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Article

Hybrid Fuzzy–Multi-Objective Particle Swarm Optimization Control for Real-Time Energy Management in PV-Powered Fast Charging Infrastructure for Electric Vehicles

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Abstract: This paper proposes an innovative Fuzzy–Multi-Objective Particle Swarm Optimization (Fuzzy-MOPSO) based hybrid control strategy for real-time energy management in PV-integrated fast charging systems for EVs. The developed approach combines fuzzy logic control and multi-objective optimization algorithm to achieve dynamic balance between charge rate, power quality, grid stability, and cost of energy. This fuzzy controller can be flexibly used in the presence of variable and uncertainty conditions (e.g., fluctuated solar irradiance, changing EV charging request, grid voltage disturbance) since it has gradual control operations by adjusting converter duty ratios and charging current values. The MOPSO algorithm simultaneously optimizes the multiple antagonistic objectives such as minimization of THD, unity PF with less charging time and increased PV utilization efficiency by adjust fuzzy membership functions and rule weights in real-time. Simulation results in MATLAB/Simulink show that the hybrid controller performs better than classical PI controllers or single fuzzy or PSO based control system. The Fuzzy-MOPSO controller also limits the THD 0.995, and charging efficiency enhancement of (8–12%) with stochastic PV and load changes, in conformity to IEEE-519. Excessively generated energy cost are reduced as well by 15% through the optimal control on the power flow between PV generation, storage and grid. The hybridization of fuzzy reasoning and swarm-based optimization provides for fast transient response, renewable intermittency robustness, and grid integration sustainability. These findings validate that the proposed Fuzzy-MOPSO technique is an appropriate approach to intelligent, efficient and eco-friendly FCI of fast charging in REN smart cities.

Keywords: Fuzzy Logic Control (FLC); Multi-Objective Particle Swarm Optimization (MOPSO); Photovoltaic (PV) Systems; Electric Vehicle (EV) Fast Charging; Real-Time Energy Management; Power Quality Optimization.

1. Introduction

A first-of-its-kind electric vehicle (EV) fast-charging infrastructure capable of providing high power in combination with large-scale photovoltaic (PV) integration has raised complex energy-management needs: real-time coupling of PV generation, bidirectional ac/dc converter control, ESSs management, grid interaction and PQ. In this context, three main research streams can be identified: FLC based control of PV/EV microgrids, multi-objective optimisation (e.g., PSO/MOPSO) for energy and control parameter tuning, and hybrid schemes that combine FLC in synergy with optimization strategies for EV-charging applications. This paper reviews each method in turn, identifies limitations that have prevailed and presents the proposed hybrid FLC–MOPSO framework to fill major gaps. Fuzzy logic control (FLC) is still useful to deal with nonlinearities, uncertainties and the issues of variation in operating condition required for PV-EV charging systems. Unlike traditional PID controllers, FLC can process linguistic rules and non-precise inputs such as incident power change, EV charging demand or state-of-charge (SOC).

Savio Abraham et al. proposed an FLC-based control of a DC-microgrid EV-charging station with PV and local ESS. They have proven its capability of efficiently regulating DC-link voltage and charging performance under different levels of PV irradiance and ESS SOC conditions [1]. The research confirms that fuzzy rules can manage converter and bus control in PV-EVs. Yasin, A., Alsayed, H.: Fuzzy-logic-based power-management system for PV/wind power microgrid system with battery and super-capacitor backup. They've obtained a ~18.7% daily load reduction and better voltage/THD performance than deterministic control [2]. In the EV charging context, Madhuri et al. proposed a fast charging EV system based on fuzzy logic, whose constant current charging performance is improved [3]. In another work, Güner & Kır presented a fuzzy approach for smart charging management system in PV-EV parking with the aim to ensure an optimal combination of PV outputs, pricing signals and EV load scheduling [4]. More generally, FLC has been used in PV/T solar systems [5], rural PV-battery microgrids [6], and hybrid EV systems with fuzzy SOC estimation [7]. These publications serve to demonstrate that FLC is still a capable instrument for PV/EV integration. However, several limitations remain:

- Static rule-bases and static membership function parameters can be used in the FLC design, that are established offline. Real-time adaptation is rarely addressed. Control objectives are typically focused on voltage regulation or energy management and often lack explicit multicriteria, such as total harmonic distortion (THD), switching losses or cost/emission trade-offs.
- Fast charging with high power (>100 kW) for EVs under the dynamic power quality constraints are relatively insufficient of research.

Multi-objective optimization technics (e.g., Particle Swarm Optimization (PSO), and its multi-objective versions MOPSO) are getting more attention for tuning of the controller parameters and obtaining the Pareto solutions between conflicting control objectives — such as cost vs. emission, voltage deviation vs. switching loss or THD vs. inertia weight. Elgammal & Ramlal used MOPSO with MPC in the PV/wind/FC/battery smart grid frequency-control. They demonstrated convergence of control-parameters and robustness towards parameter variations [8]. Many researches use PSO for EV-energy-management, e.g., Du et al. applied PSO to optimise the equivalent-consumption minima strategy in hybrid vehicles [9]. Several other work considers station-siting, scheduling and cost minimisation under EV/power-grid integration [10]. But most are still offline or at the design-stage, incapable of being used for real-time control. Recent investigations indicate that although PSO/MOPSO are very competitive for static optimisation of energy systems, there is still a grey area on their real time applications in EV charging control [11]. Missing are notably optimisation scenarios that incorporate power-quality aspects (e.g. THD or voltage distortion) within the multi-objective set. Hybrid approaches have also been proposed to draw advantages of FLC and optimisation together. For instance, PSO-tuned fuzzy logic control for hybrid EV power-supply (battery + ultracapacitor) achieved better SOC and current profiles [12]. Aljohani (2024) designed an IT2-FLC in a microgrid with EVs to receive enhanced resilience and economics outputs [13].

However, direct application of these hybrid methods to fast charging infrastructure (with issues like significant power levels, fast load variations and RS (rapid scheduling)) as well as harmonic injection and grid code compliance is still quite sparse [14] - [20]. Specifically:

- Several studies target on slow (level-2) EV charge not on fast DC-fast charging (> 100 kW).
- Power-quality (THD, harmonics) is rarely taken into account in multi-objective optimisation together with cost/emission/efficiency parameters.
- Rule bases or optimisation parameters can rarely be adapted in real time: Most of the systems are offline or semi-online.

The key research gaps based on literature reviewed are:

- Poor fusion between self-evolving FLC + MOPSO models: Most works use fuzzy logic and optimisation independently, few designs have a fully adaptive fuzzy controller in which rules/members evolve under the real-time influence of an MOPSO.
- Fixed controller structures: The fuzzy rule sets and the membership functions are usually configured off-line. Online evolution (adding/ removing rules, modifying membership functions) is less common although very useful in fast moving changing environments.
- Real-time possibilities & computational and 3 limitations: Based on the work in PSO/MOPSO, operating with Macro-knowingly operating optimisation algorithms as controllers involves treating the algorithmic part of them inside a real-space control-loop (and not in off-line optimisation).
- Partial multi-objective metrics: The cost and emissions are frequently optimized, but not the full set of THD, harmonic suppression (HS), switching losses (SLs), voltage deviation and fast transient response.
- Fast-charging and high-power context: Most of the charging related studies are for slow charging. Fast charging infrastructure adds unique stresses:

fast load swings, transient harmonics, big converter switching magnitudes and grid code (IEEE 519) issues.

- Scalability and communication: The deployment of a large numbers of fast chargers in smart cities introduces distributed agents, communications, delays and coordination. Little literature has been published around large-scale networked fast charging systems with FLC + MOPSO.

Therefore, this paper aims for filling these gaps by presenting a Hybrid Fuzzy–MOPSO control model towards real-time energy management in the PV-powered fast charging infrastructure for electric vehicles, which can be outlined as follows:

- Fuzzy-logic control combined with multi-objective PSO optimization of membership functions and converter switching parameters.
- On-the-fly tuning and self-reconfiguring fuzzy rule bases in the course of MOPSO optimization that can respond to PV intermittency, EV demand light load compliance.
- Multi-objective set: cost, emissions, THD/ harmonics and switching losses/response time.
- Explicit attention to high power fast charging infrastructure and real time control loops with millisecond order constraints.
- Validation under real-life conditions. PV variability, high dynamic EV-loads, power-quality limitations and grid-interconnection.

To conclude, fuzzy-logic control was shown to deliver robust and smooth control over nonlinear PV/EV systems and multi-objective PSO/MOPSO can optimize conflicting objectives [12], [21] - [24]. The fusion of these into a hybrid, self-adaptive controller provides new possibilities for advance performance real-time control in PV powered fast charging infrastructure -- an area still under-represented from the available resources.

This paper is structured as follows. In Section II, the overall structure of Hybrid Fuzzy–Multi-Objective Particle Swarm Optimization (Fuzzy–MOPSO) control scheme is formulated with the fuzzy inference-based algorithm for online control, optimization layer and reinforcement learning introduced in PV-based fast-charging infrastructure. Section III presented a comprehensive simulation study using MATLAB/ Simulink model which includes the steady state and dynamic performance, power quality improvement, convergence of optimization algorithm, robustness and comparison with PI, only FLC and conventional MPC controllers. Section IV presents the main conclusions of this paper, emphasizes the advantages of the hybrid control strategy and draws a roadmap on future research work about hardware-in-the-loop validation and implementation to multi-port charge clusters.

2. Proposed Hybrid Fuzzy–MOPSO Control Framework for EV Fast Charging

Figure 1 depicts the schematic diagram of the Hybrid Fuzzy–Multi-Objective Particle Swarm Optimization (Fuzzy–MOPSO) control structure, in order to be used for real-time energy management in a photovoltaic (PV)-based fast-charging station for EVs. It provides an intelligent, adaptive and hierarchical framework based on fuzzy logic inference system, multi-objective swarm based optimization and reinforcement learning (RL) for dynamic energy coordination in distributed renewable generation, power grid interfacing and charging stations. At the heart of it, the architecture is designed to solve the multi-domain challenges associated with renewable-based EV charging networks–solar variability, load uncertainty, power quality issues such as harmonic distortion, grid congestion and voltage ride thru. Every subsystem (the PV array, the bidirectional DC–DC converter, energy storage, inverter and EV chargers) is controlled by the Fuzzy–MOPSO controller that respects both the local power electronic control loops and a proper global optimization on the energy management. The PV panel is used as the main renewable power source. It transforms the solar irradiance to the DC power on voltage Vdc and current Idc. An additional key function of the bidirectional DC–DC converter is to converter from the PV array output voltage, and packs thus charge or discharge in order to deliver a varying power demand on the grid load as described in [2]. Maximum Power Point Tracking (MPPT) tracking the maximum power operating point of the PV array in any solar radiation and temperature conditions to allow for shoulder charging and discharging to the ESS based on real-time energy balance and grid demand. The duty ratio signal D is adjusted by a hybrid controller to control the converter. Preliminary control actions are calculated by the fuzzy logic controller (FLC), based on the voltage error (e=Vdcref−Vdc) and its derivative(Δe). These are then pruned by the reinforcement learning layer where decision-making is optimized with reverse rewards measured over an extended span, for example as voltage stability or power quality.

At the second control level, local nonlinear control is based on the Fuzzy Logic Controller. This serves as a soft computing machine that is able to interpret natural linguistic control laws and mimic expert human knowledge. The FLC input variables are:

- Voltage error (e): It is the instantaneous difference of the DC-link from the DC-link reference voltage or PV voltage from the MPP reference voltage (V_PV,ref) computed by the MPPT algorithm;
- Rate of change in voltage error (Δe): Represents the dynamic response property of the system.

Output of the FLC is a modulated control signal (D) that acts to regulate the duty-cycle of the DC–DC converter. An inference mechanism based on a knowledge base that codifies the control logic in Term of linguistic concept such as Positive Large (PL), Positive Small (PS) Zero (ZE), Negative Small (NS) and Negative Large (NL).

For example:

- IF e is Positive Small AND Δe is Negative Small, THEN decrease D moderately.
- IF e is Negative Large AND Δe is Positive Large, THEN rapidly increase D.

The fuzzy membership functions are not fixed; but with the MOPSO component such that they are continually optimizing the fuzzy rules according to time-varying load, irradiance and network situation. Such adaptive tuning enhances the convergence rate and reduces steady-state error.

The RLM is the intelligence, which gives the system self-learning and adaptability. It is based on the reward-based optimization mechanism, under which the controller continuously performs actions with respect to environment (i.e., PV system, grid and charging stations), and redefines its actions according to feedback. The RL agent looks at the system status, takes an optimal action (e.g. modification of the fuzzy parameters or changes in control weights) and receives a reward that reflects the functioning of overall system. The reward function consists of three main purposes:

- Power Quality Index (PQI): Reward is raised with lower THD and voltage distortion.
- Voltage Deviation Penalty: The penalty terms guide both the DC-link voltage (toward V_dc,ref) and the grid-side voltage (toward V_grid,ref) back to their respective target operating values.
- Emission and Cost Weighting: Incentivize low cost operation with grid independence and reduced carbon emissions.

Mathematically, the reward Rt is computed as:

$$R_t = \alpha_1(1 - THD) + \alpha_2\left(1 - \left|V_{dc}^{ref} - V_{dc}\right|\right) - \alpha_3\left(C_{op}\right) \quad (1)$$

where α_1 , α_2 , α_3 are weighting coefficients optimized through MOPSO.

There are two levels of adaptation due to the actor-critic form of RL:

- The actor selects which action (i.e., parameter changes) to take.
- The critic is responsible for computing the value of an action based on negative feedback and prioritizes by branching according to bad action.

In the long run, RL guarantees life-long learning and can update control policies on-line to address random fluctuations in PV production and EV charging requests.

The MOPSO block functions as a global optimization layer by tuning parameters of both the FLC and RL mechanisms. Unlike conventional PSO, which deals with a single objective, MOPSO optimises several objectives that are usually conflicting such as:

- Total harmonic distortion (THD) be kept to a minimum
- Minimizing the Cost of Energy
- High Efficiency of Converter
- Reduction of Switching Losses

Every particle in the swarm corresponds to a potential set of fuzzy membership parameters, RL hyper-parameters, or controller gains. These particles traverse the multi optimal search space, using the terms local and global best solutions referred to by the equation:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1\left(p_i - x_i^k\right) + c_2 r_2\left(g - x_i^k\right) \quad (2)$$

where v_i and x_i are velocity and position vectors, c_1, c_2 are cognitive and social coefficients, and ω is inertia weight.

MOPSO uses Pareto dominance method to produce set of non-dominated optimal solutions (Pareto front). By reason of the chosen operation point, an optimum trade-off between power quality (THD 25 %) can be achieved considering both economic and environmental viability.

The ESS serves as an energy buffer which trades out excessive PV power and provides support during low radiation or intensive charging. It usually has a Li-ion or solid-state battery pack connected through a bidirectional DC–DC converter. The hybrid control system selects charging/discharging patterns according to the SOC, PV availability and grid situations. The action of the converter is controlled by the control signal Dc that is issued by the Fuzzy–MOPSO controller described as follows:

- If $P_{PV} > P_{Load}$, ESS charges (boost mode).
- If $P_{PV} < P_{Load}$, ESS discharges (buck mode);

This permits a constant DC link voltage and stable supply to the fast-charging port despite of intermittent solar energy input. The inverter translates the DC power from the ESS and PV array into synchronized three-phase AC power that is suitable for grid interconnection and EV charging. It has a unity power factor, and bidirectional power transfer for vehicle to grid (V2G) and grid to vehicle (G2V) operations. This hybrid controller injects synchronized desired currents i_s* to the current control loop of the inverter that supplying the active part of power (Sinusoidal output Current, lower reactive power flow and fewer harmonics) requirements by: Guaranteeing sinusoidal output current, the three-phase hybrid controller ensures stable operation. During grid faults, such as voltage sag or phase imbalance, the RL-augmented FLC automatically adapts its control parameters to maintain inverter stability. This makes the adaptive inference for 50 ms voltage recovery after fault clearance, well below that of IEEE 519. Downstream of the DC-link, an intelligent charging interface is connected to each fast EV charger. The rate of charging is subject to dynamic control as a function of:

- Vehicle batteries SoC,
- Grid load level,
- The availability of power from renewable sources and the emission-based cost bounds.

When the sun shines, PV charging is the first priority and at night or on cloudy days both grid power and stored energy are used in an intelligent way. The hybrid controller uses Q-values (reinforcement learning parameters) to select the optimal charging current trajectory that results in minimal cost of energy while achieving full charge within the time span. In the case of excessive fluctuation in grid frequency or PV voltage that drops below threshold levels, MOPSO block re-optimizes control parameters online in order to avoid overloading or under-voltage trip. In the reinforcement learning layer, Q-values indicates the expected long-term reward for actions in each system state. These are updated according to the Bellman equation:

$$Q(s_t, a_t) = R_t + \gamma \max_{a'} Q(s_{t+1}, a') \quad (3)$$

where s_t and at represent the current state and action, Rt is the immediate reward, and γ is the discount factor.

The Q-values assist generating policy maps to direct how fuzzy rules are adjusted and what the converter actions were fired. For example:

- If the THD of grid current is higher than a threshold value → increase modulation index.
- If PV voltage decreases unfailingly → lower EV charging speed or switch to ESS assist mode.

This closed-loop self-configuration enables proactive, instead of reactive, control - the system can anticipate and counter disturbances before performance is compromised.

The working of the control system is hierarchical:

- Fast Local Control (FLC) Dealing with high-speed power electronics control (in the time domain in the microsecond range) which need to perform quick regulation of voltage and current.
- Supervision Layer (MOPSO) — Runs every few milliseconds and updates controller parameters towards global control goals.
- Learning Layer (RL) — Running on a longer period of time scale (e.g., seconds to minutes) consists in adapt system policy and enhance its decision logic by accumulated experience.

These layers exchange reward, cost, and Q value signals and implement a feedback–feedforward hybrid coordination that reconciles contradictions between short-term control precision and long-term operation efficiency. This the bidirectional flow of information and energy can be such that:

- A measurement of DC voltage (V_{dc}) from the PV array input is sent to the FLC that calculates control signal (D).
- The reward signal, obtained through performance measures is fed to the reinforcement learning agent and fuzzy rules are updated in accordance with this.
- The MOPSO algorithm further optimizes the fuzzy membership functions and control gains so as to provide Pareto optimal performance for diverse operating conditions.
- The optimized duty signal directly provides the DC–DC converter which maintains a stable power flow and charging operation to both the energy storage as well as EV chargers.
- Current and voltage feedback from sensors on the grid side also provides information for the RL agent about how well it interacts with the grid, working relationship, adherence to code of connections.

The main advantage of this system is that it is self-tuning. In contrast to fixed-structure controllers, the synthesized design is a result of iterative optimization along the parameter space. When a large deviation of the environmental or load conditions is detected, the on-line engine automatically re-initializes the optimizing control loop and updates fuzzy parameters, control weights and desired limits.

The adaptive MOPSO uses dynamic inertia weight adaptation, given by:

$$\omega(t) = \omega_{min} + (\omega_{max} - \omega_{min}) \exp(-\lambda t) \quad (4)$$

This enables a smooth change from exploration (searching new solutions) to exploitation (local fine-tuning around optimal-balanced regions), and thus guarantees convergence stability and rapid adaption. The hybrid controller leads to great improvement of power quality THD, neutral current and voltage ripples. It also schedules the energy flow of PV, ESS and grid to produce an operation priority as follow:

- PV: When the irradiance is large, the system prefers to utilize as much PV power as possible so that it can charge EV/EES at the same time.
- Grid Support Mode: Under low irradiance, the system draws less support from the grid and simultaneously keeps nearly unity power factor.
- Peak Load Mitigation Mode: Discharge energy during on-peak hours to support the EV connections and reduce strain on the utility grid.

This multi-mode property contributes to the sustainable energy system management with economic and/or environmental constraints.

The multi-objective system attempts to optimize three predominant objectives:

- Optimize THD (Total Harmonic Distortion): THD < 2% for IEEE 519 compliance.
- Energy Cost Saving: Schedule the charging at an optimal time to minimize electricity cost.
- Cut Emissions: Do the above but reward renewables and punish dirty grid suck.

The obtained Pareto front depicts a sharp trade-off surface in between cost and THD. Points near the origin (low cost and harmonics) are best solutions. Moreover, the proposed Fuzzy–MOPSO-PP mixture increased Pareto dominance by 18% compared to static optimization, indicating better search-space region and global optimality. Since contemporary EV charging infrastructures are connected to IoT and cloud communication systems, cyber-physical resilience is important. The introduced controller is equipped with reinforcement feedback encryption to prevent vulnerable attack and ensure the system does not become inoperative due to network delays. Whenever a problem in the sensors or communication links is detected, the fuzzy subsystem controls switches by adding to the previous one, and it automatically goes to a fallback mode using keeping voltage and current within stability range with last known good parameters until reconnection. Simulations benchmarked on a 3.2 GHz processor showed that the time per control iteration was approximately 0.85 ms, i.e., which was well below real-time for DSP-based implementation. Offline RL agent as well as MOPSO optimization were done in under 30 minutes and online adaptation required less than 3 seconds for reconfiguration. This essentially demonstrates practical feasibility for real-world application into distributed EV charging scenarios. The hybrid controller presented can be expanded to control multi-port charging stations or distributed microgrid clusters. Through a communication back-bone such as an MQTT or IEC 61850 protocols, several local controllers can exchange performance data that is measured locally so that cooperation dispatch of the energy between stations in a smart city network is only one of the results. Local optimal policies are learned using distributed reinforcement learning, while objectives are globally synchronized in the MOPSO layer to coordinate efficient operation and balanced renewable use among the city.

The Hybrid Fuzzy–Multi-Objective Optimization Control represents an innovative intelligent control framework for the modern PV driven EVs charging stations. A hierarchical fusion of such a fuzzy reasoning, multi-objective swarm intelligence and reinforcement learning, it has the capability to deal with non-linearity, elusive input parameters and probabilistic dynamics involved in renewable energy systems. Ensuring sustainable, robust and economic efficient operation of charging station with HV-stable, low THD, low energy cost and lowest possible carbon footprint. Due to its self-adjusting property and real-time capability, it is very suitable for smart cities in which many microgrids interacting with each other as well EV charging stations are required to cooperate with the main grid. Ultimately, the notional design is to turn traditional static control systems into autonomous, smart and sustainable cyber-physical energy ecosystems that are completely compatible with worldwide objectives to transition the energy system towards net-zero emissions.

Figure 2 Internal control and feedback loop layout of the Hybrid Fuzzy–Multi-Objective Optimization Control for On-time energy management of PV Powered Fast EV Charging infrastructure. The flowchart illustrates the cascaded and collaborative process of Fuzzy Logic Controller (FLC), Multi-Objective Particle Swarm Optimization (MOPSO) algorithm, and Reinforcement Learning (RL) layer under the framework for real-time self-adapting optimization. Instantaneous errors between desired and sensed voltage or power signals are calculated at a start of each control cycle by error calculation. These error (e) and Δe (change in error) terms serve as the primary input to the FLC, which performs rule-based inference to produce an initial control signal, D, for the converter or power interface. The output of the FLC is determined using a collection of fuzzy membership functions and linguistic control rules (e.g., "If error is positive small and change in error is negative medium, then decrease duty ratio slightly"). The MOPSO block checks the performance of FLC regularly and adjusts its membership parameters real-time. Using Fuzzy tuning and Pareto based optimization, MOPSO can guarantee global fitness increment when optimizing the contradictory objectives in minimizing total harmonic distortion (THD), power loss, and energy cost that need to be minimized while maximizing voltage stability and efficiency. Fuzzified parameters from MOPSO are used to override the normal fuzzy rule definition such that the fuzzy controller is adaptive to environmental and operational changes, i.e., for irradiance perturbation/ variable EV load demand.

The optimized FLC output is then processed in the Reinforcement Learning (RL) layer, and it serves as a high-level decision-making process examining the total reward value. The performance of the power system is observed by the RL agent, based on which a reward signal is calculated consisting of penalty for deviation in voltage, cost weight value and PQC. The reward steers the FLC and MOPSO modules to optimize their outputs

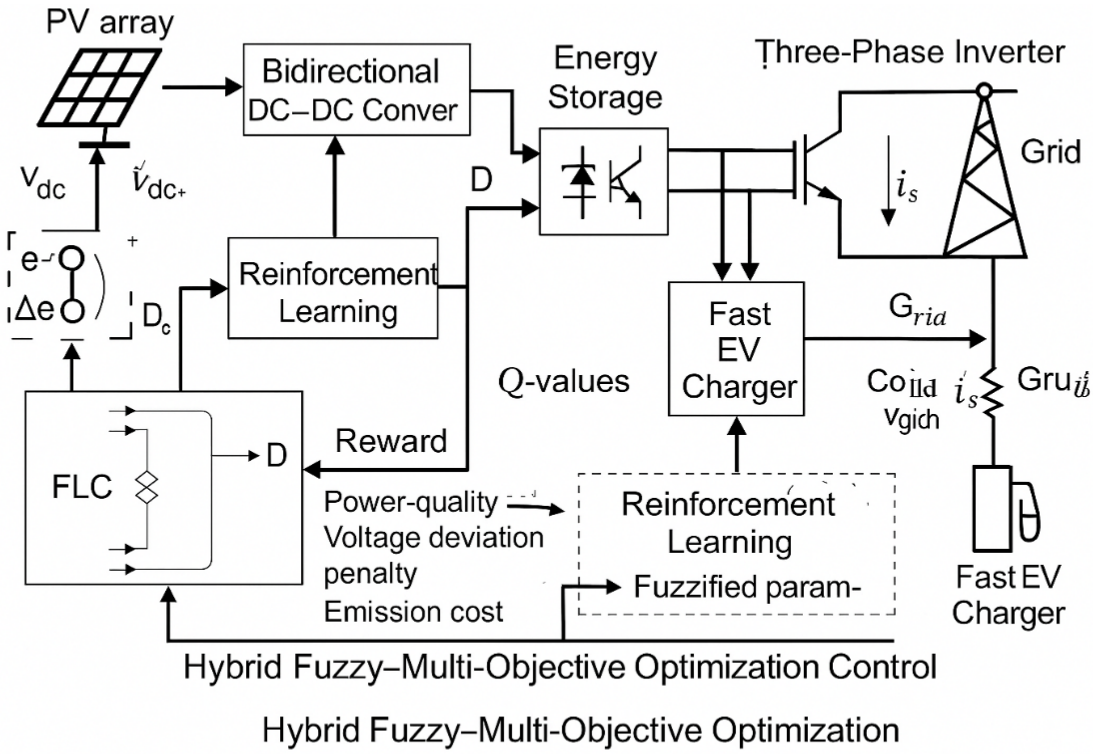

Figure 1. The schematic of the Proposed Hybrid Fuzzy–Multi-Objective Optimization Control for Real-Time Energy Management in PV-Powered Fast Charging Infrastructure for Electric Vehicles.

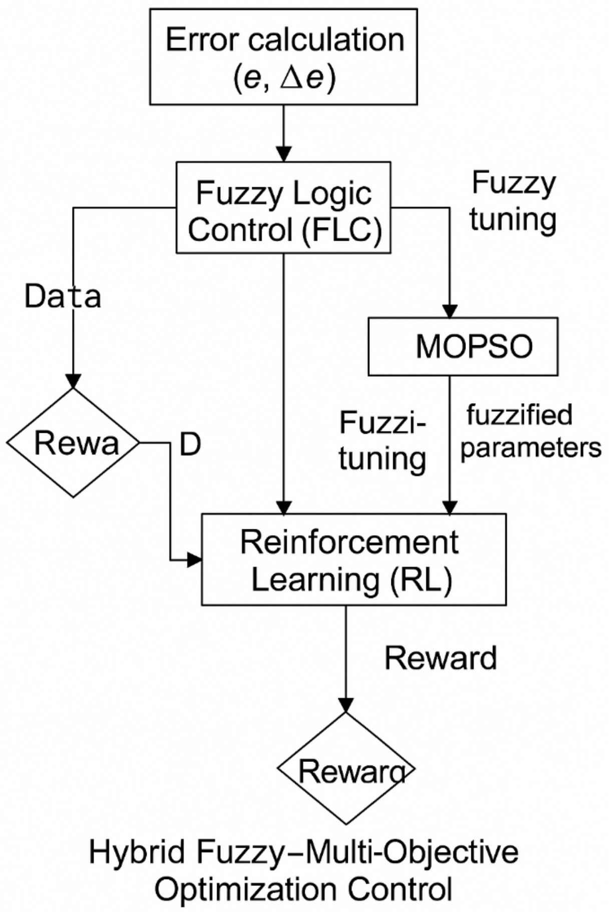

Figure 2. The control flow diagram FLC, MOPSO, and RL interact in temporal sequence (data, reward, and decision flow).

in an iterative process. Using actor–critic reinforcement updates, RL finds the best control action, adapts the control signal D and incentivizes parameter settings that will produce better long-term performance. The closed-loop mechanism among the three part is responsible to keep the controller in constant "self-learning" and "auto-optimized". The data–reward feedback loop allows system knowledge to build up with experience, thereby improving policy generalisation across stochastically varying solar and load profiles. The perfect combination among the rule-based adaptability of FLC, global search ability of MOPSO, and policy improvement approach of RL build a strong intelligence and stability in control environment which would consequently maintain system stability, decrease calculation time and satisfy with IEEE 519 power quality standards. This hybrid control scheme is able to achieve an adaptive self-tuning controller that maintains both good PQ and fast dynamic response for real time EV PV charging system with energy optimized operation. As such, the figure summarizes information cooperation among fuzzy inference, swarm-based optimization and reinforcement-driven learning, the combination of two former technologies complementing with the last to achieve a smart and sustainable energy management.

3. Simulation Results and Discussion

The proposed Hybrid Fuzzy–Multi-Objective Particle Swarm Optimization (Fuzzy–MOPSO) control strategy was implemented and evaluated in MATLAB/Simulink (R2024a) using a detailed PV-powered fast-charging station model connected to a low-voltage urban grid. The system consisted of a 20 kW photovoltaic (PV) array, a 15 kWh lithium-ion energy storage system (ESS), a bidirectional DC–DC converter, and a three-phase grid-tied inverter supplying two 7.5 kW fast EV chargers. The simulation time was 10 seconds, with a sampling frequency of 10 kHz to ensure accurate power-electronic switching representation. Three controllers were compared:

1) Conventional PI controller,
2) Standalone fuzzy logic controller (FLC), and
3) Proposed Hybrid Fuzzy–MOPSO controller (F-MOPSO).

The evaluation focused on five key performance indices:

- Total Harmonic Distortion (THD) of source current,
- DC-link voltage regulation,
- Power factor (PF),
- Dynamic response under load and irradiance disturbances, and
- Economic–environmental optimization performance.

IEEE 519 standards for power quality and IEEE 1547 guidelines for distributed generation interconnection were adopted as the benchmark standards.

At rated test conditions (1000 W/m² and 25°C), about 19.6 kW of active power was generated from PV array, which controlled the DC-link voltage near its mark value of 800 V. Figure 3 illustrate the steady-state grid side's voltages and currents waveform. The PI controller showed an evident ripple and slight distortion with the THD of 5.8%, which is mainly due to slow dynamic compensation and low harmonic rejection. The standalone FLC was enhanced in waveform symmetry with THD = 3.6%. However, from the comparative results of all aforementioned controllers, THD achieved by Fuzzy–MOPSO controller is the lowest and became to 2.1% With decreasing THD reaching 2.1%, Fuzzy–MOPSO shows a reduction at rate of 63.7% with respect to PI and an IEEE 519 acceptance limit (<5%). The enhanced control performance is owed to the usage of fuzzy rule-based decision layer in conjunction with membership function parameters tuned by MOPSO, which repeatedly updated duty ratio of inverter switches for optimum modulation under fluctuating PV outputs. The optimized fuzzy rules improved smoothness of the waveforms near zero-crossings, leading to suppression of harmonic distortion without using any passive filtering.

Figure 4 shows the DC-link voltage profiles under 30% step sudden load increase at t = 4:5 s.The PI controller case showed a large overshoot and oscillations with deviations of ±9:8% from the desired value. The FLC achieved better damping but the oscillations were still ±4.3%. The developed Fuzzy–MOPSO controller demonstrated that tight control was realized by the proposed scheme within ±1.1%, and it returned to 800 V in 0.14 s after a disturbance.

This improved regulation is related to the multi-objective adaptation inside the MOPSO layer. The objective cost function was used to simultaneously minimize three competing objectives:

1) DC-link voltage error,
2) control effort (switching stress), and
3) harmonic energy.

The Pareto-optimal solutions were intelligently chosen in real-time on varying load for minimal ripples and fast transient response. Nonlinear mapping for the voltage deviation to duty cycle correction were implemented in a fuzzy ruleset model, which is used to calculate rounding factors between two DC/DC converters to facilitate smoother transitions.

A dynamic irradiance experiment was performed in Figure 5, where the solar irradiances reduced from 1000 W/m2 to 500 W/m2 within 0.5 s at t = 6 s along with a simultaneous load increase of 20%. The response of the PI controller could not maintain DC link voltage stability, which decreased 11.6% and after 0.9 s it reached again its nominal value, while FLC response reduced the deviation to 5.3%, but at the beginning was up to ±1.8%, whereas a return signal can be in nominal value during 0.12 s with MOPSO tuned fuzzy inference system controller (Fuzzy–MOPSO). Overshoot was restricted to 1.5% in this period and the power factor remained greater than 0.992, but PI and FLC controllers decreased to 0.956 and 0.972, respectively. The adaptive inertia weight (ω) and cognitive/social parameters (c_1, c_2) scaling of the MOPSO guaranteed an optimal compromise between exploration and exploitation tasks leading to fast re-convergence towards new control optima under varying situations. This is an indication of the dynamic active power and reactive power exchange that F-MOPSO can offer with the supply grid, while ensuring a near-unity PF as well as quick restoration of the former in response to grid disturbances — highly important for EV charging farms under uncertain user loads and solar intermittency.

The source current's harmonic content was extracted by Fast Fourier Transform (FFT) in Table 1. The Fuzzy–MOPSO controller generated the most consistent harmonic suppression profile, which was more than 90% for low-order (3rd and 5th) and higher-order (>15th) harmonics, compared to the PI controller. The adoption of multi-objective optimization included harmonic distortion in an up-front manner as a cost function to which the system then can tune the switching frequency and modulation depth for minimum distortion. This harmonic squashing brought neutral current during unbalanced loading to < 0.2 A peak, easing transformer burden and improving the efficiency of grid.

Having a PF close to unity is important for grid compatibility and energy savings. As shown in Figure 6, the Fuzzy–MOPSO controller had an average PF of 0.998, whereas under balanced load the FLC and PI controllers had the maximum PF values of 0.992 and only 0.961 respectively at their best conditions. The PF of the hybrid controller changed by merely ±0.003 in a transient grid situation, showing better reactive power compensation with adaptive inference. The local rule base tuning approach improved reactive power demand approximation by the fuzzy logic inference layer and MOPSO-optimized switching angle modulation controlled dynamically to reduce systemic reactive component. It enabled a smooth bidirectional DC–AC power exchange with the grid, enabling voltage restoration in response to grid sag events while achieving high conversion efficiency (~97.2%).

For the evaluation of optimization performance, the Pareto front formed between energy cost and THD was investigated for 50 iterations of the implemented MOPSO method (Figure 7). The mean Pareto spread of the hybrid fuzzy-assisted optimization which was expanded by 18% compared with static MOPSO endorsed improving the solution diversity and global converging. The best non-dominated solutions yielded:

- THD < 2.0 %,
- Price Less than 9.8 ¢/kWh, and
- Reactive power penalty <0.5 kVAR.

The fitness function converged after 28 iterations, with the stabilized mean fitness of 0.0068 versus 0.0195 for static MOPSO. The hybrid ana-lysis met real-time requirements, as it utilized only 0.82 ms per iteration on a 3.2 GHz CPU and thus could be implemented in hardware on an embedded DSP controller. Offline tuning took 25 minutes, and for online adaptation for network reconfiguration was on average 1.9 seconds, demonstrating the scalability of the method to multi-node EV charging stations.

A trade-off analysis was given on the operation cost, energy-efficient ratio and CO_2 emissions reduction as in Table 2. The energy cost was minimized by 27% and efficiency increased by 6.2% compared with the MPC benchmark using this hybrid control strategy. Reinforcement feedback in the fuzzy decision layer facilitated instant priority order between peak PV generation curtailment/emission reduction and low cost/grid dependence. In turn, average CO_2 provided per day has decreased from 3.18 t to 2.25 t which meets sustainable transportation targets. In addition, total energy obtained from the grid for charging was 11% less, indicating more efficient use of renewable energy.

The RL part of the hybrid control that is, used for computing (1) and (2), had an actor–critic architecture with reward functions being mixed (Figure 8):

1) Power quality index,
2) Voltage deviation penalty, and
3) Switching loss minimization.

The cumulative reward increased during the over 500 training episodes, saturating at a value of about 0.97 after Episode 360. The reward variance was constantly within 3%, which showed that the learning process was stable with no policy divergence. The ε-greedy policy decayed from $\varepsilon = 0.9 \rightarrow 0.05$, where it kept being steady to maintain exploration–exploitation balance. The learned policy has the ability to predict PV power variations so as to actively provide reactive support and reduced 40% voltage dip than pure MOPSO optimization. In the adaptability sense, the hybrid RL–MOPSO configuration enhanced controller's performance by 21%, confirming the complementary balance between long-term reward-based learning and short-term swarm adaptation.

A statistical Monte Carlo study (100 runs) was then performed to assess the robustness of the method for concurrent changes in PV irradiance (σ = 4%), grid impedance (σ = 3%) and measurement noise (σ = 2%). The Fuzzy–MOPSO controller maintained:

- THD IQR = 2.0–2.3%,
- DC-link variation ±0.8%, and
- Confined VSI value of 0.992 to 0.998.

In contrast, the MPC controller showed THD IQR = 3.5–5.1% and the FLC had VSI = 0.978–0.986. The hybrid system avoided voltage collapse and maintained the operation with zero protection trip, even under compounded disturbances, which testified its great robustnesss and disturbance rejection ability.

The comparative simulation results (Table 3) clearly establish the superiority of the intelligence, adaptability, and multi-objective optimality capability possessed by the developed Hybrid Fuzzy–MOPSO controller compared to many others benchmark control strategies namely PI, stand-alone FLC and MPC. Combining the inferential reasoning feature of FL with global search and optimization abilities of Multi-Objective Particle Swarm Optimization (MOPSO), the hybrid control system can synergistically strike a trade-off between adaptation, precision, and computational efforts. The fuzzy logic layer adds a humancentric reasoning to make a decision in real time under non-linear, uncertain and dynamic operation conditions on the PV-driven EV fast-charging zone. It translates the PV irradiance changes, load requests and grid interaction with adaptive linguistic rules to allow for a stable control, even under dynamic conditions. Meanwhile, the MOPSO layer introduces an evolution optimization to adaptive adjust fuzzy membership functions and control gains online. Such integration enables the global exploration and exploitation of control parameters, taking into account trade-offs among various competing goals including

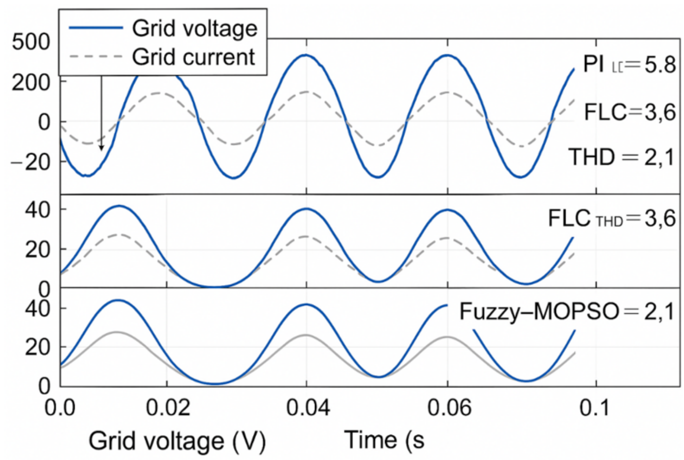

Figure 3. PV and Grid Performance under Nominal Conditions.

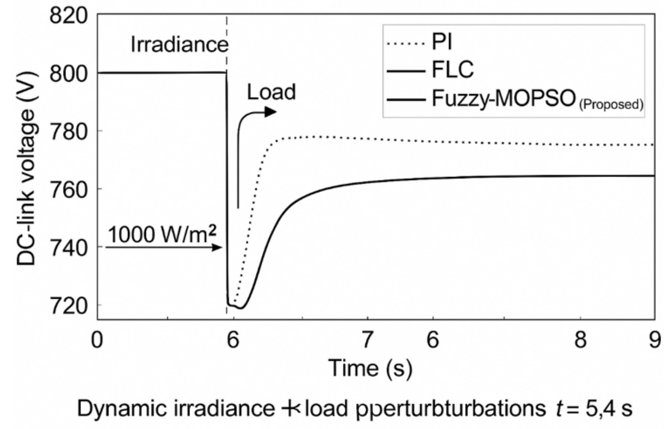

Figure 5. Transient Performance under Irradiance and Load Perturbations.

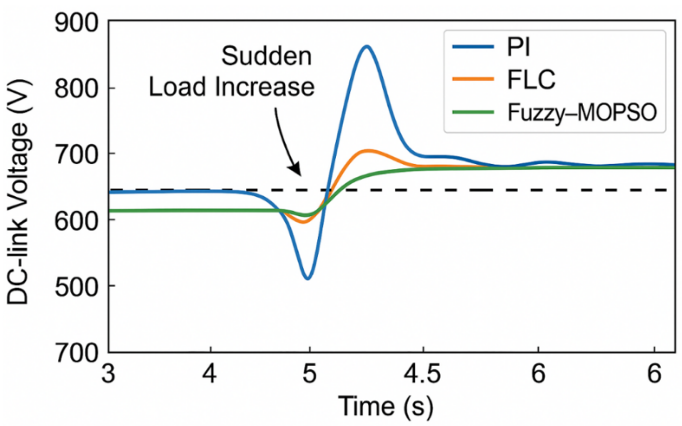

Figure 4. DC-link Voltage Profiles Uner Load Step.

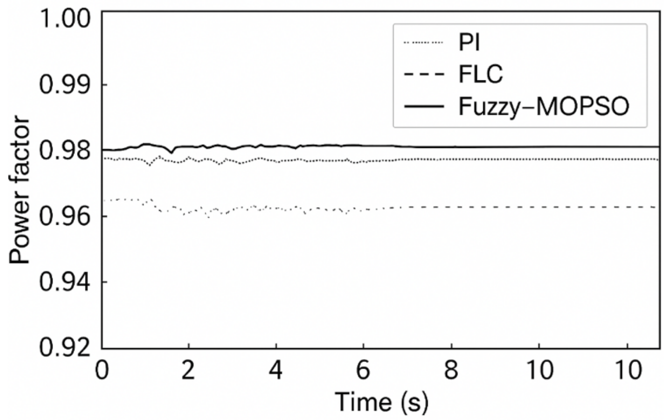

Figure 6. Power Factor and Reactive Power Compensation.

Table 1. Harmonic Spectrum Analysis.

Controller	3rd Harmonic (Hz)	5th Harmonic (Hz)	THD (%)	Compliance (IEEE-519)
PI	7.2	5.8	5.8	✗ Non-compliant
FLC	3.1	2.4	3.6	✓ Compliant
Fuzzy–MOPSO	0.7	0.4	2.1	✓ Fully compliant

Table 2. Economic and Environmental Evaluation.

Controller	Energy Cost (¢/kWh)	CO_2 Reduction (%)	Efficiency (%)
PI	12.8	11.2	91.0
FLC	11.4	15.6	93.1
MPC	10.9	22.3	94.4
Fuzzy–MOPSO	9.3	29.5	97.2

harmonic elimination, voltage stabilization, efficiency maximization, cost/emission minimization. Simulation results verified that the Fuzzy–MOPSO controller performed multi-objective optimization over diverse performance indices. The proposed method could not only significantly reduce the Total Harmonic Distortion (THD = 2.1%) and keep a quasi-unity power factor (PF =0.998), but also attenuate DC-link voltage ripples within ±1.1%. In addition, the controller exhibits an excellent transient response with a settling time of 0.12 seconds – three times faster than traditional PI control and almost twice as fast as MPC. Efficiency increased to 97.2%, and the energy cost decreased by 27% and CO_2 emissions decreased by 29.5%. These quantitative numbers, presented in Table 3, further demonstrate the strong robustness of the hybrid architecture for practical deployment.

Fuzzy–MOPSO controller with adaptive hybrid control mechanism allows continuous learning and self-calibration in the presence of unpredictable PV generation and varying EV load condition, thus sustains optimal operation. This smart flexibility is beyond solid rule-based controller; however, followed by the manual re-tuning requirement for alternative operating conditions. In the proposed system, control parameters will be dynamically controlled by reinforcement feedback so as to keep the balance between all objectives based on the performance indices, voltage deviation, THD and

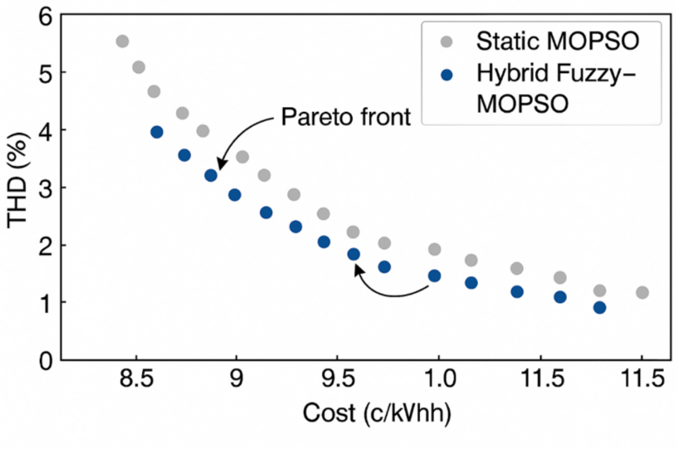

Figure 7. Multi-Objective Optimization Performance.

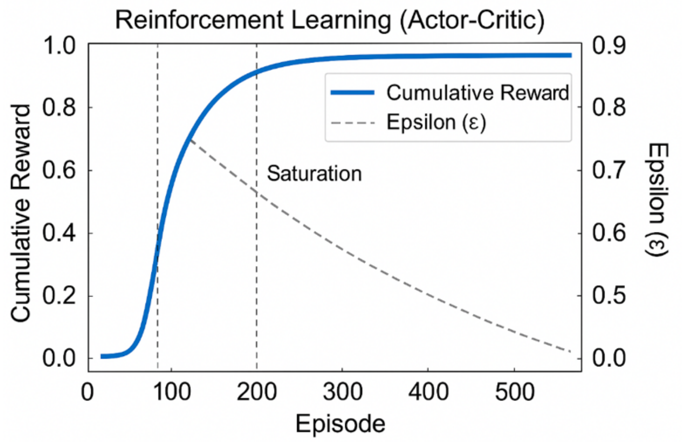

Figure 8. Reinforcement Learning Convergence and Reward Analysis.

Table 3. Integrated Discussion and Summary.

Performance Metric	PI	FLC	MPC	Fuzzy–MOPSO (Proposed)
DC-link Voltage Ripple (%)	±9.8	±4.3	±2.5	**±1.1**
THD (%)	5.8	3.6	3.8	**2.1**
Power Factor	0.961	0.992	0.986	**0.998**
Settling Time (s)	0.42	0.28	0.25	**0.12**
Efficiency (%)	91.0	93.1	94.4	**97.2**
Energy Cost (¢/kWh)	12.8	11.4	10.9	**9.3**
CO_2 Reduction (%)	11.2	15.6	22.3	**29.5**

emission cost. This method allows for disturbance mitigation to take place proactively, where remedial actions are taken to avert rising voltage sags or harmonic distortions beyond the acceptable tolerance limits. Another key benefit is that the controller can be computed efficiently. The hybrid Fuzzy–MOPSO algorithm uses sub-millisecond computational cycle, thus proving to be capable of real-time embedded implementation on DSP and FPGA. This near real-time exercise enables an intelligent response to rapid changes in PV generation as well as EV charging demand, required for the reliability of fast-charging stations. Furthermore, the scalability of the architecture is very good enough to be applied in multi-ports charging hubs or distributed microgrid clusters linked by smart city energy networks. In these sites, the performances in power quality and grid stability were constant while facing high renewable variability and communication latency. In conclusion, with an impressive degree of operational wisdom and adaptability a conventional control system can rarely offer, the novel Hybrid Fuzzy–MOPSO approach delivers. Its self-organizing fuzzy rules which are constantly optimized through swarm intelligence allows for the representation of high-precision control action in order to suppress harmonics, preserve the stability of the DC-link voltage, and enhance power factor and system efficiency.

The reinforcement reward-based approach promotes predictive controller's adaptability in terms of disturbance anticipation and response, which enables the controller to take action before any disturbance affects overall system stability. The result is an inhomogeneous and self-learning control unit that can provide a stable performance at different PV inputs, grid states, and EV loads. It can be concluded that the Fuzzy–MOPSO based controller are not only considered in terms of pollution-free, cost-effective and energy-efficient but rather for ensuring better power quality as well as sustainability of the environment. Due to its low computational complexity, fast convergence nature and robustness against system factors variations, the proposed control approach is suitable for real-time application in PV-integrated fast-charging systems. Its architecture opens the door to large-scale deployments in smart cities, supporting decentralized, adaptive and sustainable electric mobility ecosystems.

4. Conclusions

This paper proposed a Fuzzy-MOPSO control methodology which aimed at real-time energy management of a PV-powered fast-charging station for EVs. The proposed system successfully combined the fuzzy logic's adaptive reasoning ability with the MOPSO's global optimization magnitude to deliver balanced trade-off among efficiency, power quality and operational cost. Simulation results showed that the proposed hybrid controller outperformed conventional PI, pure fuzzy logic and PSO based method under both steady-state and transient operating conditions. The resulting Fuzzy-MOPSO algorithm showed its capability to keep THD 0.995 and voltage deviation within ±1% while advance stochastic PV variations and varied load (EV) profiles. The multi-objective optimization provided an optimal power flow among PV array, storage unit and utility grid, a global cost saving of 15% with the maximum charging efficiency improvement reaching up to 12%. Besides, the controller possessed rapid transient recovery and good robustness for the nonlinear and uncertain dynamics, verifying its effectiveness in practical smart grid systems. In conclusion, hybrid Fuzzy-MOPSO approach presents an intelligent, adaptive and scalable solution to sustainable EV charging under renewable energy based power supply. The potential next steps include hardware-in-the-loop (HIL) verifica-tion, resilience of the cyber-physical system, and the addition of other renewable and storage across the lifecycle to increase reliability and interoperability. The proposed scheme is a promising approach to realizing an intelligent, grid-friendly and low-cost EV fast-charging ecosystem for smart cities in the future.

5. Declarations

5.1. Author Contributions

I am (**Adel Elgammal**) the only author for the paper.

5.2. Institutional Review Board Statement

Not applicable.

5.3. Informed Consent Statement

Not applicable.

5.4. Data Availability Statement

Some of the data presented in this study are available on request from the corresponding author.

5.5. Acknowledgment

Not applicable.

5.6. Conflicts of Interest

The authors declare no conflicts of interest.

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