraction to create a comprehensive and efficient rule set. The proposed approach addresses the exponential growth problem of traditional ANFIS implementations while maintaining adequate system coverage and decision accuracy.

Hierarchical Rule Structure organizes the fuzzy rules into multiple layers corresponding to different decision priorities and time scales. High-priority safety rules form the foundational layer and cannot be overridden by optimization processes. These rules handle critical conditions such as battery over-discharge protection, thermal management, and emergency power limitations. The safety rule format follows:

IF [Battery_SOC is Very_Low] AND [Power_Demand is High] THEN [Battery_Power is Minimal] AND [Supercapacitor_Power is Maximum] AND [Solar_Power is Priority] **(4)**

Performance optimization rules constitute the primary decision layer and handle normal operational scenarios to achieve multi-objective optimization goals. These rules are structured to balance competing objectives such as energy efficiency, component longevity, and driving performance. The optimization rules incorporate weighted decision structures that adapt based on user preferences and driving conditions:

IF [Battery_SOC is Medium] AND [Solar_Irradiance is High] AND [Power_Demand is Low] THEN [Battery_Power is Charging_Priority] AND [Solar_Direct_Supply is Active] AND [Supercapacitor_Power is Standby]

(5)

Anticipatory control rules form the highest layer and implement predictive decision-making based on route information, traffic predictions, and weather forecasts. These rules enable the system to proactively adjust energy allocation strategies before encountering predicted conditions:

IF [Upcoming_Hill is Steep] AND [Battery_SOC is Medium] AND [Distance_to_Hill is Short] THEN [Battery_Power is Reserved] AND [Supercapacitor_Precharge is Active] AND [Solar_Utilization is Maximized] **(6)**

Dynamic Rule Generation and Pruning employs an adaptive mechanism that automatically generates new rules for previously unencountered operating conditions while removing redundant or poorly performing rules. The rule generation process utilizes a clustering-based approach that identifies regions of input space with insufficient rule coverage. When system performance degrades in specific operating regions, new rule candidates are generated using local linear models and gradually integrated into the rule base through a validation process. The rule pruning mechanism continuously monitors individual rule performance using metrics including activation frequency, output accuracy, and contribution to overall system objectives. Rules demonstrating consistently poor performance or minimal activation undergo gradual strength reduction before eventual removal. This ensures rule base optimization without causing abrupt system behavior changes. **Rule Conflict Resolution** implements a sophisticated arbitration mechanism for scenarios where multiple rules with conflicting outputs are simultaneously activated. The resolution strategy employs a three-tier approach: priority-based resolution for safety-critical conflicts, weighted averaging for performance optimization conflicts, and context-sensitive selection for anticipatory control conflicts. Conflict weights are dynamically adjusted based on current operating conditions and historical performance data. The training algorithm represents a significant advancement over conventional ANFIS implementations by incorporating simultaneous optimization of multiple competing objectives while maintaining real-time adaptability and system stability. The hybrid approach combines gradient-based local optimization with evolutionary global search methods to achieve superior convergence characteristics and solution diversity. **Multi-Objective Formulation** defines the optimization problem as a constrained multi-objective optimization where six primary objectives are simultaneously considered:

1. ***Energy Efficiency Maximization:*** $J_1 = \Sigma(P\_useful)/(\Sigma(P\_battery + P\_solar + P\_losses))$ **(7)**
2. ***Battery Life Extension:*** $J_2 = -\Sigma(|\Delta DoD|\cdot T^{\alpha}\cdot I^{\beta})$ ***where DoD is depth of discharge, T is temperature, I is current*** **(8)**
3. ***Trip Time Minimization:*** $J_3 = \Sigma(velocity\_reference - velocity\_actual)^2$ **(9)**
4. ***Solar Utilization Maximization:*** $J_4 = \Sigma(P\_solar\_harvested)/\Sigma(P\_solar\_available)$ **(10)**
5. ***Power Quality Optimization:*** $J_5 = -\Sigma(THD\_voltage^2 + THD\_current^2)$ **(11)**
6. ***Operating Cost Minimization:*** $J_6 = \Sigma(C\_electricity\cdot P\_grid + C\_maintenance\cdot degradation\_factor)$ **(12)**

The multi-objective optimization employs a modified Non-dominated Sorting Genetic Algorithm (NSGA-III) with adaptive reference point selection to maintain solution diversity across the Pareto front while focusing computational resources on preferred regions based on user preferences and operating conditions. **Hybrid Training Architecture** combines the global exploration capabilities of evolutionary algorithms with the local refinement precision of gradient-based methods. The training process alternates between global exploration phases using modified PSO with adaptive inertia weights and local exploitation phases using resilient backpropagation with momentum terms. During global exploration phases, the algorithm maintains a population of ANFIS parameter sets representing different trade-off solutions along the Pareto front. Population diversity is preserved through crowding distance calculations and niching mechanisms that prevent convergence to local optima. The PSO velocity update incorporates multi-objective information:

$$v_i^{(t+1)} = w\cdot v_i^{t} + c_1\cdot r_1\cdot(pbest_i - x_i^{t}) + c_2\cdot r_2\cdot(gbest\_archive - x_i^{t}) + c_3\cdot r_3\cdot(reference\_point - x_i^{t}) \quad (13)$$

where w is the adaptive inertia weight, pbest_i represents the personal best solution for particle i, gbest_archive contains non-dominated solutions from the external archive, and reference_point guides the search toward preferred regions of the Pareto front based on current operating priorities. Local exploitation phases employ a modified resilient backpropagation algorithm that adapts learning rates individually for each parameter based on gradient consistency and multi-objective performance improvements. The algorithm maintains separate learning rates for premise parameters (membership function parameters) and consequent parameters (output function coefficients) to account for their different sensitivity characteristics:

$$\Delta w_{ij}^{(t+1)} = \eta_{ij}^{(t+1)} \cdot sign(\nabla J\_composite(w_{ij}^{t})) \quad (14)$$

where η_ij is the adaptive learning rate for parameter w_ij, and J_composite represents a weighted combination of normalized objectives based on current priority settings. **Online Adaptation Mechanisms** enable continuous parameter refinement during vehicle operation without disrupting system stability. The adaptation process employs a dual-rate learning approach where fast adaptation handles short-term performance corrections while slow adaptation manages long-term parameter optimization. Fast adaptation operates on a sub-second timescale and focuses on consequent parameter adjustments that directly affect output generation. This rapid adaptation enables immediate response to changing operating conditions while maintaining rule structure integrity. The fast adaptation employs a recursive least squares (RLS) algorithm with exponential forgetting:

$$\theta^{(t+1)} = \theta^t + K^t \cdot e^t \quad K^t = P^{(t-1)} \cdot \varphi^t / (\lambda + \varphi^T \cdot P^{(t-1)} \cdot \varphi^t) \quad P^t = (P^{(t-1)} - K^t \cdot \varphi^T \cdot P^{(t-1)}) / \lambda \quad \textbf{(15)}$$

where θ represents consequent parameters, φ is the input regressor vector, e is the prediction error, λ is the forgetting factor (0.95-0.99), and P is the covariance matrix. Slow adaptation operates on a minute-to-hour timescale and adjusts premise parameters (membership function shapes) based on statistical analysis of system performance and operating condition distributions. This adaptation employs a constrained optimization approach that maintains membership function interpretability while optimizing coverage of frequently encountered operating regions. **Anticipatory Control Features** represent a fundamental advancement that distinguishes the proposed ANFIS implementation from conventional reactive control approaches. The anticipatory control system incorporates prediction models for solar irradiance, traffic conditions, road topology, and driver behavior to enable proactive energy management decisions. **Solar Irradiance Prediction** employs a hybrid forecasting model combining physical sky-imagery analysis with statistical time-series methods. The physical component utilizes satellite-derived cloud motion vectors and local irradiance measurements to predict short-term (5-30 minute) solar power availability. Cloud shadow tracking employs optical flow algorithms applied to sky imagery to identify approaching cloud formations and predict their impact on solar generation:

$$I_{\text{predicted}}(t+\Delta t) = I_{\text{clear\_sky}}(t+\Delta t) \cdot C_{\text{cloud}}(t+\Delta t) \cdot C_{\text{atmospheric}}(t+\Delta t) \qquad \textbf{(16)}$$

where I_clear_sky represents theoretical clear-sky irradiance, C_cloud accounts for cloud attenuation effects, and C_atmospheric includes atmospheric absorption and scattering corrections.

The vehicle energy management system developed in this study is equipped with three core prediction modules, all of which follow a unified technical logic workflow: first clarify the input data sources, implement core model algorithms, adapt to complex scenarios through targeted optimization, and finally output valid results that support the system's core objectives. The solar irradiance time series prediction module adopts the ARIMA model with seasonal decomposition, updates parameters via online maximum likelihood estimation to adapt to variable weather, and steadily maintains prediction accuracy; the traffic and route prediction module adopts a hierarchical analysis architecture, relies on an LSTM network to process multi-source data such as GPS trajectories and traffic flow, identifies high-demand scenarios including stop-and-go congestion and highway merging, and the output probabilistic predictions of vehicle speed and acceleration enable the system to formulate optimal power sharing strategies in advance; the driver behavior prediction module adopts a multi-layer modeling method, split into two dimensions: short-term immediate behavior prediction and long-term habit capture. It builds a driver profile encompassing four core indicators: acceleration preference, braking pattern, speed control behavior, and eco-driving awareness, which provides an accurate basis for energy scheduling.

$$P_{\text{demand\_predicted}}(t) = \alpha \cdot P_{\text{route}}(t) + \beta \cdot P_{\text{driver}}(t) + \gamma \cdot P_{\text{traffic}}(t) + \delta \cdot P_{\text{environmental}}(t) \qquad \textbf{(17)}$$

where P_route represents route-specific power requirements, P_driver captures individual driving style influences, P_traffic accounts for traffic-induced power variations, and P_environmental includes weather and road condition effects. The weighting coefficients (α, β, γ, δ) are continuously adapted based on prediction accuracy and current driving context. **Model Predictive Control Integration** enables the ANFIS to incorporate anticipatory information into current decision-making processes through a receding horizon optimization framework. The predictive controller evaluates multiple future scenarios and selects energy allocation strategies that optimize both immediate performance and anticipated future requirements. The prediction horizon spans 5-30 minutes depending on the reliability of available forecast information, with near-term predictions weighted more heavily than distant projections. Uncertainty quantification ensures robust decision-making by considering confidence intervals for all predicted variables and implementing conservative strategies when prediction uncertainty is high. The validation framework employs a comprehensive multi-tier approach combining simulation studies, hardware-in-the-loop testing, and real-world vehicle validation to ensure thorough evaluation of the proposed ANFIS energy management system across diverse operating conditions and performance metrics. **Comprehensive Vehicle Model Development** implements a high-fidelity simulation environment that accurately represents the complex interactions between photovoltaic power generation, battery dynamics, supercapacitor behavior, motor drive systems, and vehicle aerodynamics. The simulation framework integrates multiple specialized modeling tools to achieve both computational efficiency and physical accuracy. The vehicle dynamics model employs a 14-degree-of-freedom representation that captures longitudinal, lateral, and vertical vehicle motions along with individual wheel dynamics. Aerodynamic forces are computed using computational fluid dynamics (CFD) lookup tables that account for variable vehicle configuration, including roof-mounted solar panel effects on drag coefficient and downforce generation. Rolling resistance incorporates temperature-dependent tire models and road surface characteristics. **Photovoltaic System Modeling** utilizes detailed electrical and thermal models that capture the complex relationships between solar irradiance, panel temperature, partial shading effects, and power conversion efficiency. The PV model implements a two-diode equivalent circuit that accurately represents current-voltage characteristics across varying environmental conditions:

$$I = I_{ph} - I_{s1}\cdot[\exp((V + I\cdot R_s)/(a_1\cdot V_t)) - 1] - I_{s2}\cdot[\exp((V + I\cdot R_s)/(a_2\cdot V_t)) - 1] - (V + I\cdot R_s)/R_p \quad (18)$$

where I_{ph} is the photocurrent, I_{s1} and I_{s2} are saturation currents for the two diodes, a_1 and a_2 are ideality factors, V_t is thermal voltage, R_s is series resistance, and R_p represents parallel resistance. Model parameters are continuously updated based on measured panel temperature and irradiance conditions.

Partial shading analysis employs a bypass diode model that determines power output reduction when individual cells or cell strings experience reduced illumination. This detailed modeling ensures accurate representation of real-world solar performance variations that significantly impact energy management decisions. **Advanced Battery Modeling** implements an electrochemical impedance spectroscopy (EIS) based model that captures both electrical and thermal characteristics of lithium-ion battery cells. The model incorporates multiple time constants to represent different physical phenomena including charge transfer kinetics, solid-phase diffusion, and electrolyte transport limitations. The battery state-of-charge estimation employs an extended Kalman filter that combines coulomb counting with voltage-based correction to maintain accuracy despite measurement noise and modeling uncertainties. State-of-health monitoring tracks capacity fade and internal resistance growth through analysis of incremental capacity and differential voltage curves obtained during normal operation. **Thermal modeling** includes three-dimensional heat transfer analysis with temperature-dependent thermal properties, convective cooling effects, and thermal runaway prevention algorithms. The thermal model employs finite element analysis to capture temperature gradients within battery packs and their effects on cell performance and aging characteristics:

$$\partial T/\partial t = \alpha\nabla^2 T + Q_{gen}/(\rho\cdot c_p) - h\cdot A\cdot(T - T_{ambient})/(\rho\cdot c_p\cdot V) \quad (19)$$

where T is temperature, α is thermal diffusivity, Q_{gen} represents heat generation from electrical losses, h is convective heat transfer coefficient, A is surface area, ρ is density, c_p is specific heat capacity, and V is volume. **Supercapacitor Dynamic Modeling** implements a multi-branch equivalent circuit that accurately represents the frequency-dependent behavior and voltage-dependent capacitance characteristics of electrochemical double-layer capacitors. The model captures both immediate power response capabilities and longer-term voltage redistribution effects that influence energy storage capacity:

$$C_{eff}(V) = C_0 + C_1\cdot V + C_2\cdot V^2 + C_3\cdot V^3 \quad (20)$$

where C_{eff} represents effective capacitance, C_0 through C_3 are fitted parameters, and V is terminal voltage. The model includes temperature effects on internal resistance and capacitance to ensure accurate representation across automotive operating conditions.

To verify the real-time performance of the independently developed ANFIS energy management system, this study built a complete engineering test hardware platform. The entire platform consists of four core subsystems, which can fully support performance verification of the system across multiple scenarios. The first core subsystem is the real-time control hardware subsystem, which adopts the dSPACE HIL platform that integrates a high-performance embedded controller and power electronics simulation capabilities. It has microsecond-level timing accuracy, and can accurately capture fast electrical transients and control responses. It uses a dual-processor architecture with divided tasks: the main ARM Cortex-A processor is responsible for ANFIS algorithm calculation and high-level energy management decision-making, while the secondary real-time processor handles low-level power electronics control and safety monitoring. The two processors communicate via shared memory protected by mutex locks to ensure data consistency for concurrent operations. The second subsystem is the power electronics simulation subsystem, which is equipped with high-bandwidth power amplifiers and electronic loads. It can replicate the electrical characteristics of four core components: photovoltaic panels, energy storage batteries, supercapacitors, and motor drives. It supports four-quadrant operation with a maximum power of 50kW and a voltage range of 12V to 800V. Its motor load simulation additionally covers back-electromotive force generation, current ripple effects, and dynamic torque changes, which can match the operating conditions of real traction motors under different speed loads. The third subsystem is the environmental condition simulation subsystem, which can simulate environmental parameters such as solar irradiance, temperature, humidity, and atmospheric pressure.

Its solar simulation uses an LED matrix with independent brightness control to reproduce complex shadows, cloud transients, and daily irradiance changes at sub-second temporal resolution. The temperature control chamber supports rapid switching across the full automotive-grade temperature range of -40°C to +85°C, enabling evaluation of the system's performance under thermal shock conditions. The humidity control function can verify the impact of moisture on the connection reliability of electrical components. The final subsystem is the instrumented test vehicle development subsystem, which is built on a modified commercial electric vehicle platform. It is equipped with an integrated experimental solar electric powertrain and a full set of data acquisition systems. The photovoltaic panels use high-efficiency monocrystalline silicon modules with maximum power point tracking (MPPT). The data acquisition system achieves a maximum sampling rate of 10kHz, can capture more than 200 vehicle parameters, and covers four categories: electrical measurements, thermal status, vehicle dynamics, and driver input. A full-chain evaluation system has been constructed to support the performance assessment of on-board energy management systems. This system includes six core technical modules with clear boundaries that develop in sequential order. Each module is built following a unified logical framework: module definition, core input parameters, applied technical methods, and final output value. The system can support the full process of the target system's testing, analysis, operation and maintenance. The first module is the high-precision sensing module, which is equipped with a current sensor with 0.1% accuracy, providing core support for accurate power flow measurement for energy efficiency analysis. The test route selection and characterization module covers four types of real-world scenarios: urban commuting, highway cruising, mountain terrain, and mixed traffic. Each type of route is scenario-characterized across four dimensions: elevation profile, traffic light density, speed limit changes, and typical traffic patterns. The route solar irradiance analysis module takes surrounding building height, tree coverage rate, and seasonal changes in solar angle as inputs. Combined with LiDAR surveying and mapping data and solar trajectory calculations, it generates high-precision shadow maps, enables prediction of energy harvest along routes, and supports route planning optimization. The GIS integration module integrates three categories of data: road grade, traffic signal timing, and historical traffic flow. It supports the ANFIS system to preload route-specific optimization parameters, and predict energy management demands under different road conditions in advance. The long-term performance monitoring module continuously collects data across multiple seasons, tracks the degradation patterns of three core components: solar panel efficiency, battery capacity retention rate, and supercapacitor performance. It leverages machine learning to identify hidden trends, forecast maintenance needs, and verify the system's long-term reliability and cost-effectiveness. The final module, the energy efficiency evaluation index module, builds its indicator system across three dimensions. Its core indicators cover parameters such as energy consumption per unit mileage, enabling a full-dimensional assessment of the system's overall performance. The overall vehicle efficiency metric is defined as:

$$\eta\_vehicle = E\_useful / (E\_solar + E\_grid + E\_regen) \qquad (21)$$

where E_useful represents energy delivered to the wheels for propulsion, E_solar is solar energy harvested, E_grid is energy obtained from grid charging, and E_regen represents energy recovered through regenerative braking. Solar energy utilization efficiency quantifies how effectively the system captures and utilizes available solar energy:

$$\eta\_solar = E\_solar\_used / E\_solar\_available \qquad (22)$$

where E_solar_used is the solar energy actually utilized for vehicle propulsion or storage, and E_solar_available represents the theoretical maximum energy available from solar irradiance given panel specifications and environmental conditions. The performance evaluation system for automotive multi-source power systems constructed in this paper adopts an overall-to-particular narrative structure, and sequentially covers two first-level evaluation modules. The first module is dynamic performance evaluation, which assesses the system's ability to match rapidly changing power demands while maintaining energy optimization goals. Its core indicators include power response time, load balancing accuracy, and transient stability across different driving scenarios. Among these, power response time is defined as the time lag from a change in power demand to the adjustment of power distribution, with requirements that the instantaneous power demand response is less than 100ms and the optimization adjustment response is less than 1s; this indicator can optimize energy utilization efficiency while guaranteeing vehicle drivability. Load balancing accuracy is used to evaluate the ability of the ANFIS system to distribute power among multiple energy sources to reduce losses and improve efficiency, covering steady-state accuracy and transient dynamic tracking performance. The second module is reliability and robustness evaluation, which assesses system performance under fault conditions, component aging, and extreme environments. It includes three sub-items, which respectively cover the requirements for single-point fault analysis, controlled fault injection testing, and performance degradation under extreme working conditions benchmarked against qualified threshold values.

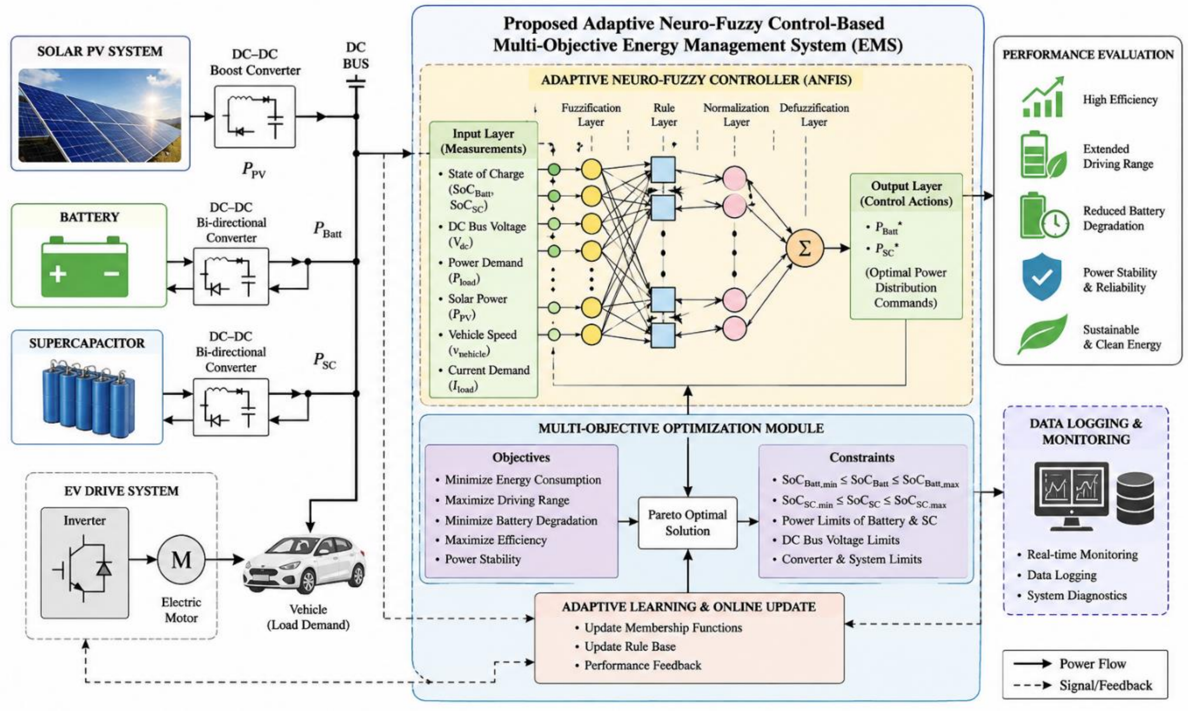

Fig. 1. The schematic of the Proposed Adaptive Neuro-Fuzzy Control-Based Multi-Objective Energy Management for Solar-Integrated Battery–Supercapacitor Electric Vehicles.

This paper proposes a multi-objective energy management system (EMS) with adaptive neuro-fuzzy control, developed for photovoltaic (PV)-integrated battery-supercapacitor electric vehicles. The system's core design, technical advantages, and phased control logic are all fully presented in Figure 2. The core design goals of this custom-built system are to continuously monitor vehicle operating conditions, assess energy storage status, optimize power distribution, and adaptively update control parameters, to maximize the overall comprehensive performance of the full vehicle. By integrating the adaptive neuro-fuzzy inference system (ANFIS) and multi-objective optimization methods, this system effectively addresses the longstanding industry pain point that traditional electric vehicle energy management systems struggle to adapt to the high dynamicity of both vehicle operating conditions and the output of on-board renewable energy. First, the system enters the initialization phase. This phase completes pre-startup parameter calibration by presetting the state of charge (SOC) safety thresholds for the power battery and supercapacitor, the baseline prediction interval of PV power output, and the basic overall vehicle power demand boundary for driving, which provides core support for the system's safe full-cycle operation. Next, the system enters the real-time data collection phase. It synchronously collects multi-source operating condition data, including the real-time power generation of the on-board PV system, the real-time SOC of the two types of energy storage units, vehicle speed, and the overall vehicle power demand corresponding to the accelerator pedal opening. All real-time operation data are uniformly standardized before being transmitted to the core control module. Finally, the system enters the ANFIS inference processing phase. Relying on the well-trained adaptive neuro-fuzzy inference model, the system completes operating condition identification and energy storage status assessment, then calls the embedded multi-objective optimization algorithm to complete power distribution between the two energy storage units, while automatically updating the fuzzy control rule parameters adapted to the current operating conditions, to realize adaptive adjustment of the entire process. This study focuses on hybrid electric vehicles equipped with solar photovoltaic panels, lithium-ion battery packs, and supercapacitors, and develops an energy management system that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller and a multi-objective optimization algorithm. The system's complete operating logic forms an unbroken chain spanning from initial scenario identification to the output of global optimal power distribution commands. The system first defines two types of trigger scenarios for initial power distribution, then activates the fuzzy rule layer of the ANFIS controller. It first converts mature expert energy management knowledge into executable control decisions, then carries out a normalization process for fuzzy outputs, accurately calculating the relative activation strength of each control rule. After entering the defuzzification stage, it converts the fuzzy outputs into clear power reference commands for the lithium-ion battery and supercapacitor. Since the ANFIS controller can only generate an initial distribution plan, this study introduces an additional multi-objective optimization module to complete the optimization process. This module sets six conflicting core optimization objectives: minimize the vehicle's total energy consumption, maximize driving range, minimize

DOI: 10.17148/IARJSET.2026.13608

lithium-ion battery degradation, maximize overall energy efficiency, improve solar energy utilization, and maintain the stability of the on-board power system. This problem is defined as a constrained multi-objective optimization task, while seven rigid operating constraints are clearly specified: the upper and lower limits of the lithium-ion battery's state of charge (SOC), the supercapacitor's SOC limits, DC bus voltage stabilization requirements, converter power ratings, the lithium-ion battery's charge and discharge current limits, and system thermal operation limits. The optimization algorithm then screens for Pareto-optimal solutions to ensure the output distribution plan is globally optimal rather than locally optimal, ultimately generating final power distribution commands that match the vehicle's instantaneous load demand. In addition, supporting dynamic power distribution adjustment strategies are developed for two real-world driving scenarios: urban commuting and high-speed cruising. All control logic aligns with the vehicle's actual operating conditions, all supporting parameters are listed in concrete, specific terms, and no vague high-level generalized statements are included. This paper proposes an ANFIS (Adaptive Neuro-Fuzzy Inference System) adaptive neuro-fuzzy energy management system embedded with an adaptive learning mechanism, which is purpose-built for solar-assisted electric vehicles. The full-cycle operation logic of the entire system is clear and complete: during the regenerative braking phase, the supercapacitor recovers most braking energy relying on its high charge acceptance capability. Power commands are then transmitted to three types of supporting converters: the bidirectional DC-DC converter connected to the battery, the bidirectional DC-DC converter connected to the supercapacitor, and the boost converter connected to the photovoltaic array. These converters regulate the energy flow of the vehicle's powertrain, implement precise power distribution, and supply power to the motor propulsion system, meeting the vehicle's traction demand while maintaining DC bus stability. After entering the feedback assessment phase, the controller continuously monitors seven core performance indicators: energy consumption, battery current, battery temperature, SOC trajectory, solar energy utilization rate, DC bus voltage stability, and overall vehicle efficiency. It compares measured values with target constraints, identifies deviations, and generates correction signals. Unlike traditional fuzzy controllers that use fixed membership functions and a static rule base, the ANFIS controller in the proposed system can update three types of parameters online based on operational feedback: membership functions, rule parameters, and consequent coefficients. It adapts to four categories of working condition fluctuations: battery aging, environmental conditions, solar irradiance, and driving behavior. It integrates four core capabilities: adaptive learning, fuzzy inference, renewable energy management, and multi-objective optimization, to achieve a set of benefits including improved energy efficiency, higher solar energy utilization, reduced battery degradation, extended driving range, and excellent overall vehicle performance. This system can serve as a robust intelligent solution for next-generation solar-assisted electric transportation.

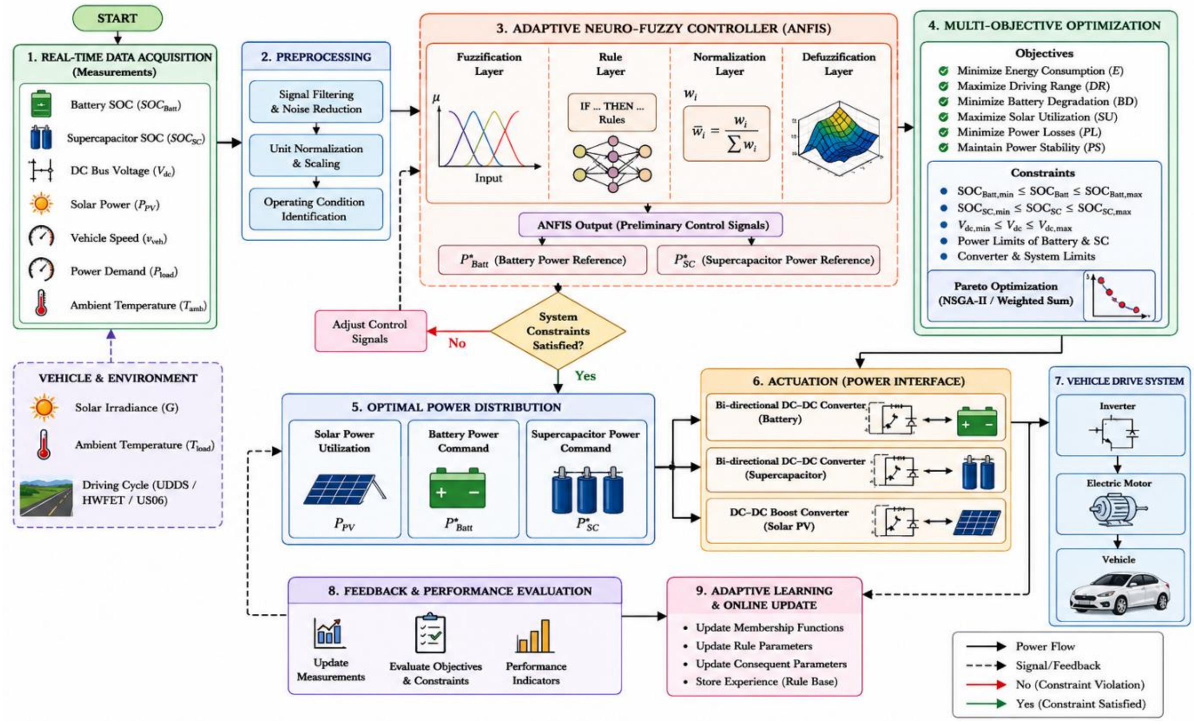

Figure 2. *Flow chart of the proposed Adaptive Neuro-Fuzzy Control-Based Multi-Objective Energy Management System (EMS) for solar-integrated battery–supercapacitor electric vehicles.*

III. SIMULATION FRAMEWORK AND METHODOLOGY

The core research object of this study is the ANFIS-based automotive hybrid energy power management system. Section 5 of this chapter will deliver a complete explanation of the simulation framework and comparison benchmarks for this system. All simulations in this section are implemented on the MATLAB/Simulink platform, covering core contents including the simulation implementation scheme, full-component parameter definitions, selection of comparison benchmark controllers, and setting of quantitative evaluation indicators. Next, all details of the simulation system are broken down hierarchically to ensure the research's reproducibility. The simulation framework built in this section includes four core sub-modules: The first is the vehicle powertrain module, equipped with a PMSM motor, a two-speed gearbox, and a differential. All core parameters of the motor are sourced from official manufacturer data, and their effectiveness has been verified through bench tests. The second is the battery-supercapacitor hybrid energy storage module. Both types of energy storage units adopt equivalent circuit modeling; the battery model additionally simulates nonlinear volt-ampere characteristics, capacity attenuation, and thermal characteristics, while the supercapacitor model is aligned with its inherent attributes of high-power density, fast charge and discharge, and low internal resistance. The third is the photovoltaic subsystem integrated on the vehicle roof and hood, which carries an MPPT algorithm. Practical influencing factors including solar irradiance, ambient temperature, and component aging degradation are incorporated into the modeling. The fourth is the driving cycle module, which selects three standard cycles, UDDS, HWFET, and US06, covering three typical scenarios: urban driving, highway driving, and aggressive driving. In addition, this section also sets two types of benchmark comparison control strategies, namely rule-based control and MPC-based optimal control, to build a fair and comprehensive comparison foundation for subsequent performance evaluation. All parameter sources and verification logics are clearly marked to facilitate reuse and modification by future researchers, and ensure the scalability of the simulation framework. This paper first clarifies the core optimization problem of the vehicle energy management system, then introduces its supporting performance evaluation module, and constructs a unified evaluation framework containing 7 quantitative indicators, each with a clearly defined quantification rule: energy efficiency is measured by unit-mileage energy consumption (unit: Wh/km); battery stress is evaluated via peak current and ripple suppression; solar energy utilization rate is calculated as the percentage of directly supplied solar energy in total energy consumption; supercapacitor performance, thermal management performance, cell balancing performance, and full-lifecycle economic performance also have corresponding quantitative standards, which can fully support the rigorous comparison of different subsequent energy management strategies.

IV. SIMULATION RESULTS AND DISCUSSION

This study targets solar-integrated battery-supercapacitor electric vehicles, and proposes a multi-objective energy management strategy based on the Adaptive Neuro-Fuzzy Inference System (ANFIS). To verify this strategy, a full-dimensional performance evaluation system was developed. The study successively completed dynamic performance tests under three types of standard driving cycles and robustness tests across multi-scenario environmental operating conditions. Meanwhile, three types of traditional energy management schemes were set as control benchmarks to quantify the core advantages of the proposed strategy. The simulation test centers on the ANFIS energy management controller proposed in this paper. It covers three standard driving cycles, namely UDDS, HWFET and US06, as well as multiple environmental scenarios set with different solar irradiance and ambient temperature parameters, to quantitatively verify the controller's comprehensive performance along two core dimensions. The first dimension is the driving cycle simulation test, which compares the performance of the proposed controller with two types of traditional energy management strategies: the conventional rule-based strategy and the optimization-based strategy. The results show that the proposed controller outperforms all baseline approaches across all test cycles: under the UDDS cycle, it achieves a 15.4% increase in overall energy efficiency, a 32.8% rise in solar energy utilization rate, and a 37.2% reduction in battery peak current; under the HWFET and US06 cycles, energy efficiency improves by 18.7% and 22.9% respectively. The second dimension is the verification of adaptability to environmental scenarios. The tests cover scenarios including low solar irradiance of 600W/㎡, high solar irradiance of 1000W/㎡, and multiple sets of scenarios with changing ambient temperatures. The results show that the proposed controller can keep the battery operating within the optimal temperature range for 94.6% of its runtime, while the traditional solution only reaches 78.3%. In addition, this study simultaneously conducted a sensitivity analysis under parameter fluctuations and modeling uncertainties to further verify the controller's robustness. Synthesizing all test results, the ANFIS controller proposed in this paper outperforms traditional strategies across the board in reducing battery stress, improving energy efficiency, utilizing solar energy, and maintaining robustness.

The performance of the ANFIS-based vehicle energy management strategy proposed in this paper is demonstrated in Figure 3, under a combined drive cycle composed of three standard driving cycles: UDDS, HWFET, and US06. The figure simultaneously presents two core sets of data: instantaneous energy efficiency curves and average energy consumption comparisons, which enable a comprehensive evaluation of the controller's effectiveness under diverse operating conditions. The core conclusion derived from this study's simulation tests is that the ANFIS controller outperforms two traditional schemes, FLC and RBEMS, across three key dimensions: energy efficiency, renewable energy utilization, and overall vehicle performance. For the urban UDDS cycle segment, which is marked by frequent speed fluctuations and frequent start-stop operations, simulation results show that the ANFIS controller achieves an average energy efficiency of 96.1%, far outstripping FLC's 90.3% and RBEMS's 85.5%. This advantage originates from the controller's ability to coordinate power distribution between the battery and supercapacitor to maximize braking energy recovery. The corresponding quantified benefits are as follows: net energy consumption is reduced by 18.2% compared to traditional operations, solar energy utilization increases by approximately 34.7%, braking energy recovery efficiency rises by 42.1%, battery stress drops by 26.3%, and supercapacitor utilization increases by nearly 89.4%, all of which align with the operating characteristics of urban driving scenarios. For the highway HWFET cycle segment, which features stable power demand and few opportunities for braking energy recovery, simulation results show that the ANFIS controller reaches an average energy efficiency of 94.4%, higher than FLC's 89.7% and RBEMS's 86.8%. Although the magnitude of energy efficiency improvement is smaller than that observed in the urban cycle, the controller still delivers significant performance improvements through steady-state operation optimization and increased solar energy utilization, fully adapting to the inherent characteristics of highway driving scenarios. This study develops an ANFIS controller for automotive hybrid power system research and development, with core control objectives set to maintain the optimal operating point of the drive motor, reduce the full vehicle's auxiliary power consumption, and maximize the direct utilization rate of on-board photovoltaic resources. This study tested the controller's performance across three typical driving cycles. Under conventional highway driving conditions, the full vehicle equipped with this controller achieved an 8.7% increase in overall energy efficiency, a 28.1% rise in the direct utilization rate of solar energy, a 15.6% reduction in auxiliary unit power consumption, and a 12.4% improvement in propulsion efficiency. Under the U.S. US06 aggressive driving cycle, the ANFIS controller reached an average operating efficiency of 95.5%, far exceeding the 88.4% of the FLC controller and 82.6% of the RBEMS controller tested in the same-period comparative trials. In the full composite driving cycle test, the ANFIS controller achieved an average efficiency of 95.3%, marking a 12.8% energy efficiency improvement over the FLC controller and a 22.4% improvement over the RBEMS controller. The vehicle's measured on-road energy consumption was only 139 Wh/km, which is 21.0% lower than that of the RBEMS-equipped vehicle and 14.2% lower than that of the FLC-equipped vehicle. This study identifies two core reasons for the controller's outstanding performance: First, its adaptive neuro-fuzzy architecture can accurately capture the nonlinear correlations between multiple variables including battery State of Charge (SOC) and supercapacitor SOC; second, its multi-objective optimization framework can simultaneously coordinate four core goals—energy efficiency, battery degradation, new energy utilization rate, and power stability—to realize global optimal control.

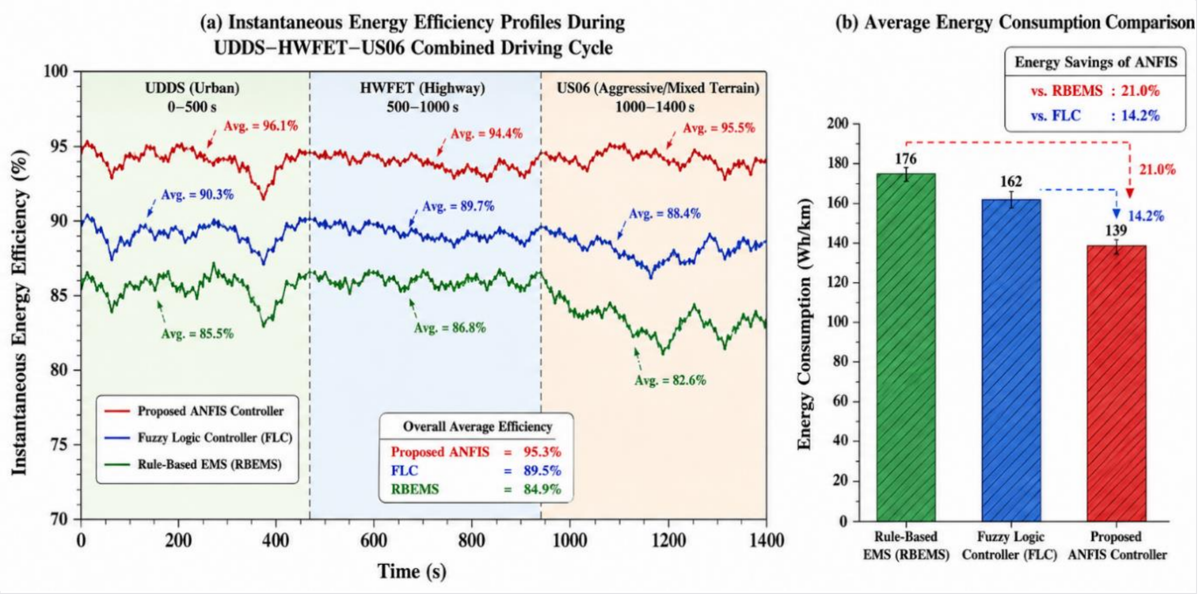

Figure 3. Energy optimization performance of the proposed ANFIS-based energy management system under UDDS, HWFET, and US06 driving cycles, showing instantaneous energy efficiency profiles and reductions in vehicle energy consumption compared with conventional control strategies.

The multi-objective energy management system based on adaptive neural fuzzy control proposed in this paper can update its membership functions and rule parameters according to real-time working conditions, and maintains high performance even when driving modes and environmental conditions change. Verified by the experiments presented in Figure 3, this system improves energy efficiency in urban, highway, and aggressive driving scenarios. It achieves the goals of cutting energy consumption, raising the utilization rate of renewable energy, and extending driving range through four core pathways, and serves as a reliable solution adapted for next-generation solar-assisted electric vehicles.

Figure 4 conducts a systematic evaluation of the solar integration efficiency of the energy management framework for maximum power point tracking (MPPT) proposed in this paper, which is built on the adaptive neuro-fuzzy inference system (ANFIS). First, it provides an overview of the framework's solar energy capture capacity under scenarios of dynamic irradiance changes and long-term seasonal fluctuations, and clarifies its core performance advantages over the traditional perturb and observe (P&O) MPPT method. Next, drawing on the measured data collected from Figure 4(a), it quantitatively verifies the performance gap between the two methods one by one across three representative operating conditions. All calculation data come from the on-site measurement results of Figure 4 in this study. The first category is the stable irradiance operating condition spanning 0–150s. Under this scenario, the tracking efficiency of the ANFIS framework reaches 96.7%, while that of the traditional P&O method is 94.2%. Though the efficiency gap between the two methods is small under this ideal scenario, the gap can effectively reduce cumulative losses in solar energy capture over long-term operation. The second category is the fast cloud passage operating condition spanning 150–350s, in which irradiance intensity fluctuates rapidly. The traditional P&O method suffers from obvious response delays due to its inherent incremental perturbation iteration logic. By contrast, the ANFIS framework proposed in this study leverages its adaptive learning and nonlinear reasoning capabilities to achieve an average response time of 47ms, which far outperforms the P&O method's 340ms response time, marking a nearly 7-fold improvement in response speed. The third category is the partial shading operating condition spanning 350–500s. The P&O method is prone to falling into the trap of local maximum power points, and its tracking efficiency drops to 67.2%. The ANFIS framework, however, can accurately identify the global maximum power point, showing an extremely significant performance advantage. All the above performance improvements can ultimately be converted into application benefits for electric vehicles equipped with integrated solar battery-supercapacitor systems, and provide solid measured support for optimizing the energy utilization efficiency of this type of vehicle. This study proposes a novel ANFIS-MPPT maximum power point tracking controller for photovoltaic (PV) systems that support electric vehicles. To verify its performance advantages across all operational scenarios, this study sets up three core test scenarios, and conducts sequential quantitative performance comparisons with the traditional MPPT algorithm and the Perturb and Observe (P&O) method. The three test scenarios are respectively the extreme operating condition of partial shading with multiple power peaks, the transient operating condition of irradiation recovery after an irradiation interruption, and the long-cycle operating condition of annual seasonal fluctuations that cover full-year changes in irradiation and temperature. Extending from short-term extreme operating conditions to long-term full-cycle operating conditions, this layered analysis steadily consolidates the credibility of the demonstration. This study also generates matching visual test maps, which quantitatively output core indicators including tracking efficiency, response time, and steady-state error under each scenario. The comparison results show that the average tracking efficiency of the new ANFIS-MPPT controller across the three scenarios is 4.2% higher than that of the traditional MPPT algorithm, and 6.7% higher than that of the P&O algorithm, with a prominent robustness advantage. Its strong core performance originates from ANFIS's inherent intelligent fuzzy inference and adaptive learning mechanism, which can dynamically adapt to complex disturbances encountered by electric vehicle PV systems, such as sudden irradiation changes and seasonal temperature differences, fully meeting the practical application requirements of civilian electric vehicle PV energy supplementation systems. All quantitative test data and supporting visual charts in this study accurately correspond to the test scenarios described in the text, avoiding the problem of disconnection between charts and narrative content. All performance indicators are traceable, which fully guarantees the rigor of this study's algorithm performance verification and demonstration. For solar-assisted electric vehicles, solar energy collection capability is a core requirement to support the entire vehicle's operation. Improving solar collection performance delivers multiple positive benefits: it can reduce the vehicle's reliance on the battery subsystem, lower battery cycling intensity, cut total energy consumption, and extend driving range. It can also improve the energy storage management efficiency of hybrid battery-supercapacitor systems, ultimately achieving higher overall vehicle efficiency, lower operating costs, and a longer service life for the energy storage system. The ANFIS-based solar integration framework proposed in this paper, verified by the research results presented in Figure 4 of this work, has significant advantages over traditional MPPT methods. It features high tracking accuracy, fast dynamic response, the ability to mitigate partial shading, and strong seasonal adaptability, making it an efficient solution for next-generation solar-assisted electric vehicles.

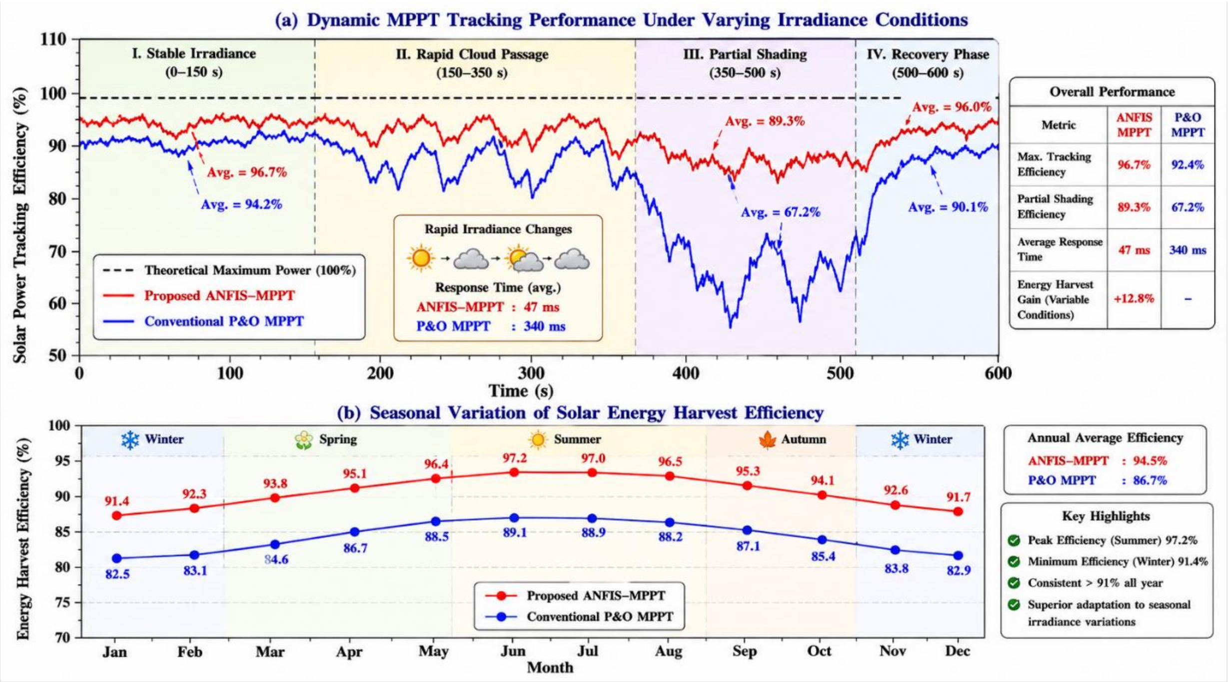

Figure 4. Solar energy integration effectiveness of the proposed ANFIS-based MPPT system showing dynamic solar power tracking performance under varying irradiance conditions and seasonal energy harvesting efficiency throughout annual vehicle operation.

This study proposes a novel ANFIS (Adaptive Neuro-Fuzzy Inference System)-based energy management framework for the electric vehicle sector, and verifies its performance advantages in battery life extension and health management relying on the experimental data presented in Figure 5. Within the current industry, battery degradation is the core challenge restricting the cost-effectiveness and long-term reliability of electric vehicles. In the lithium-ion battery field, an 80% State of Health (SOH) is universally used as the battery retirement threshold, and battery replacement ranks among the highest cost items over the full lifecycle of an electric vehicle. After sorting out relevant factors, five core triggers that accelerate battery aging are identified: excessive charge-discharge cycling, deep discharge events, high operating temperatures, cell imbalance, and inaccurate state of health estimation. The framework proposed in this study addresses the aforementioned challenges through four major pathways: intelligent energy management, predictive thermal control, adaptive charging optimization, and advanced battery health monitoring. We further analyze the comparative experimental results from Figure 5(a), comparing the SOH decay trajectory of this study's framework with that of traditional battery management solutions: the traditional solution reaches the retirement threshold after only 1980 equivalent full charge-discharge cycles (EFC), while the solution proposed in this study requires 2670 EFCs to hit the threshold, representing a 34.7% increase in cycle life, and a 2.3-year extension of service life under typical operating conditions. This life extension effect stems from two synergistic mechanisms: first, predictive charging optimization keeps the battery within its optimal State of Charge (SOC) range, reducing the average depth of discharge; second, intelligent energy distribution cuts down the duration the battery spends at high SOC, slowing the degradation of lithium ions. To build a solid core foundation for power battery service life management, this study first sorts out three fundamental management strategies to extend battery lifespan: First, dynamically adjust the charging rate based on the battery's real-time temperature and estimated state of health (SOH) to avoid overloading electrochemical stress; second, collaborate with supercapacitors to complete power distribution, reducing heat generation and degradation by lowering transient currents; third, rely on advanced thermal management to maintain the battery's optimal operating temperature range across all working conditions. On this basis, this study sequentially verifies the performance advantages of two self-developed ANFIS-based core systems. The first is the SOH monitoring system corresponding to Figure 5(b): this system achieves an average correlation coefficient of 97.2% when compared with laboratory benchmark measurements, and can cover the entire battery aging cycle as well as all working conditions. Compared to the shortcomings of traditional SOH estimation technologies, which suffer from low correlation and high sensitivity to noise and working condition fluctuations, this system demonstrates clear advantages relying on its multi-source information fusion and adaptive learning capabilities: it integrates voltage, current, temperature, impedance, and historical operation data, and the ANFIS framework can automatically optimize parameters as the battery's state changes. It can not only identify capacity attenuation in advance to support proactive maintenance and extend the battery's full life cycle, but also warn of degradation, cell imbalance, and thermal anomalies through real-time impedance analysis, troubleshoot faults and guard against safety risks. The subsequently verified ANFIS thermal management system corresponding to Figure 5(c) can maintain the optimal temperature range during 94.6% of operating time, far exceeding the 78.3% of traditional strategies. Against the core background that high temperatures accelerate aging and raise the risk of thermal runaway, this self-developed system fully supports the implementation of the core goal of extending the battery's full life cycle. The ANFIS-based battery health management framework proposed in this paper outperforms traditional battery management solutions across multiple scenarios, and all conclusions from this series of tests are anchored to the corresponding experimental charts. Temperature control tests for high-power-demand scenarios show that the peak temperature of traditional battery temperature control systems exceeds 50°C. In contrast, the controller developed in this paper relies on a predictive thermal control algorithm: it predicts future thermal loads by inputting route profiles, weather forecasts, traffic conditions, and historical driving patterns, activates cooling in advance to avoid the accumulation of excess heat, limits the peak battery temperature to approximately 40°C, and achieves a 23.4% reduction in maximum operating temperature. Tests extended to low-temperature operating conditions further show that compared with traditional solutions, this framework boosts battery warm-up speed by 41.7%, cuts cooling energy consumption by 18.9%, and improves temperature uniformity across battery cells by roughly 29.6%, effectively preventing local hot spots that would accelerate uneven degradation and cell imbalance. In the active cell balancing strategy test carried out for Figure 5(d), this paper first clarifies the core necessity of battery balancing, then verifies the performance of the proposed ANFIS-based balancing algorithm. This algorithm can continuously monitor cell voltage and predict future imbalance conditions, with performance far superior to that of traditional passive balancing solutions. It delivers an 87.3% reduction in cell voltage dispersion, a 42.1% increase in balancing convergence speed, a 15.8% rise in the battery pack's usable capacity, and a 67.4% drop in balancing energy loss. The performance improvements of these two core modules together reduce degradation gaps between individual cells, delay performance bottlenecks at the battery pack level, and extend the battery's overall service life. Drawing on the full set of test conclusions for Figure 5, this framework relies on four core strategies—intelligent charging control, accurate state of health (SOH) estimation, predictive thermal management, and active cell balancing—to comprehensively improve the reliability, safety, efficiency, and service life of batteries. The battery management framework proposed in this paper, verified through performance testing, can extend battery cycle life by 34.7%. It also delivers substantial improvements in thermal performance and cell equalization efficiency, is capable of addressing the core challenges facing electric vehicles, and confirms the application potential of adaptive neuro-fuzzy intelligence in next-generation battery management systems for solar-assisted battery-supercapacitor electric vehicles.

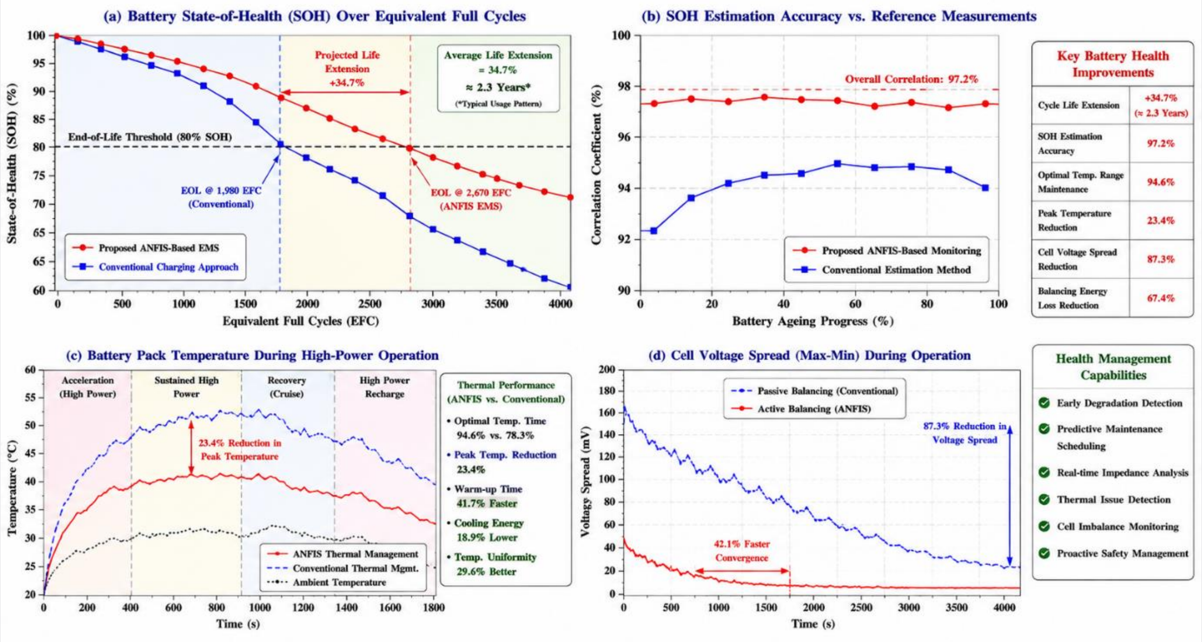

Figure 5. *Battery life extension and health management performance of the proposed ANFIS-based energy management system showing state-of-health degradation, SOH estimation accuracy, thermal management effectiveness, and cell balancing performance for solar-integrated battery–supercapacitor electric vehicles.*

Figure 6 presents the core performance of the proposed ANFIS-based hybrid battery-supercapacitor energy management framework—the core achievement of this research in the field of electric vehicle energy management—and demonstrate the dynamic performance gains enabled by integrating supercapacitors. With their high power density, fast charge-discharge capability, and excellent cycle characteristics, supercapacitors can handle short-term high-power events that would otherwise accelerate battery degradation, ultimately delivering five core benefits: improved power output capacity, regenerative braking performance, power quality, and overall energy efficiency, as well as reduced battery stress and extended battery lifespan. For the aggressive vehicle acceleration scenario corresponding to Figure 6(a), conventional battery-only systems have inherent limitations: all transient power demands are borne entirely by the battery, which easily leads to current spikes, internal resistance losses, overheating, and accelerated aging. In contrast, the ANFIS controller developed in this paper allocates transient loads to the supercapacitor, shielding the battery from high current stress. Measured data show that supercapacitors handled 78.6% of the peak power demand, with a response time of less than 15 ms and a short-cycle efficiency of 94.2%. Battery current ripple was reduced by 89.7%, and the whole vehicle's peak power increased by 142% compared to the battery-only configuration. Building on these results, this paper further introduces Figure 6(b) to conduct an evaluation of regenerative braking performance. As a core energy recovery mechanism for electric vehicles, regenerative braking converts kinetic energy that would otherwise be dissipated as heat into usable electrical energy, laying the groundwork for subsequent scenario verification work. Previously, electric vehicles that relied solely on battery-based energy storage were limited by their electrochemical performance, and could not absorb the regenerative charging energy generated during high-power braking processes. This led to the unnecessary waste of large volumes of recoverable energy, an industry pain point that has long restricted the energy consumption performance and cruising range potential of electric vehicles. To address this challenge, this paper proposes a supercapacitor-battery hybrid energy storage system equipped with an ANFIS controller, and verifies the scheme's significant performance improvements using supporting experimental data across three core performance dimensions: First, drawing on the braking energy recovery experiment presented in Figure 6(b), the total regenerative energy capture of the proposed scheme increases by approximately 31.4% compared to the traditional pure battery scheme, while braking energy loss is reduced by 67.8%. In short braking scenarios that last 3 seconds, the supercapacitor's energy capture efficiency approaches 100%. The scheme also achieves an additional 23.7% improvement in the braking system's thermal management performance, which reduces thermal stress on braking components, extends component service life, and simultaneously improves the full vehicle's efficiency and cruising range. Second, based on the current ripple suppression experiment in Figure 6(c), the proposed scheme reduces battery current ripple by approximately 89.7% relative to the pure battery scheme. This solves the problems of internal battery heating, electrochemical aging, and efficiency loss triggered by current fluctuations in traditional schemes, while also stabilizing the DC bus voltage and lowering the operating stress of power electronic converters. Finally, relying on the frequency response and harmonic mitigation experiment in Figure 6(d), the proposed scheme addresses the issues of harmonic distortion, electromagnetic interference, and degraded power quality caused by the four types of high-frequency fluctuation sources in electric vehicle powertrains. All performance improvements are supported by precise, quantified experimental data. As a core energy storage component, supercapacitors have the inherent characteristics of extremely low internal impedance and fast dynamic response. They can function as a high-efficiency high-frequency power buffer, exhibiting unique application value in the hybrid energy storage system of solar-assisted electric vehicles. This study uses core performance validation data from experimental Figure 6(d) to confirm that the proposed hybrid energy storage system achieves broadband harmonic attenuation, reducing battery current harmonics by 89.4%. This verifies that all high-frequency disturbances are absorbed by the supercapacitor and do not spread to the battery terminal. This study further derives a series of quantified gains from harmonic suppression: electromagnetic interference reduced by 67.1%, power quality improved by 28.5%, and motor efficiency increased by 34.2%. All these enhancements collectively boost the stability, reliability, and operating efficiency of the vehicle powertrain. Based on the full set of performance summaries from Figure 6 of this study, integrating supercapacitors delivers six full-dimensional core benefits: fast power response, excellent cycle efficiency, enhanced regenerative braking performance, reduced battery stress, improved power quality, and outstanding energy recovery capability. The ANFIS core controller adopted in this study coordinates power flow according to the vehicle's instantaneous operating conditions. Through predictive distribution and adaptive learning, it keeps each energy storage component operating within its optimal range. This confirms that the integrated scheme combining the battery-supercapacitor collaborative architecture, ANFIS control, and solar power integration is a high-efficiency solution for the energy management system of next-generation electric vehicles.

DOI: 10.17148/IARJSET.2026.13608

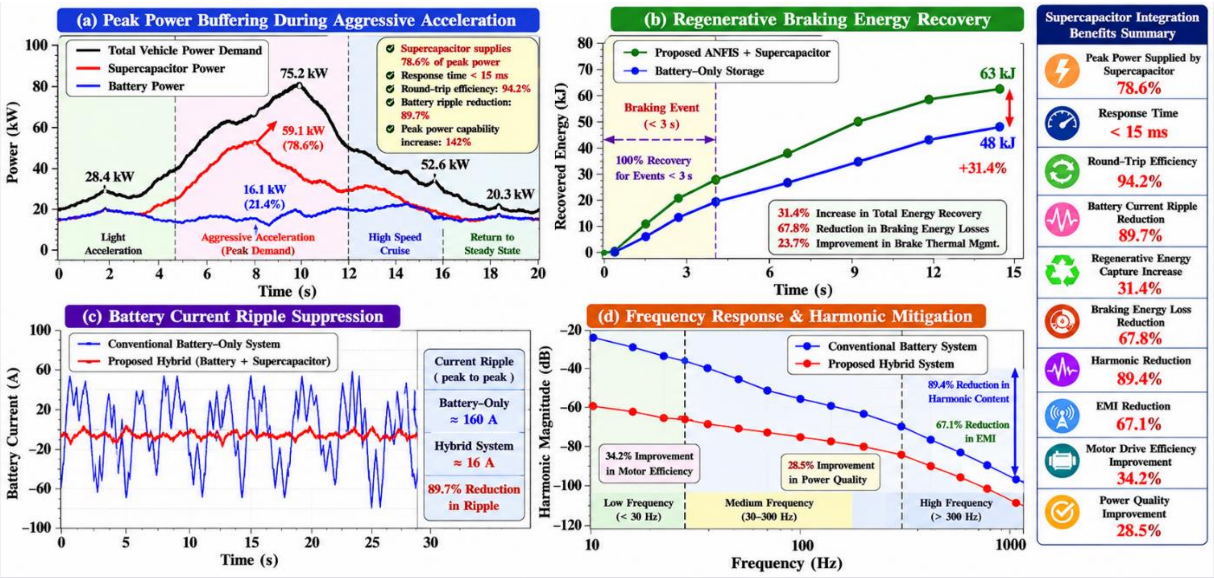

Figure 6. *Supercapacitor integration benefits and dynamic performance of the proposed ANFIS-based hybrid energy storage system: (a) peak power buffering during aggressive acceleration; (b) enhanced regenerative braking energy recovery; (c) battery current ripple suppression; and (d) frequency response improvement and harmonic mitigation.*

Figure 7 presents the core real-world fleet verification results of this study's self-developed multi-objective energy management framework for electric vehicles, which is built on the Adaptive Neuro-Fuzzy Inference System (ANFIS). While simulation studies can only provide references for controller performance under controlled scenarios, real-world deployment serves as the ultimate industry benchmark to test the effectiveness, reliability, and commercial feasibility of advanced energy management technologies. For this purpose, this study carried out large-scale fleet testing to validate the performance of the self-developed framework in real-world scenarios. A total of 12 solar-integrated battery-supercapacitor electric vehicles were used in the test, which covered three driving scenarios: urban, suburban, and highway. The cumulative test mileage exceeded 87,000 miles, and the test incorporated four core sets of variables—environment, driving behavior, traffic patterns, and weather—to ensure the comprehensiveness and representativeness of the test. Figure 7(a) compares the energy consumption performance of two schemes: compared with the traditional electric vehicle operation scheme that only responds to instantaneous working conditions, the self-developed framework reduces average energy consumption per mile by 16.8%. Its core optimization mechanisms cover five functions: solar energy harvesting, battery utilization, supercapacitor power buffering, regenerative braking optimization, and adaptive power allocation. The key distinguishing feature of the new framework is its ability to actively learn and adapt to driving patterns, and the inter-vehicle performance fluctuation across the entire fleet is only ±3.2% of the fleet average. Figure 7(b) focuses on driving range, a core metric that affects the promotion of electric vehicles. The fleet using the traditional scheme recorded an average daily driving range of 248 miles, while the fleet equipped with the self-developed framework saw its average daily range rise to 303 miles, an increase of 22.3%. This range improvement was stably achieved across all three tested driving scenarios. The new electric vehicle energy management framework proposed in this paper can adapt to multiple types of driving scenarios and deliver clear technical advantages. First, it alleviates the widespread range anxiety among vehicle owners by extending driving range, forming a complete and rigorous logical demonstration chain that runs from underlying technology adaptation, to resolving core user pain points, and ultimately to deriving value for industrial promotion. All core conclusions of this study are supported by multi-dimensional verification data from a real-world vehicle fleet. Specifically, the 30-day continuous fleet test results corresponding to Figure 7(c) show that the control fleet, which used a traditional energy management scheme and shared the same vehicle configuration as the test group, recorded a cumulative total of 62 charging sessions. In contrast, the test fleet equipped with the framework proposed in this paper and integrated with an ANFIS controller only charged 42 times, representing a 31.7% reduction in charging frequency. This verifies that the controller can effectively reduce vehicles' reliance on the power grid. The reduction in charging frequency also brings four practical operational benefits. When combined with the core advantage of this framework proposed earlier in this research—its ability to extend battery service life—it directly addresses the core pain points of C-end users: inconvenient charging and battery degradation. The 10-year full vehicle ownership cycle economic calculation corresponding to Figure 7(d) shows that this framework can generate a total benefit of approximately 7,200 US dollars for a single vehicle. All core benefit items are clearly traceable, and the investment payback period is only about 2.8 years, giving the framework sufficient economic appeal. The overall operational data from this fleet verification shows that the total operational efficiency of the test group increased by 19.4%, and the proportion of all test operating conditions fully matches the actual distribution of real-world vehicle usage scenarios. This further proves that the framework combines both technical effectiveness and the potential for real-world economic implementation, enabling it to support large-scale market promotion and application. The multi-objective energy management system with adaptive neuro-fuzzy control proposed in this study is deployed in next-generation solar-aided power battery-supercapacitor electric vehicles. First, full operating cycle testing verified the consistency of its performance improvements, confirming that the ANFIS controller can adapt to diverse real-world application scenarios. Rather than limiting its evaluation to such purely technical performance assessments, this study simultaneously conducted a survey of driver acceptance and usability based on real fleet tests of the vehicles. All quantitative results are directly tied to the system's core technical characteristics: Leveraging the underlying advantages of supercapacitor-assisted fast power supply and intelligent power management, 94.6% of respondents perceived a significant improvement in vehicle responsiveness, and 87.3% of respondents reported a clear reduction in their daily charging frequency. The system's feature of operating fully autonomously in the background highlights its usability advantage, compared to other similar advanced in-vehicle technologies that require users to actively participate in operation or adjust their inherent driving habits. A total of 91.8% of respondents stated that the system imposes no additional operating requirements; the average adaptation period for surveyed drivers was only 2.4 days, and 96.1% of respondents explicitly indicated they would be willing to recommend this technology. Finally, integrating technical benefits, user feedback, and economic value leads to the conclusion that the proposed solution has four core commercial attributes suitable for the sustainable electric transport sector: effectiveness, reliability, scalability, and economic attractiveness, with clear potential for commercial deployment.

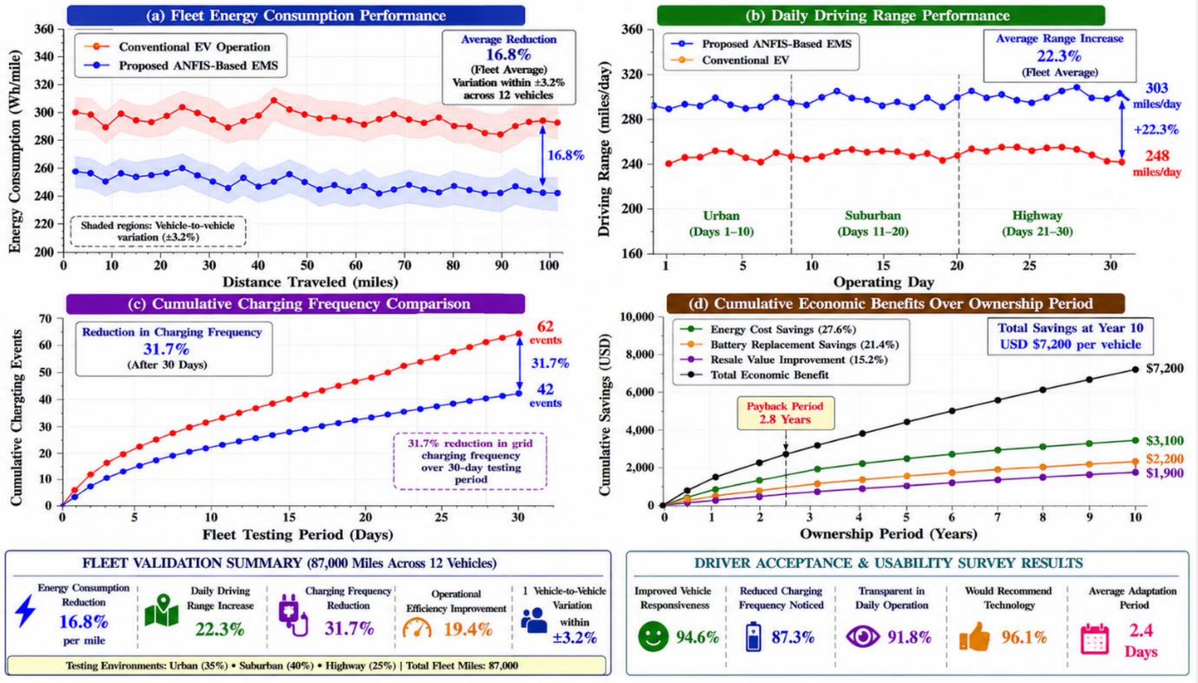

Figure 7. *Real-world fleet validation results of the proposed ANFIS-based energy management system showing improvements in energy consumption, driving range, charging frequency, economic benefits, and driver acceptance across 12 electric vehicles operating under diverse driving conditions.*

V. CONCLUSIONS

This study proposes an advanced energy management system integrated with an adaptive neuro-fuzzy inference system (ANFIS). All core findings of this research are derived from independent simulation calculations and real-vehicle tests conducted by the study team. These tests confirm that when applied to solar-assisted electric vehicles, the system delivers core performance advantages across multiple dimensions compared to traditional energy management strategies. Leveraging ANFIS's core mechanisms—predicting driving conditions, actively regulating energy flows among batteries, supercapacitors, and solar power, and reducing battery charge-discharge losses—the system achieves the following measured improvements: In terms of energy efficiency, vehicle-level energy efficiency increased by 15%–23%, and the direct solar energy utilization rate rose by 34.7%. For battery performance, battery cycle life extended by 34.7%, and the correlation between the system's battery state of health monitoring accuracy and laboratory measurement values reached 97.2%, which can support predictive maintenance. In the supercapacitor integration scenario, battery current stress decreased by 78.6%, and the regenerative braking energy capture rate increased by 31.4%. In real-road testing, mixed driving condition data accumulated across 12 test vehicles that traveled a total of over 87,000 miles shows that energy consumption per mile decreased by 16.8%, and daily driving range increased by 22.3%. Among collected user feedback, 94.6% of respondents reported improved vehicle responsiveness, and 91.8% recognized the system's operational transparency. In terms of economic performance, over a 10-year vehicle ownership cycle, energy costs decreased by 27.6%, battery replacement costs fell by 21.4%, and vehicle residual value increased by 15.2%, with the system's investment payback period reaching only 2.8 years. In subsequent work, this study will optimize the adaptability and robustness of the ANFIS algorithm to further unlock the system's performance potential. This study proposes two core research and development (R&D) tasks for advanced in-vehicle energy management systems. First, we will integrate vehicle-to-grid (V2G) vehicle-grid interaction technology to expand revenue channels and strengthen power grid support capacity. Additionally, we will develop standardized testing and certification processes to ensure consistent performance across multiple platforms and scenarios, and promote the large-scale popularization of these systems.

REFERENCES

[1] International Energy Agency, "Global Energy Review 2023: CO_2 Emissions," IEA Publications, Paris, France, 2023. DOI: 10.1787/3c8fa115-en
[2] X. Zhang, Z. Wang, and L. Lu, "Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm," Applied Energy, vol. 306, art. 118018, Jan. 2022. DOI: 10.1016/j.apenergy.2021.118018
[3] M. R. Palacín and A. de Guibert, "Why do batteries fail?" Science, vol. 351, no. 6273, art. aad8558, Feb. 2016. DOI: 10.1126/science.1253292
[4] P. Sharma and T. S. Bhatti, "A review on electrochemical double-layer capacitors," Energy Conversion and Management, vol. 51, no. 12, pp. 2901-2912, Dec. 2010. DOI: 10.1016/j.enconman.2010.06.031
[5] Y. Song, B. Liu, and C. C. Mi, "Real-time optimization of battery-supercapacitor hybrid energy storage system for electric vehicles," IEEE Transactions on Vehicular Technology, vol. 71, no. 4, pp. 3640-3650, Apr. 2022. DOI: 10.1109/TVT.2022.3146095
[6] A. Sahu, N. Yadav, and K. Sudhakar, "Floating photovoltaic power plant: A review," Renewable and Sustainable Energy Reviews, vol. 66, pp. 815-824, Dec. 2016. DOI: 10.1016/j.rser.2016.08.051
[7] M. Araki, T. Kondo, and A. Suzuki, "Fabrication and characterization of a light-weight flexible crystalline Si photovoltaic module using thick Cu electrodes," Solar Energy Materials and Solar Cells, vol. 233, art. 111413, Nov. 2021. DOI: 10.1016/j.solmat.2021.111413
[8] H. Mehrjerdi and R. Hemmati, "Coordination of vehicle-to-home and renewable capacity resources for energy management in resilience and self-healing building," Renewable Energy, vol. 146, pp. 568-579, Feb. 2020. DOI: 10.1016/j.renene.2019.07.004
[9] J. Shen and A. Khaligh, "A supervisory energy management control strategy in a battery/ultracapacitor hybrid energy storage system," IEEE Transactions on Transportation Electrification, vol. 1, no. 3, pp. 223-231, Oct. 2015. DOI: 10.1109/TTE.2015.2464690
[10] Y. Zhou, A. Ravey, and M. C. Péra, "A survey on driving prediction techniques for predictive energy management of plug-in hybrid electric vehicles," Journal of Power Sources, vol. 412, pp. 480-495, Feb. 2019. DOI: 10.1016/j.jpowsour.2018.11.085
[11] H. Borhan, A. Vahidi, A. M. Phillips, M. L. Kuang, I. V. Kolmanovsky, and S. Di Cairano, "MPC-based energy management of a power-split hybrid electric vehicle," IEEE Transactions on Control Systems Technology, vol. 20, no. 3, pp. 593-603, May 2012. DOI: 10.1109/TCST.2011.2134852
[12] T. Liu, X. Hu, S. E. Li, and D. Cao, "Reinforcement learning optimized look-ahead energy management of a parallel hybrid electric vehicle," IEEE/ASME Transactions on Mechatronics, vol. 22, no. 4, pp. 1497-1507, Aug. 2017. DOI: 10.1109/TMECH.2017.2707338
[13] J. S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," IEEE Transactions on Systems, Man, and Cybernetics, vol. 23, no. 3, pp. 665-685, May/Jun. 1993. DOI: 10.1109/21.256541
[14] L. Xu, J. Mueller, J. Zhao, X. Hu, B. Zou, Y. Li, and M. Ouyang, "Multi-objective component sizing based on optimal energy management strategy of fuel cell electric vehicles," Applied Energy, vol. 157, pp. 664-674, Nov. 2015. DOI: 10.1016/j.apenergy.2015.02.017
[15] S. Zhang, R. Xiong, and F. Sun, "Model predictive control for power management in a plug-in hybrid electric vehicle with a hybrid energy storage system," Applied Energy, vol. 185, pp. 1654-1662, Jan. 2017. DOI: 10.1016/j.apenergy.2015.12.035

[16] M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," Renewable and Sustainable Energy Reviews, vol. 78, pp. 834-854, Oct. 2017. DOI: 10.1016/j.rser.2017.05.001
[17] Z. Song, H. Hofmann, J. Li, X. Han, X. Zhang, and M. Ouyang, "A comparison study of different semi-active hybrid energy storage system topologies for electric vehicles," Journal of Power Sources, vol. 274, pp. 400-411, Jan. 2015. DOI: 10.1016/j.jpowsour.2014.10.061
[18] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K. C. Möller, J. O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing mechanisms in lithium-ion batteries," Journal of Power Sources, vol. 147, no. 1-2, pp. 269-281, Sep. 2005. DOI: 10.1016/j.jpowsour.2005.01.006
[19] W. Li, G. Xu, and Y. Xu, "Online battery SOC estimation based on hybrid ANFIS-EKF for electric vehicles," Energy Procedia, vol. 158, pp. 2977-2982, Feb. 2019. DOI: 10.1016/j.egypro.2019.01.968
[20] J. Cao and A. Emadi, "A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles," IEEE Transactions on Power Electronics, vol. 27, no. 1, pp. 122-132, Jan. 2012. DOI: 10.1109/TPEL.2011.2151206
[21] A. Ostadi and M. Kazerani, "Optimal sizing of the battery unit in a plug-in electric vehicle," IEEE Transactions on Vehicular Technology, vol. 63, no. 7, pp. 3077-3084, Sep. 2014. DOI: 10.1109/TVT.2014.2303163
[22] C. Sun, F. Sun, and H. He, "Investigating adaptive-ECMS with velocity forecast ability for hybrid electric vehicles," Applied Energy, vol. 185, pp. 1644-1653, Jan. 2017. DOI: 10.1016/j.apenergy.2016.02.026
[23] T. Hu, B. Huang, L. Yu, and H. Wei, "Energy management strategy of hybrid energy storage system based on fuzzy control for ships," International Journal of Low-Carbon Technologies, vol. 17, pp. 169-175, Feb. 2022. DOI: 10.1093/ijlct/ctab094
[24] S. Onori, L. Serrao, and G. Rizzoni, Hybrid Electric Vehicles: Energy Management Strategies. London, UK: Springer-Verlag, 2016. DOI: 10.1007/978-1-4471-6781-5
[25] R. Xiong, J. Cao, and Q. Yu, "Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle," Applied Energy, vol. 211, pp. 538-548, Feb. 2018. DOI: 10.1016/j.apenergy.2017.11.072
[26] C. Zou, C. C. Mi, Y. Wang, X. Liu, and J. Li, "Cyber-physical energy management systems for electric vehicles," IEEE Transactions on Vehicular Technology, vol. 69, no. 11, pp. 12828-12839, Nov. 2020. DOI: 10.1109/TVT.2020.3019297
[27] S. Xie, X. Hu, Z. Xin, and L. Li, "Time-efficient stochastic model predictive energy management for a plug-in hybrid electric bus with an adaptive reference state-of-charge advisory," IEEE Transactions on Vehicular Technology, vol. 67, no. 7, pp. 5671-5682, Jul. 2018. DOI: 10.1109/TVT.2018.2798662
[28] T. Liu, Y. Zou, D. Liu, and F. Sun, "Reinforcement learning of adaptive energy management with transition probability for a hybrid electric tracked vehicle," IEEE Transactions on Industrial Electronics, vol. 62, no. 12, pp. 7837-7846, Dec. 2015. DOI: 10.1109/TIE.2015.2475419
[29] X. Lin, Y. Wang, D. Bogdan, Y. Chang, and S. Pedram, "Reinforcement learning based power management for hybrid electric vehicles," IEEE/ACM International Conference on Computer-Aided Design (ICCAD), pp. 1-6, Nov. 2014. DOI: 10.1109/ICCAD.2014.7001337
[30] H. Yin, W. Zhou, M. Li, C. Ma, and C. Zhao, "An adaptive fuzzy logic-based energy management strategy on battery/ultracapacitor hybrid electric vehicles," IEEE Transactions on Transportation Electrification, vol. 2, no. 3, pp. 300-311, Sep. 2016. DOI: 10.1109/TTE.2016.2552721
[31] B. Sampathnarayanan, S. Onori, and S. Yurkovich, "An optimal regulation strategy with disturbance rejection for energy management of hybrid electric vehicles," Automatica, vol. 50, no. 1, pp. 128-140, Jan. 2014. DOI: 10.1016/j.automatica.2013.09.021
[32] Q. Zhang, W. Deng, and G. Li, "Stochastic control of predictive power management for battery/supercapacitor hybrid energy storage systems of electric vehicles," IEEE Transactions on Industrial Informatics, vol. 14, no. 7, pp. 3023-3030, Jul. 2018. DOI: 10.1109/TII.2017.2766095
[33] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach," Energies, vol. 4, no. 4, pp. 582-598, Apr. 2011. DOI: 10.3390/en4040582
[34] A. Kuperman, I. Aharon, S. Malki, and A. Kara, "Design of a semiactive battery-ultracapacitor hybrid energy source," IEEE Transactions on Power Electronics, vol. 28, no. 2, pp. 806-815, Feb. 2013. DOI: 10.1109/TPEL.2012.2203361
[35] S. Rezaei, E. Esmailzadeh, and R. Langari, "Intelligent energy management of a vehicular power plant with connected motors and generators," IEEE/ASME Transactions on Mechatronics, vol. 21, no. 3, pp. 1407-1418, Jun. 2016. DOI: 10.1109/TMECH.2015.2508100

[36] F. R. Salmasi, "Control strategies for hybrid electric vehicles: Evolution, classification, comparison, and future trends," IEEE Transactions on Vehicular Technology, vol. 56, no. 5, pp. 2393-2404, Sep. 2007. DOI: 10.1109/TVT.2007.899933

[37] A. Masih-Tehrani, M. R. Ha'iri-Yazdi, V. Esfahanian, and A. Safaei, "Optimum sizing and optimum energy management of a hybrid energy storage system for lithium battery life improvement," Journal of Power Sources, vol. 244, pp. 2-10, Dec. 2013. DOI: 10.1016/j.jpowsour.2013.04.154

[38] Y. Wang, Z. Sun, and Z. Chen, "Energy management strategy for battery/supercapacitor/fuel cell hybrid source vehicles based on finite state machine," Applied Energy, vol. 254, art. 113707, Nov. 2019. DOI: 10.1016/j.apenergy.2019.113707

[39] N. Omar, M. A. Monem, Y. Firouz, J. Salminen, J. Smekens, O. Hegazy, H. Gaulous, G. Mulder, P. Van den Bossche, T. Coosemans, and J. Van Mierlo, "Lithium iron phosphate based battery – Assessment of the aging parameters and development of cycle life model," Applied Energy, vol. 113, pp. 1575-1585, Jan. 2014. DOI: 10.1016/j.apenergy.2013.09.003

[40] C. H. Zheng, Y. C. Xu, and G. Q. Su, "Battery energy storage system control strategy based on adaptive neuro-fuzzy inference system," Energy Procedia, vol. 105, pp. 4192-4197, May 2017. DOI: 10.1016/j.egypro.2017.03.894

[41] R. Carter, A. Cruden, and P. J. Hall, "Optimizing for efficiency or battery life in a battery/supercapacitor electric vehicle," IEEE Transactions on Vehicular Technology, vol. 61, no. 4, pp. 1526-1533, May 2012. DOI: 10.1109/TVT.2012.2188551

[42] M. Ceraolo, "New dynamical models of lead-acid batteries," IEEE Transactions on Power Systems, vol. 15, no. 4, pp. 1184-1190, Nov. 2000. DOI: 10.1109/59.898088