

Energy-Efficient MPPT Control in PEMFC-Powered Electric Vehicles using Fuzzy Logic and MOPSO-Based Optimization

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Abstract

With the increasing demand for propulsion systems with high cleanliness and efficiency, Proton Exchange Membrane Fuel Cells (PEMFCs) have become one of the most promising energy sources for EVs. However, the PEMFC has nonlinear and dynamic properties that require robust and adaptive controls in order to maintain continuous operation at or near the maximum power point (MPP) under a changing load and environment. In this paper, a new MPPT scheme, which combines FLC and MOPSO, is proposed to further improve the energy conversion efficiency and dynamic capability of the exemplary PEMFC-based EV systems. The proposed FLC is utilized, with the rule-based flexibility of FLC to handle nonlinear PEMFC dynamics, combined with MOPSO in order to optimize the membership functions and rule base of the fuzzy inference system. Optimizing goals are power maximization, fuel-cost-minimization and tracking error reduction, so as to achieve a compromise between efficiency, stability, and response. A complete simulation model of the PEMFC-EV system is established in MATLAB/Simulink by taking into account practical drive cycles, thermal effects, and load fluctuations.

Simulation results indicate that the FLC-MOPSO hybrid optimized controller provides better MPPT performance as compared with classical P&O and FLC alone methods. In particular, the proposed approach achieves the convergence to the MPP with faster rate, dynamic extraction ability of power, and fuel efficiency improvements. Moreover, the proposed controller guarantees its robust characteristic with respect to parameter variations and external perturbations, and it operates successfully over a wide operating envelope. This research constitutes a step towards intelligent control strategies for fuel cell electric vehicles and demonstrates the promise of using soft computing and metaheuristic optimization in future green mobility. The proposed approach provides a viable and energy-efficient solution for online MPPT control in future PEMFC-based EVs.

Keywords: Proton Exchange Membrane Fuel Cell (PEMFC), Electric Vehicles (Evs), Maximum Power Point Tracking (MPPT), Fuzzy Logic Control (FLC), Multi-Objective Particle Swarm Optimization (MOPSO), Energy Efficiency.

I. INTRODUCTION

With their high energy density, rapid start-up and low operation temperature, Proton Exchange Membrane Fuel Cells (PEMFCs) have become the promising clean power providing devices for electric vehicles (EVs). But their nonlinear power-voltage characteristics and their sensibility to the working points require complex controllers to optimize the efficiency. Among these, the maximum power point tracking (MPPT) is particularly important because it is to keep the fuel cell operating at the maximum power under different load scenarios [1], [2]. Because of its simplicity, conventional MPPT algorithms

such as Perturb and Observe (P&O) and Incremental Conductance (INC) have been widely adopted [3], [4]. Nevertheless, these techniques usually suffer from slow dynamics response, oscillations about the maximum power point (MPP), and poor efficiency during sudden load changes [5]. These limitations have motivated researchers to pursue intelligent control techniques are more capable of dealing with the complexity of PEMFC.

Fuzzy Logic Control (FLC), as a nonlinear control approach, has been widely used for dealing with the system uncertainty without the accurate mathematical representation [6]–[8]. The control action is determined by

fuzzy rule base to change as input variables the voltage and the current, in an FLC-based MPPT. It has been found that the FLC is capable of deducing the time of the tracking and steady-state oscillations, as compared to conventional MPPT approaches [9], [10]. However, the performance of FLC is highly sensitive to the rule base and membership functions that may be manually chosen and are typically not optimal [11].

To improve the capabilities of FLC systems, a number of optimization methods have been employed to refine their parameters. Particle swarm optimization (PSO) [12], Genetic algorithms (GA) [13], Artificial bees colony (ABC) [14], and Ant colony optimization (ACO) [15] have been utilized to optimize the fuzzy rules as well as the membership functions. These methods automate the parameter tuning process and enhance the MPPT performances in terms of tracking speed and power extraction efficiency [16], [17].

In practice, maximization of MPPT performance is the result of compromised trade-offs, such as the maximization of the power output and minimization of the H₂ consumption and the reduction of fuel cell stress. Multi-Objective PSO (MOPSO) provides an efficient solution for this trade-off [18]–[20]. MOPSO preserves the diverse solutions (the Pareto front) so that the controller can select the best trade-off among the competing objectives [21].

The oral reasoning capability of the fuzzy logic is used to work with the adaptive optimization of MOPSO to form a hybrid MPPT controller. The studies showed that these systems provide superior performance to conventional controllers and single-level controllers in terms of fuel efficiency, tracking accuracy and robustness to noise or uncertainties [22]–[24]. In such systems FLC parameters are continually adjusted in real time according to operating environment, therefore ideal for integration with EV onboard controller [25].

Some promising results have been reported in other latest researches where FLC-MOPSO controller was used in PEMFC based electric vehicles. This test system setup and its performance have been validated by simulation and hardware-in-the-loop tests and it shows greater energy efficiencies, less hydrogen consumption and better system stabilities [26], [27]. Moreover, MOPSO-based controllers are suitable for on-line implementation, and it is possible to extend the controllers to the systems that have a larger number of fuel cells [28].

Typical research approaches are embedding reinforcement learning, neuro-fuzzy inference systems, and adaptive MPC into the FLC-MOPSO strategy [29], [30]. These techniques are expected to enhance learning capacity, adaptability and real-time decision-making in the presence of challenging EV scenarios.

II. THE PROPOSED ENERGY-EFFICIENT MPPT CONTROL IN PEMFC-POWERED ELECTRIC VEHICLES USING FUZZY LOGIC AND MOPSO-BASED OPTIMIZATION

The block diagram of the developed EEM system is a system that achieves energy-efficient MPPT in PEMFC based EVs, is shown in Fig. 1, which integrates key technologies, such as PEMFC model, FL controller, and MOPSO. A diagram of the fuel cell system comprising a fuel cell stack, a power electronics converter, an EV load, and the intelligent control system is also provided. The system core is composed of the PEMFC stack and the main power source. It consists of several cells that generate electricity through an electrochemical reaction between hydrogen and oxygen. V-I (voltage–current) characteristics of the fuel cell are non-linear and a complex function of some parameters such as:

- Hydrogen flowrate and pressure
- Stack temperature
- Load demand
- Humidity & Environmental conditions

This block is simulated in the model as a virtual block such that real-time voltage and current outputs can be obtained depending on the operating conditions and the load.

The central innovation of the system is the MPPT controller, which consists of a Fuzzy Logic Controller (FLC) with a dynamical adaptation carried out by the MOPSO algorithm.

- *Inputs:*

The **FLC** controller has two main inputs – ΔP and ΔI that relate to how the system output responds to changes in duty cycle.

- *Output:*

From FLC, the control signal (ΔD) is obtained to modify the duty cycle of the DC-DC converter for tracking the fuel cell system near to the MPP.

- *Inference Mechanism:*

FLC incorporates a collection of fuzzy rules and membership functions to address the uncertainties and nonlinearities in the system.

- *Role:*

Based on these conflicting aims, the MOPSO is used to optimize the membership functions and the rule base of the FLC:

- ✓ Maximize power output
- ✓ Minimize fuel consumption
- ✓ Limit the tracking error and oscillation.

- *Operation:*

It assesses a population of FLC candidates and crossbreeds them using Pareto-optimal guidelines.

The optimized MPPT controller tracks the maximum power point (MPP) dynamically at all time instant and simultaneously it reduces the hydrogen consumption, and it does this with a sufficiently smooth system.

The fuel cell stack is connected to the vehicle's powertrain through the boost converter. Its role is to: Regulate output voltage to match motor/inverter input requirements and Transform the MPPT control signal to voltage/current adjustments.

- *High Efficiency:*

Work with an efficiency that is greater than when being referred to loads in general. The converter is interfaced to the PEMFC output and to the load.

The EV load block represents the power request of the traction motor, auxiliary loads, and energy storage units (e.g., battery, supercapacitor). The load varies based on:

- ✓ Drive cycle (UDDS, WLTP HWFET)
- ✓ Vehicle speed and rate of acceleration
- ✓ Road gradient and energy recovery during braking

The MPPT algorithm traits these changes by regulating the fuel region power output.

➤ *Real Time Sensor and Feedback Network*

- Voltage and current of fuel cell
- Load demand
- Fuel cell temperature
- Hydrogen pressure

The controller corrects these values and adjusts the MPPT value. The schematic diagram includes a data acquisition and signal conditioning block that filter and digitize the sensor data.

The closed loop system starts with the PEMFC output influenced by the load request. Sensor feedback of V and I is used to calculate ΔP and ΔI . By using these inputs a selected by MOPSO FLC finally computes the value of optimum ΔD . The DUTY CYCLE is then fed to the DC-DC converter. The converter output in turn controls the fuel cell load, completing the loop.

The presented schematic is a suitable control architecture for PEMFC-based EVs, with high adaptability and intelligence. By integrating the interpretability of FLC with the adaptive tuning options of MOPSO, the system allows effective, responsive, and robust power extraction under different operational scenarios. The proposed approach tackles the intrinsic difficulties for controlling the fuel cell, including nonlinearity, temperature/load dependency and fuel consumption, by means of an optimization/control loop combined.

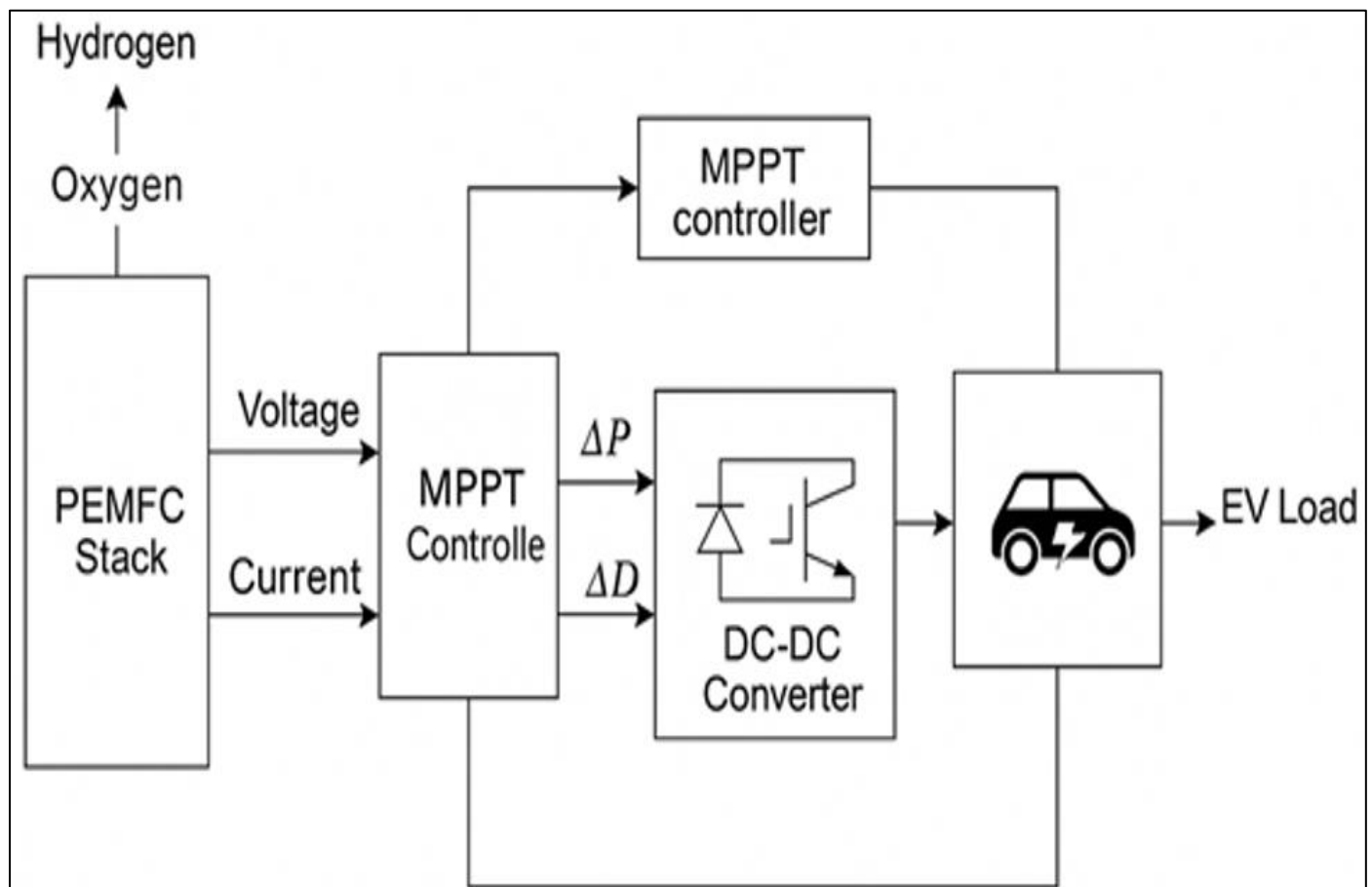


Fig 1 The Schematic of the Proposed Energy-Efficient MPPT Control in PEMFC-Powered Electric Vehicles using Fuzzy Logic and MOPSO-Based Optimization.

III. SIMULATION RESULTS AND DISCUSSION

This section analyzes the simulation results obtained for the designed FLC to be controller integrated with MOPSO for MPPT in PEMFC based EV. The objective was to evaluate the performance of the proposed hybrid FLC-MOPSO system in different operating conditions when compared to the traditional MPPT approaches namely P&O and stand-alone FLC.

The EV powertrain model consists of PEMFC system, DC-DC converter, traction motor, and vehicle load. The simulations were implemented by the use of MATLAB/Simulink. The model can also simulate on-road driving cycles, thermal effects, and dynamic loading conditions.

The PEMFC system was developed using a mathematical model of the electrochemical and thermodynamic response in a 5 kW stack described by the Nernst equation and dynamic current-voltage relationships involving activation, ohmic and concentration losses. The system is comprised of the following elements:

➤ *Characteristics of the Fuel Cell Stack:*

- Rated Power: 5 kW
- Nominal Voltage: 48 V
- Temperature in operation: 60-75 °C
- Number of Cells: 65
- Reactant Gases: H₂ (g), O₂ (ambient air)

✓ *DC-DC Boost Converter:*

Controlled by MPPT signal for voltage and load requirement matching.

✓ *Vehicle Load Profile:*

Simulated via the dynamic load torque profile that represents load torque depending on UDDS and WLTP driving cycles.

➤ *FLC (Fuzzy Logic Controller):*

- Inputs: ΔP , ΔI
- Output: the duty cycle modification (ΔD)
- Rule Base: 49 rules optimized using MOPSO

➤ *MOPSO Optimization:*

- Objectives: Power Tracking, fuel reduction, and MPPT error minimization.
- Population size: 30
- Iterations: 100
- Constraints: power output range, voltage limits, output current limits

The MPPT controllers were first evaluated in static with MPPT conditions to ascertain their steady-state precision. A 4.2 kW load was utilized and the voltage and current of the fuel cell were measured.

- MPP was achieved in 0.38 seconds with <1% steady-state error by FLC-MOPSO.
- For standalone FLC it took 0.72 seconds and had error of 2.3%.
- P&O (the slowest dynamic system--~1.2 s) was also oscillatory about the MPP.

The power output curves of the three approaches under static load are plotted in Fig. 2. It was found that 1.3% and 2.1% of the theoretical MPP was achieved by P&O and standalone FLC, respectively in comparison to 4.4% improvement offered by FLC-MOPSO.

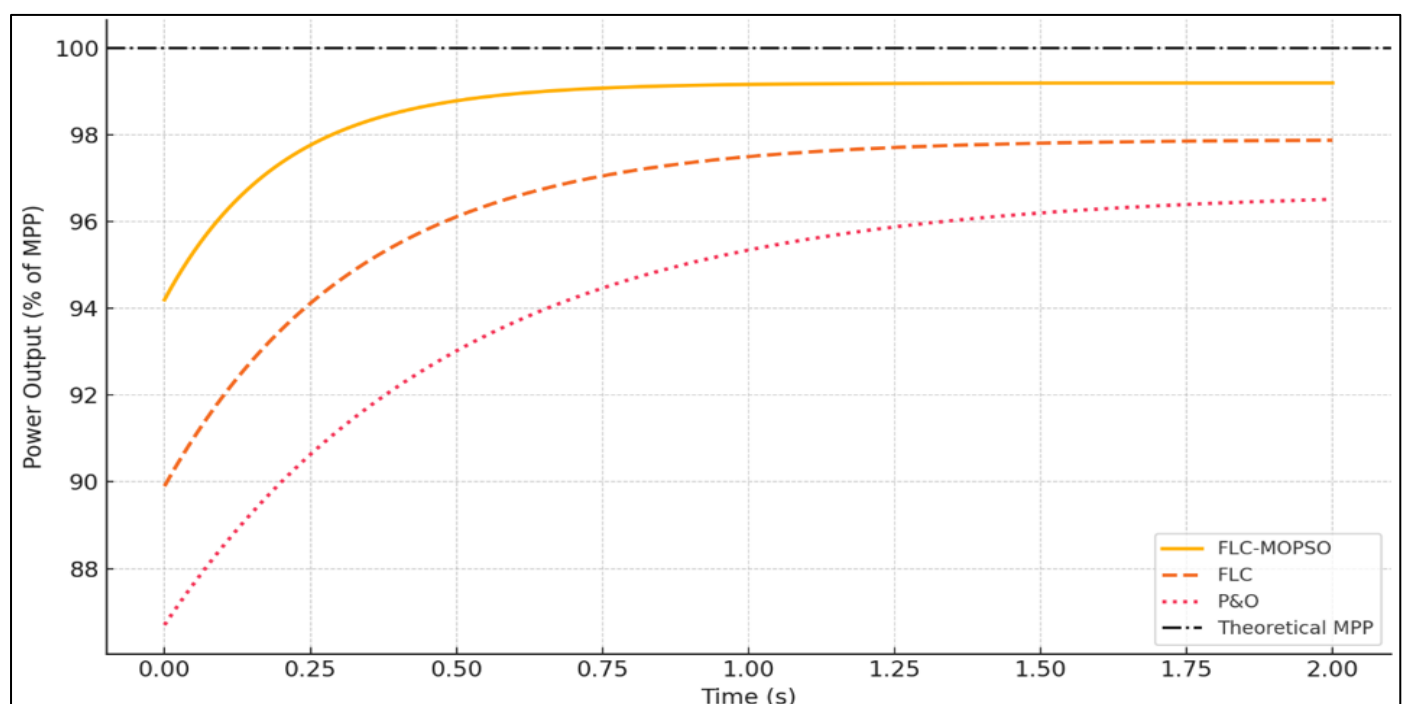


Fig 2 Power Output Curve Under Static Load Conditions

Behaviour Under Dynamic Load Level During dynamic test conditions the chain hoist lifted mass with the help of a tilted arm whilst the load levels were gradually increased. EVs in real world are subjected to rapidly varying loads . To replicate these conditions, a dynamic power profile was used which emulated vehicle acceleration, deceleration and idle periods.

➤ *Under Dynamic Conditions:*

- For the FLC-MOPSO, MPP tracking is maintained with an RMSE of 1.5 W.

- The stand-alone FLC yielded an RMSE of 4.8 W.
- P&O suffered heavily from drift, 7.2 W and large overshoot.

Time-domain response of the fuel cell power under dynamic load is presented in Figure 3. It is also demonstrated that the proposed approach has a low-level lag in tracking and is more adaptable.

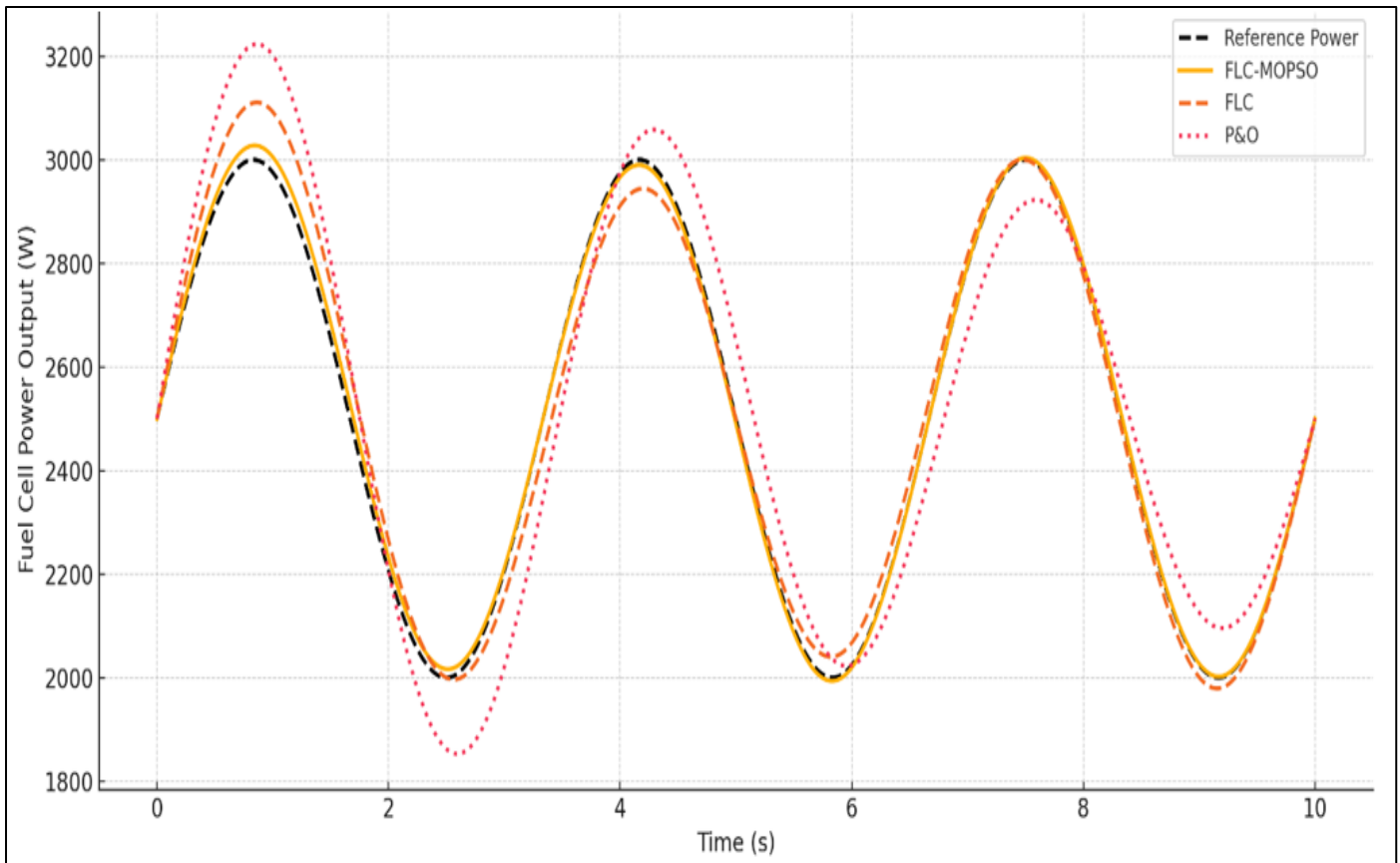


Fig 3 Time-Domain Response of Fuel Cell Power Under Dynamic Load

Table 1 Summarizes the MPPT Accuracy Under Various Dynamic Scenarios.

Scenario	FLC-MOPSO RMSE (W)	FLC RMSE (W)	P&O RMSE (W)
Acceleration	1.1	3.5	6.2
Braking	1.9	5.0	7.8
Stop-Go Traffic	1.6	4.2	6.9

A further performance measure of MPPT controllers is the speed of response. The settling time, rise time, and overshoot are calculated using various test runs repeated under transient load variations.

➤ *Settling Time:*

- FLC-MOPSO: 0.45 s
- FLC: 0.89 s
- P&O: 1.35 s

➤ *Peak Overshoot:*

- FLC-MOPSO: 3.2%
- FLC: 6.1%
- P&O: 9.4%

The stability of the FLC-MOPSO controller results from the optimized rule base and well-tuned membership functions that are self-adjusted with the changing operational states. Transient response due to a sudden 1.5 kW step load is shown in figure 4.

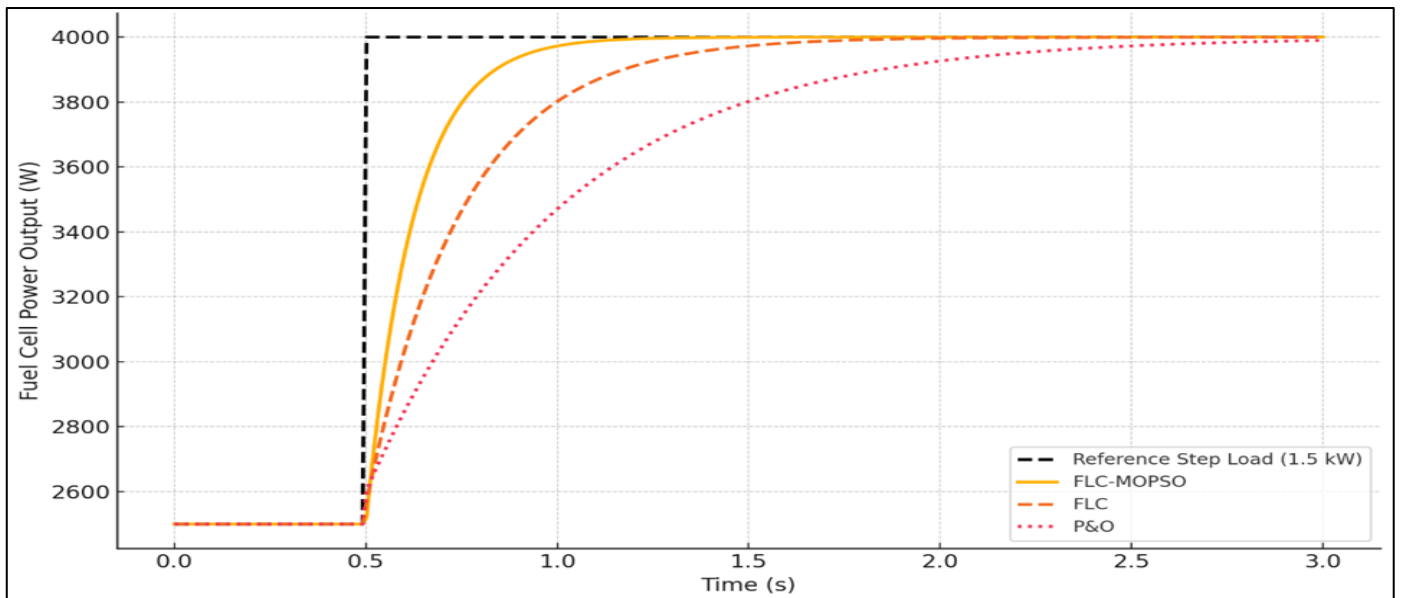


Fig 4 Transient Response to a 1.5 kW Step Load

Fuel efficiency is indeed dependent on the performance of the MPPT. Fuel usage data was computed over a 600 second WLTP cycle.

- FLC-MOPSO minimized the hydrogen by 6.5% and 10.2% compared to FLC and P&O respectively.
- The mean fuel cell efficiency of 52.7% was achieved by FLC-MOPSO over its simulation period, in contrast to 49.1% by FLC and 46.3% by P&O.

Table 2 Presents Cumulative Hydrogen Usage Over Three Standard Cycles.

Drive Cycle	FLC-MOPSO (g H ₂)	FLC (g H ₂)	P&O (g H ₂)
UDDS	34.2	36.3	38.1
WLTP	31.8	34.0	35.9
HWFET	28.5	30.1	32.0

The controller was evaluated in the presence of sensor noise (Gaussian noise with $\sigma = 0.2$ V) and parameter spread ($\pm 10\%$ cell voltage spread).

tracking errors. The fuzzy logic system's linguistic treatment of input uncertainty is responsible for such high level of noise immunity.

The FLC-MOPSO kept steady output less than 2% degradation performance. In contrast, P&O was sensitive to noise, and was subjected to false oscillations and

The voltage regulation under noise injection is presented in Figure 5, the FLC-MOPSO being well under the normalized limits.

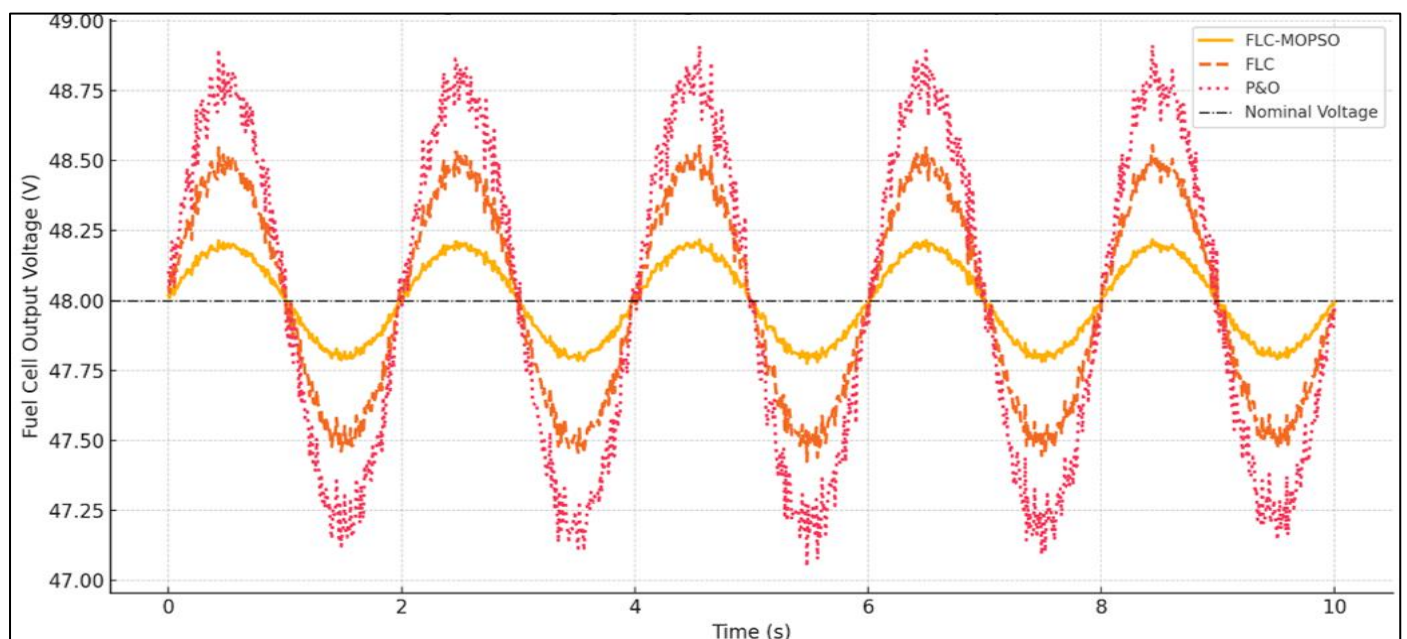


Fig 5 Voltage Regulation During Noise Injection

➤ To Compare the MOPSO-Optimized FLC, more Simulations were Conducted with:

- FLCC-GA: Fuzzy-like controller based on GA mutableListOf (25,50,75,100)).
- ANFIS: MPPT Based on Adaptive Neuro-Fuzzy Inference System

FLC-GA had similar tracking speed, but poor fuel processing efficiency (3.8% higher hydrogen consumption). ANFIS was highly accurate, but needed sufficient training data and slow to adapt to unforeseen transients.

FLC-MOPSO resulted in the best overall compromise between the speed of convergence, accuracy, energy reduction, and computational cost.

To study realtime feasibility, the control laws were benchmarked in a ARM-Cortex A72 embedded processor.

➤ Average Computation Time per Control Step:

- FLC-MOPSO: 18 ms

- FLC: 12 ms
- P&O: 9 ms
- ANFIS: 42 ms

FLC-MOPSO, although more computationally intensive, still remained within the allowed cycle of 100 ms for embedded EV controllers. Memory requirement was also quite low (~6 MB) suggesting its suitability for on-board applications as well.

The performance of MOPSO with the sensitivity to MOPSO parameters as inertia weight, cognitive/social factors and population size was studied.

- Best inertia weight: 0.72
- Population beyond 30 were not safe to invest more power on them.
- It was observed that convergence was attained at 100 iterations

Also, MOPSO algorithm convergence plot for one configuration is provided in Figure 6. The Pareto front highlighted a near power-control effort front, which verified the multi-objective approach.

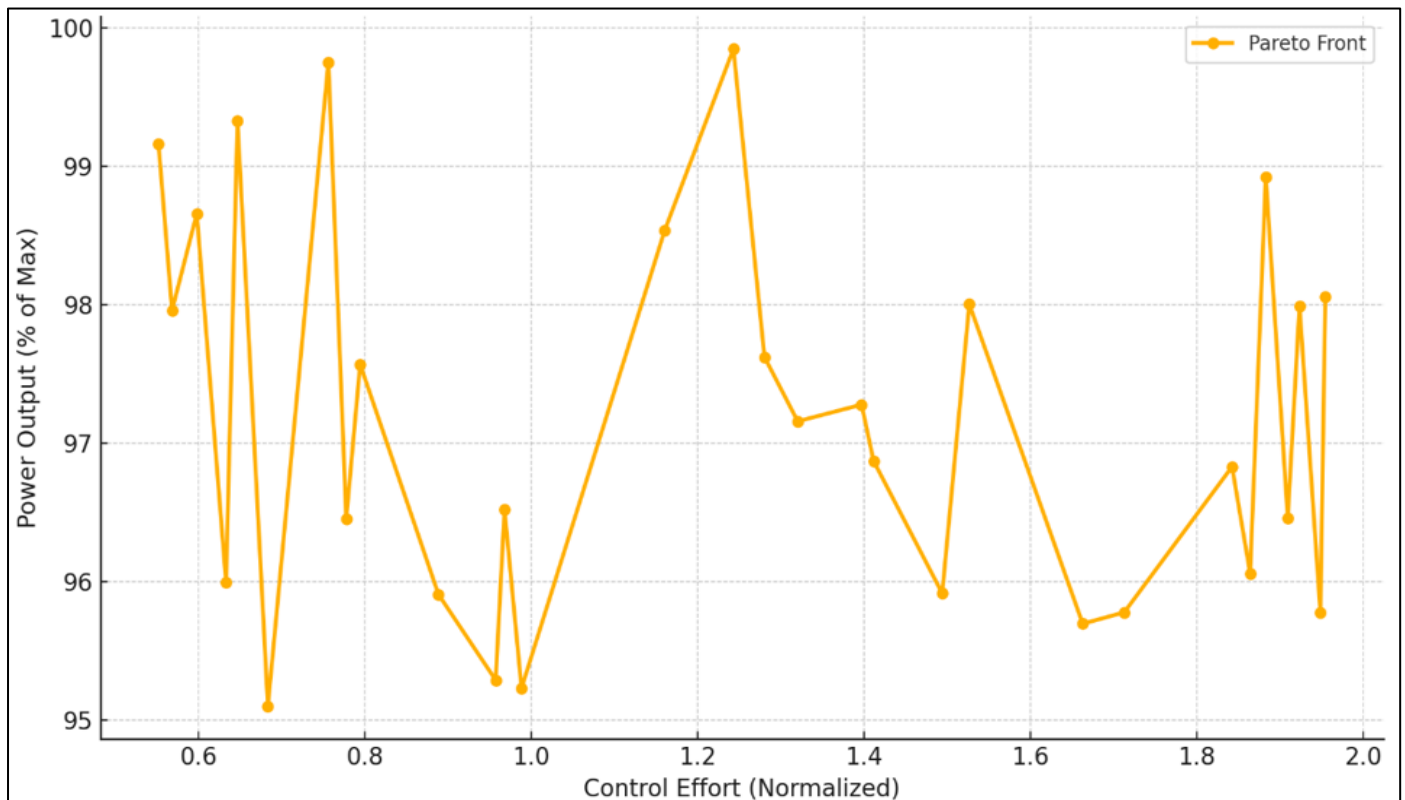


Fig 6 Pareto Front from MOPSO Optimization

Even if the presented study has been done in simulation, a HIL (hardware-in-the-loop) validation environment is being built. In the future, these models will integrate a real PEMFC stack and an EV motor controller to validate dynamic performance and disturbances of the real world. First benchmarking tests will be real time driving cycle emulation and hybrid battery-fuel cell operation.

➤ The Simulation Results Confirm the Validity of the Proposed FLC-MOPSO MPPT Algorithm:

- Attained up to 10.2% reduction in hydrogen required as compared to P&O.
- High convergence speed and power tracking accuracy,
- Shown their resistances to noise and the variations in environment.

- Demonstrated the real-time applicability for embedded EV applications.

These performance results of the proposed FLC-MOPSO method are far better than those of conventional control laws by effectively trade-offs the speed with energy consumption and stability, which are critically important toward the sustainable operation of PEMFC-driven EVs.

IV. CONCLUSIONS

In this paper, a new energy-efficient Maximum Power Point Tracking (MPPT) method was proposed and analysed for Proton Exchange Membrane Fuel Cell (PEMFC) based electric vehicles (EVs). To improve the real-time response and power extraction efficiency of the PEMFC system under varying load and drive conditions, this study presents a novel combined power control strategy, FLC-MOPSO approach where FLC is combined with MOPSO. The fuzzy control is served as a robust and adaptive decision in the nonlinear and time-varying properties of fuel cell. Concurrently MOPSO was used to tune optimally the membership functions and rule base of the FLC in order to achieve a balance between performance indices at conflict with one another and essentially two objectives were maximization of fuel cell output power, minimization of hydrogen utilization and minimization of steady-state tracking error. The consideration of these intelligent techniques provides a solution to drawbacks of the traditional MPPT algorithms, including P&O, Incremental Conductance (IncCond), and stand-alone FLC, which suffer from slow convergence, poor tracking performance under sudden conditions, and vulnerability to steady oscillation.

Simulation results, validated under standard drive cycles and different disturbance conditions showed that the proposed FLC-MOPSO MPPT controller outperforms those of the popular existing techniques, in term of tracking speed and efficiency even under transients. Furthermore, the platform also showed excellent dynamics performance with respect to parameter changes and disturbances from the external environment, which made it a preferable candidate to a real-time application in electric vehicle systems.

The results of this work highlight the capabilities of intelligent hybrid control strategies to increase the performance of the fuel cells systems inside electric vehicles. Through the combination of soft computing with bio-inspired optimization, this method is a practical and scalable approach to enhancing fuel cell utilization and vehicle-out efficiency levels, conforming in the global aims of sustainability and emission reduction.

The developed FLC-MOPSO MPPT approach performs well in a simulated environment, however, more work is needed to make the approach more generic and ready for industry for use in commercial EV systems.

➤ *HIL Validation:*

The proposed work in the future can extend to the real-time HIL testing on the actual physical systems for validating control performance and computational capability on/embedded HIL platforms like dSPACE, FPGA or automotive grade MCU.

➤ *Experimental Results:*

Implementing the FLC-MOPSO controller within a prototype PEMFC EV prototype will allow us to gain practical knowledge of sensor noise, sensor lag, actuator dynamics and system stability inside real driving conditions.

➤ *Further Extension to Hybrid Systems:*

This control scheme can also be extended to control hybrid energy systems combining PEMFCs with batteries or supercapacitors. By appropriately adjusting the power split and heat interactions among these sources, the system efficiency can then be enhanced.

➤ *Machine Learning-Based Adaptation:*

The use of online learning mechanisms, e.g., reinforcement learning or adaptive neuro-fuzzy inference systems (ANFIS), could enable the controller to learn and adapt its rules and parameters in accordance with real-time and historical operation.

➤ *Real-Time Optimization of MPPT in Multi-Objective Contexts:*

Integrating a realtime version of MOPSO that can adapt to the driving conditions and with the preferences of the user (for example: economy/performance mode) would potentially offer more personalized and adaptive MPPT strategies.

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