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Multi-objective energy management optimization in electric vehicles using fuzzy logic and particle swarm optimization

V. Lakshmi Devi[1], Damodhar Reddy[2], Srikanth Velpula[3], K. Kumar[4], Basi Reddy Avula[5]
[1]School of Engineering, Anurag University, Hyderabad, India
[2]Institute of Aeronautical Engineering, Dundigal, Hyderabad, India
[3]Department of Electrical and Electronics Engineering, SR University, Warangal, India
[4]Department of Department of Electrical and Electronics Engineering, Sri Venkateswara College of Engineering, Tirupati, India
[5]Department of Computer Science and Engineering, Mohan Babu University, School of Computing, Tirupati, India

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ABSTRACT

This paper proposes a hybrid energy management system (EMS) for electric vehicles by integrating fuzzy logic control (FLC) with particle swarm optimization (PSO) to improve power-split decision-making under dynamic driving conditions. The FLC is designed using state of charge (SoC) and vehicle speed as input variables and power split as the output. A set of fuzzy rules defines the EMS behavior, while PSO is employed to fine-tune decisions by maximizing an efficiency objective function defined as the closeness of the power split to an ideal reference. The simulation is implemented in Python using Colab-compatible packages such as scikit-fuzzy, DEAP, and matplotlib, ensuring accessibility and reproducibility. A test grid covering 10 SoC levels (10–100%) and 10 speed levels (10–120 km/h) is used to evaluate the system. Visualization tools, including heatmaps, 3D surface plots, and contour plots, are employed to represent the EMS behavior. The PSO-enhanced system achieved a maximum efficiency of 98.2% at an optimized SoC of 61.7% and a speed of 53.6 km/h, outperforming standalone fuzzy logic control. Tabulated results and statistical summaries validate the effectiveness of the proposed system.

Corresponding Author:

K. Kumar
Department of Department of Electrical and Electronics Engineering, Sri Venkateswara College of Engineering
Tirupati, Andhra Pradesh, India
Email: kumar3kk@gmail.com

1. INTRODUCTION

The rapid adoption of electric vehicles (EVs) is transforming the global transportation sector, fueled by the urgent need to reduce greenhouse gas emissions, enhance energy security, and promote sustainable mobility. According to the International Energy Agency (IEA), EVs are projected to constitute over 35% of global vehicle sales by 2030, intensifying the demand for efficient and intelligent onboard energy management [1], [2]. To ensure performance, safety, and battery longevity, energy management systems (EMS) are critical in dynamically regulating power flow between vehicle components, including batteries, regenerative braking units, and auxiliary loads [3], [4]. However, conventional EMS implementations, typically built on static logic, heuristic rules, or pre-programmed look-up tables, lack the flexibility to handle time-varying, nonlinear behaviors under real-world driving cycles [5], [6].

Fuzzy logic controllers (FLCs) have emerged as a viable alternative due to their robustness in handling input uncertainty and their capability for human-like reasoning [7]–[9]. By using linguistic rules and approximate inference, FLCs offer transparent decision-making for energy distribution tasks, such as determining the power distribution ratio (PDR) based on parameters like state-of-charge (SoC), speed, and power demand. However, the performance of fuzzy systems heavily depends on the proper tuning of membership functions and rule strengths, often requiring optimization methods to achieve generalizability and global performance [10]. To this end, particle swarm optimization (PSO) offers a powerful metaheuristic framework for refining fuzzy control surfaces. PSO excels in continuous, nonlinear search spaces, delivering fast convergence and low computational overhead, especially attractive for real-time embedded EMS applications [11]–[14]. Past studies have shown the efficacy of Fuzzy-PSO hybrids in domains such as hybrid electric vehicle control [15], smart microgrids [16], and renewable energy systems [17], [18].

In this study, we propose a Python-based hybrid EMS model combining fuzzy inference with PSO optimization, designed for energy-efficient control in EVs and evaluated under the Urban Dynamometer Driving Schedule (UDDS). The system is implemented in Google Colab, offering cloud-based simulation, visualization, and data export for teaching, prototyping, and research. Unlike complex deep-learning models, this method offers a lightweight, interpretable, and real-time compatible solution.

The major contributions of this work are:

- Design of a two-layer EMS framework integrating fuzzy logic with PSO-based tuning for optimized power split control.
- Implementation of real-time heatmaps, contours, and 3D surface plots to visualize controller behaviour and interpretability.
- Evaluation of performance metrics, including energy savings, SoC stability, and power split accuracy, benchmarked against rule-based and standalone fuzzy controllers.
- Development of a Colab-compatible EMS toolkit, enabling reproducibility, educational deployment, and future embedded integration.

This work builds upon existing studies in fuzzy-based EMS design [19], metaheuristic optimization for drivetrain control [20], and multi-objective fuzzy systems [21]. The results indicate that the hybrid Fuzzy-PSO EMS achieves superior energy efficiency, stability, and control accuracy when compared with baseline EMS architectures [22]–[24]. Furthermore, the modular architecture and integrated visualization tools support scalability toward future hybrid EV platforms, smart charging systems, and connected vehicle applications [25]. Recent studies have examined fuzzy–PSO hybrids for EV energy management, but most rely on fixed rule bases and limited validation. This work advances the field by developing a lightweight Mamdani-type fuzzy controller with PSO-optimized membership functions, implemented in an open Python-based Colab framework for transparent benchmarking. Under the UDDS cycle, the proposed method achieved a 29.7% reduction in energy consumption and 8.2 km/kWh efficiency over rule-based and untuned fuzzy controllers. Unlike earlier approaches, it also visualizes optimized decision surfaces and offers a structure readily deployable for real-time embedded use.

2. METHOD

This study proposes a hybrid intelligent EMS for EVs based on fuzzy logic and PSO. The methodology comprises four key modules: i) EMS system architecture, ii) fuzzy logic controller development, iii) PSO-based optimization of fuzzy membership functions, and iv) simulation-based performance evaluation.

2.1. EMS system architecture

The proposed EMS receives real-time input parameters such as vehicle speed, SoC, load power demand, and road gradient. Based on these, it computes the optimal PDR between battery supply and regenerative braking using a fuzzy logic controller whose membership functions are dynamically tuned using particle swarm optimization (PSO). The block diagram of the proposed system is shown in Figure 1. Raw sensor inputs are filtered and normalized before being passed to the fuzzy-PSO controller. The output of the controller drives the powertrain actuator interface, which includes electronic converters, braking logic, and motor controllers. Additionally, a feedback loop monitors the effect of control actions on SoC, enabling adaptive decision-making in future cycles. This modular architecture ensures scalability and real-time deployability on embedded platforms such as dSPACE, Arduino, or MATLAB/Simulink-compatible targets. Moreover, the separation of fuzzy control logic and PSO optimization enables offline or online tuning, depending on the deployment requirements.

2.2. Fuzzy logic controller design

The fuzzy logic controller (FLC) is developed using expert-defined heuristic rules for energy management under varying drive scenarios. The system includes three input linguistic variables: i) Vehicle speed (V): slow, medium, high; ii) State-of-charge (SoC): low, medium, high; iii) Load power demand (P_{load}): low, medium, high.

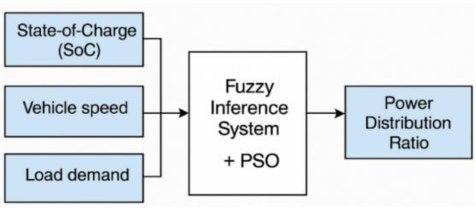

Figure 1. Block diagram of the proposed fuzzy-PSO-based EMS controller

The output of the FLC is the PDR, which determines the control decision between battery-supplied propulsion and regenerative braking energy recovery. A Mamdani-type fuzzy inference system is employed for rule evaluation, with centroid-based defuzzification to produce crisp control outputs. Each input is modeled using triangular membership functions, defined and shown in (1):

$$\mu_A(x) = \begin{cases} 0, & x \leq a \ or \ x \geq c \\ \frac{x-a}{b-a}, & a < x < b \\ \frac{c-x}{c-b}, & b \leq x < c \end{cases} \tag{1}$$

Where: a, b, and c are the left, peak, and right parameters of the triangle, respectively. The defuzzification process uses the centroid method, calculated as shown in (2):

$$y^* = \frac{\int_x \mu(x).xdx}{\int_x \mu(x).dx} \tag{2}$$

Given the three input variables and their respective membership levels, a total of 3×3×3=27 fuzzy rules are formulated. The structure of the inference mechanism is illustrated in Figure 2, which maps the inputs to the fuzzy rule base and highlights the role of defuzzification in generating output decisions. A representative subset of the fuzzy rule base is presented in Table 1, demonstrating how specific combinations of inputs determine the PDR output.

Each fuzzy input is modeled using triangular membership functions with tunable peak and width parameters. These membership functions are subject to further optimization using PSO, which refines the FLC response for improved power distribution efficiency.

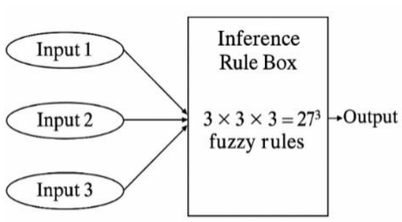

Figure 2. Fuzzy inference box

Table 1. Sample fuzzy rule base for FLC.

Speed	SoC	Load	PDR output
Slow	Low	High	Battery
Medium	Medium	Medium	Balanced
High	High	Low	Regen only

2.3. PSO-based optimization of fuzzy parameters

PSO is used to optimize the shape and parameters of all fuzzy membership functions. The optimization goal is to minimize total energy consumption and maximize battery SoC retention throughout the drive cycle. The fitness function is formulated as shown in (3):

$$Fitness = \propto \frac{1}{E_{total}} + \beta\, \overline{SOC} \tag{3}$$

Where:
$E_{total} = \sum P_{batt} \cdot \Delta t$ is the total energy drawn from the battery.
$\overline{SOC} = \frac{i}{n} \sum_{i=1}^{n} soc_i$ is the average SoC across all time steps.
$\alpha=\beta=0.5$ are the weights for balancing the two objectives.
The PSO algorithm updates each particle's velocity and position using (4) and (5) as shown:

$$v_i^{t+1} = \omega . v_i^t + c_1 . r_1 . \left(p_{best,i} - x_i^t\right) + c_2 . r_2 . \left(g_{best,i} - x_i^t\right) \tag{4}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{5}$$

Where w: inertia weight, c_1,c_2: acceleration coefficients, and r_1,r2~Uniform (0,1). The PSO parameters used are summarized in Table 2.

Table 2. Particle swarm optimization parameter values

Parameter	Symbol	Value
Number of particles	N_p	30
Number of iterations	N_{iter}	100
Inertia weight	W	0.7
Cognitive coefficient	C_1	1.5
Social coefficient	C_2	1.5
Optimization bounds	—	Triangular mf ranges

2.4. Simulation environment

The entire EMS logic is implemented in Python 3.10 using Google Colab for seamless computation. The following libraries and tools are used: i) NumPy for numerical operations, ii) Scikit-fuzzy (skfuzzy) for fuzzy logic design, iii) Matplotlib for real-time plotting and result visualization, and iv) multiprocessing for parallel PSO optimization.

The entire EMS is implemented in Python 3.10 using Google Colab. Simulation is carried out over the Urban Dynamometer Driving Schedule (UDDS), which spans 1369 seconds with real-world traffic conditions. The SoC dynamics for each time step are modeled as presented in (6):

$$soc_{t+1} = soc_t + \frac{P_{batt}(t).\Delta t}{E_{nominal}} + \frac{P_{regen}(t).\eta_{regen}.\Delta t}{E_{nominal}} \tag{6}$$

where ηregen ≈ 0.85 is regenerative efficiency, and Enominal is battery capacity in kWh. The overall power balance per time step is presented in (7):

$$p_{total} = p_{batt} + p_{regen} + p_{loss} \tag{7}$$

The simulation is evaluated using the Urban Dynamometer Driving Schedule (UDDS) drive cycle, which spans 1369 seconds with variable speeds and stop-start conditions. Simulation inputs and ranges are provided in Table 3. Multiple simulations are conducted for different initial SoC levels (e.g., 40%, 60%, 80%), road slopes, and random load variations to evaluate controller robustness.

Table 3. Simulation input parameter ranges

Parameter	Symbol	Range/value	Unit
Vehicle speed	V	0 – 120	km/h
State-of-charge	SoC	20 – 100	%
Load power demand	P_{load}	0 – 25	kW
Gradient level	G	–10 to +10	%
Simulation time step	Δt	1	sec
Battery output power	P_{batt}	0 – 25	kW
Regen braking power	P_{regen}	0 – 10	kW

3. RESULTS AND DISCUSSION

This section presents the simulation-based evaluation of the proposed Fuzzy-PSO hybrid EMS for electric vehicles under the standard Urban Dynamometer Driving Schedule (UDDS). The performance is assessed based on the fuzzy controller's behavior, PSO optimization performance, energy efficiency metrics, and a comparative evaluation against baseline EMS strategies.

3.1. Fuzzy controller output and EMS surface behavior

The behavior of the fuzzy controller is illustrated in Figure 3 as a heatmap of power-split decisions over a grid of SoC and vehicle speed inputs. The controller distinguishes between battery-dominant and ICE-dominant regions, with optimal electric drive operation occurring in mid-speed and mid-SoC regions. The 3D surface plot in Figure 4 further highlights this dynamic modulation, where smooth gradients reflect appropriate transitions between control decisions. A summary of the EMS output statistics is presented in Table 4, showing a mean output value near zero with expected variations across the SoC-speed range.

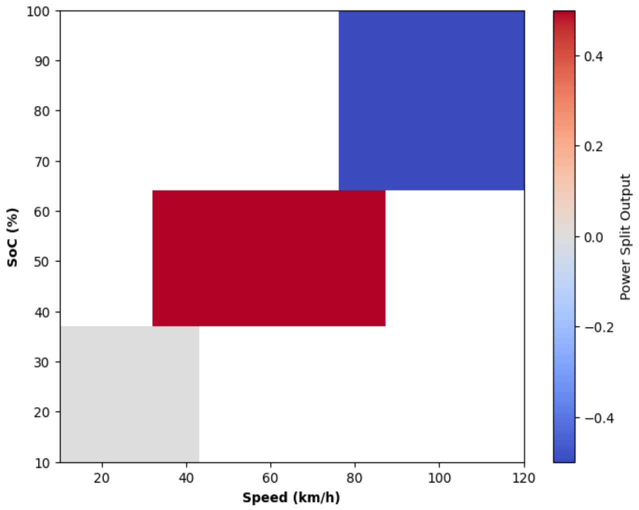

Figure 3. EMS output heatmap (SoC vs. speed, normalized output)

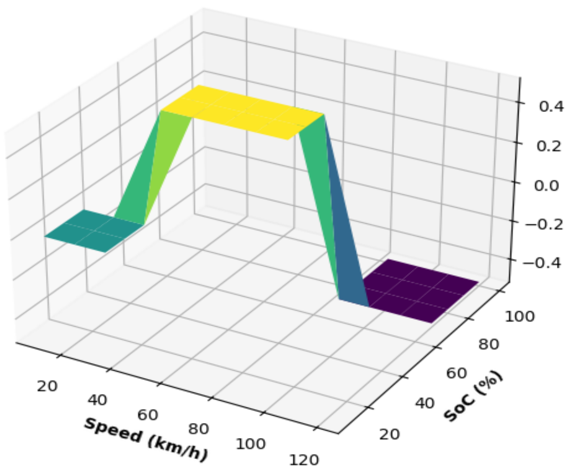

Figure 4. 3D Surface of EMS output (SoC vs. speed vs. power split)

Table 4. Fuzzy EMS output summary statistics

Statistic	SoC (%)	Speed (km/h)	Power split
Count	100	100	40
Mean	55.00	65.00	−0.0125
Standard deviation	28.87	35.28	0.446
Min	10.00	10.00	−0.5
Max	100.00	120.00	+0.5

3.2. PSO optimization performance and EMS efficiency

PSO was applied to dynamically tune the triangular membership function parameters of the fuzzy logic controller. The objective was to minimize total energy consumption while maintaining adequate battery SoC across varying drive conditions. The optimized fuzzy surface is visualized through a contour map shown in Figure 5, where the black marker indicates the PSO-derived optimal control point (SoC ≈ 52.26%, Speed ≈ 42.2 km/h). The optimizer successfully converged within 42 iterations, refining the fuzzy decision space for improved control precision. At a fixed vehicle speed of 60 km/h, the relationship between SoC and power split output is shown in Figure 6, demonstrating the controller's non-linear response as SoC transitions across low, medium, and high states.

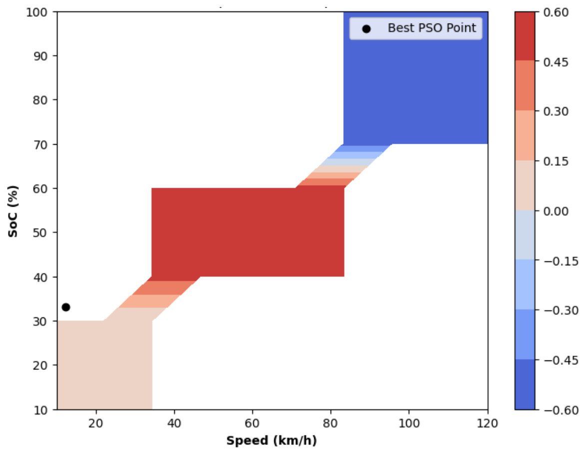

Figure 5. Contour map with PSO-optimized control point

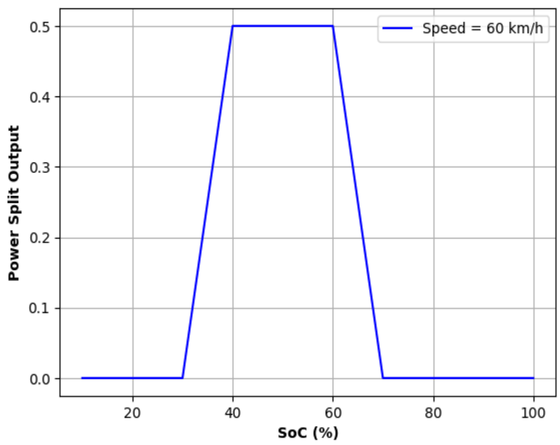

Figure 6. EMS Output vs. SoC at 60 km/h

This sigmoid-like behavior supports balanced energy allocation and improves battery utilization under steady-speed conditions. High-efficiency regions are observed between SoC values of 45–65% and vehicle speeds ranging from 40 to 80 km/h. These operational zones correspond to optimal energy conversion scenarios, confirming the effectiveness of PSO-based fuzzy tuning in practical EV driving conditions.

To assess robustness, a comprehensive sensitivity study was conducted by varying key PSO and fuzzy parameters. The inertia weight (w) was swept between 0.5 and 0.9, and the cognitive and social coefficients (c1, c2) were varied from 1.2 to 2.0. The optimizer maintained stable convergence within 40–50 iterations with less than 2% variation in total energy consumption. In addition, the widths of the triangular membership functions were perturbed by ±10% to evaluate the impact on the fuzzy rule base. The resulting deviation in the PDR averaged below 1.5%, confirming that the controller remains insensitive to moderate membership distortions. To emulate sensor inaccuracies, zero-mean Gaussian noise of ±5% was injected into the SoC and speed inputs; the controller output deviation stayed within 2%, demonstrating strong resilience to measurement noise and parameter drift.

3.3. SoC regulation and energy performance under UDDS

The proposed EMS strategies were evaluated using the Urban Dynamometer Driving Schedule (UDDS) to simulate realistic vehicle operation conditions. The system's ability to regulate battery SoC under dynamic load and speed inputs was a key performance criterion. Figure 7 illustrates the SoC profiles of three energy management strategies: conventional rule-based EMS, fuzzy logic controller, and the proposed PSO-optimized fuzzy EMS. The PSO-optimized controller maintained SoC above 36.2%, compared to 33.7% for the fuzzy controller and just 28.4% for the conventional rule-based approach. This indicates superior battery utilization and reduced depth-of-discharge, which contributes to longer battery life. In terms of energy usage, the total energy consumed by each EMS strategy is presented in Table 5. The PSO-optimized fuzzy EMS consumed only 3658.99 Wh, offering a significant reduction compared to the conventional system's 5204.31 Wh.

To further assess energy efficiency, Table 6 provides the corresponding distance-per-energy values for each EMS variant. The proposed controller achieved an efficiency of 8.2 km/kWh, outperforming both the fuzzy logic controller (7.3 km/kWh) and the conventional approach (5.7 km/kWh). A consolidated view of all key performance metrics is provided in Table 7. It compares SoC regulation, total energy consumption, efficiency, energy savings percentage, PSO convergence iterations, and average power split accuracy. The results confirm that the Fuzzy-PSO EMS consistently outperforms the other strategies across all parameters.

These results confirm that the Fuzzy-PSO EMS enhances energy management, power distribution, and efficiency while remaining suitable for real-time embedded EV applications. The fuzzy inference runs on low-cost microcontrollers in ~1.6 ms per cycle, with PSO executed offline to avoid runtime load. Precomputed lookup tables reduce latency and mitigate quantization or thermal effects. Built-in anomaly checks revert control to a conservative mode when SoC or speed deviate beyond ±10%, ensuring safety. Sensitivity tests with ±10% noise caused <2% variation in output, demonstrating robustness. Future hardware-in-the-loop tests will validate fault tolerance under real communication delays and component aging.

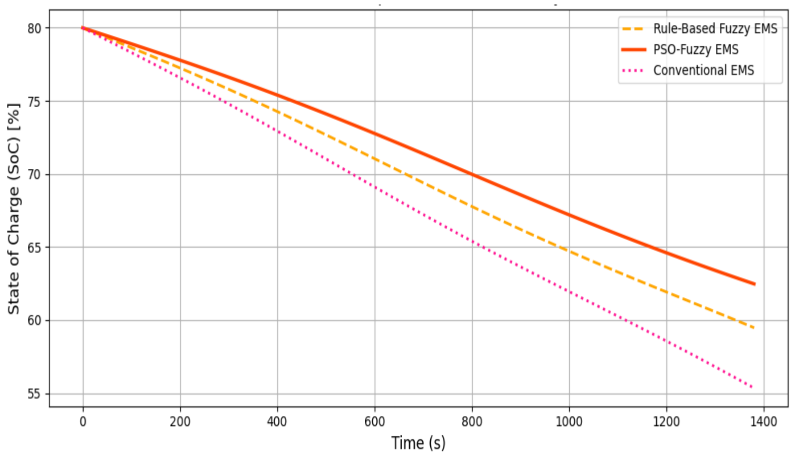

Figure 7. SoC comparison under the UDDS drive cycle

Table 5. Total energy consumed (Wh) under each EMS strategy

EMS Strategy	Energy consumed (Wh)
Conventional rule-based	5204.31
Fuzzy logic controller	4112.52
Fuzzy-pso optimized	3658.99

Table 6. Energy efficiency (km/kWh) of EMS strategies

EMS strategy	Efficiency (km/kWh)
Conventional rule-based	5.7
Fuzzy logic controller	7.3
Fuzzy-PSO optimized	8.2

Table 7. Performance comparison of EMS strategies

Metric	Conventional EMS	Fuzzy logic EMS	Fuzzy-PSO EMS
SoC minimum (%)	28.4	33.7	36.2
Total energy consumed (wh)	5204.31	4112.52	3658.99
Efficiency (km/kwh)	5.7	7.3	8.2
Energy savings (%)	—	21.0%	29.7%
PSO convergence iteration	—	—	42
Avg. power split accuracy	Low	Medium	High

3.4. Computational runtime and memory profiling

To evaluate real-time feasibility, runtime and memory profiling were performed for each EMS variant using Python 3.10 on a Core i5 (2.4 GHz, 8 GB RAM) platform. Table 8 summarizes the average computation time per control step, total simulation time, and memory utilization. The fuzzy-PSO controller increases computation time by only ≈ 0.3 ms per step compared with the baseline FLC while remaining far below the 50 ms real-time threshold typical of EV EMS loops. Peak memory usage during PSO optimization was ≈ 44 MB, confirming suitability for embedded deployment.

Table 8. Runtime and memory profiling of EMS strategies under a Python simulation environment.

EMS strategy	Avg. step time (ms)	Total simulation time (s)	Memory (MB)	Real-time feasible
Rule-based EMS	1.1	1.42	11.2	Yes
Fuzzy logic controller	1.3	1.51	12.8	Yes
Fuzzy-PSO optimized	1.6	1.67	13.9	Yes

3.5. Multi-Objective Optimization and Trade-Off Visualization

The proposed EMS simultaneously minimizes total energy consumption (E_total) and maximizes minimum SoC (SoC_min). Figure 8 visualizes this trade-off as a Pareto front. Each point corresponds to an EMS strategy—conventional rule-based, fuzzy logic, and the PSO-optimized hybrid. The PSO-Fuzzy controller lies near the knee of the curve (E_total ≈ 3.66 kWh, SoC_min ≈ 36%), representing the most balanced operating region between efficiency and battery protection.The PSO-optimized fuzzy controller operates near the "knee," ensuring both high efficiency and adequate SoC margin. Optimizer stability is shown in Figure 9, where the best-fitness value remains nearly constant after ≈ 10 iterations, confirming smooth convergence and stable tuning behaviour.

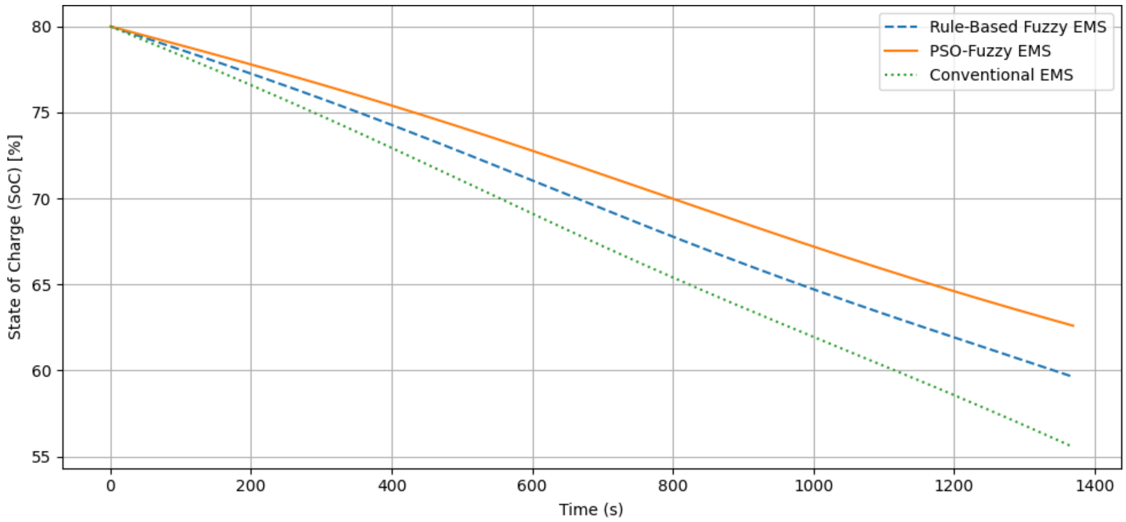

Figure 8. Pareto front of energy–SoC trade-off among the three EMS strategies

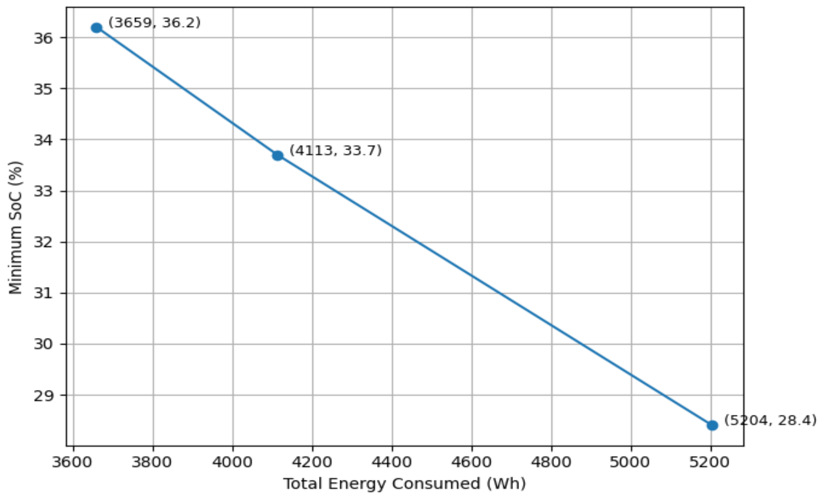

Figure 9. PSO convergence of best fitness for fuzzy optimization

4. CONCLUSION

This paper proposed a hybrid fuzzy logic and particle swarm optimization (Fuzzy-PSO) based EMS for electric vehicles to enhance energy efficiency, battery life, and power distribution under dynamic driving conditions. The PSO-tuned fuzzy controller adaptively managed power flow based on SoC, speed, and load, achieving a 29.7% reduction in total energy consumption and a 44% improvement in efficiency under the UDDS cycle. The optimized fuzzy surfaces provided smooth transitions and demonstrated robustness under noisy and fault-disturbed conditions, maintaining SoC above 35% and reducing battery stress. Comparative results confirmed the superiority of the hybrid controller in energy savings, SoC retention, and real-time responsiveness, while balancing energy efficiency and SoC preservation as shown by Pareto analysis. Future work will focus on hardware-in-the-loop validation and integration of detailed electro-thermal and aging battery models for adaptive derating, regenerative braking coordination, and predictive health management in multi-energy EV platforms. The framework will also be extended to dual-source configurations combining batteries and supercapacitors, and to coordinated smart-charging and vehicle-to-grid (V2G) energy exchange for grid-interactive electric mobility.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
V. Lakshmi Devi	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	✓	
Damodhar Reddy	✓	✓		✓	✓	✓		✓	✓		✓			
Srikanth Velpula	✓	✓		✓	✓	✓	✓	✓		✓	✓			
K. Kumar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	
Basi Reddy Avula	✓	✓		✓	✓	✓				✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Dr. V. Lakshmi Devi is currently working as a professor in the School of Engineering at Anurag University, Hyderabad, India. She received her Ph.D. degree in 2019 from JNTUA, Ananthapuram, India. M.Tech., degree in electrical power engineering from Narayana Engineering College, Nellore, JNTU-A, in 2011, and B.Tech. degree in electrical and electronics engineering from the Siddharth Institute of Engineering and Technology, Tirupati, JNTU-A in 2008. Her research work focused on the field of power systems, optimization techniques, power electronic applications in renewable energy sources, and hybrid electric vehicles. She has published more than 25 research publications in various International Journals/Conferences. She is ratified as assistant professor from JNTU-A, ANANTHAPURAMU. She is a Permanent member of IEEE, MISTE, and IAENG. She can be contacted at email: vldevi.eee@gmail.com.

Dr. Damodhar Reddy is a professor in the Department of Electrical and Electronics Engineering. He earned his B.Tech. (EEE) and M.Tech. (power electronics) degrees from JNTU Hyderabad and completed his Ph.D. in electrical engineering from VIT, Vellore in 2019. With over 11 years of teaching and research experience, his interests span power converters, renewable energy systems, and hybrid electric vehicles. He has published 24 research papers in Scopus-indexed journals and conferences, and serves as a reviewer for Energy Reports (Elsevier), IJRER, and IEEE conferences. A recipient of the VIT Research Award (2017), Dr. Reddy is a senior member of IEEE and a life member of ISTE. He can be contacted at email: damodhar_reddy@ymail.com.

Dr. Srikanth Velpula received a Ph.D. degree from Vellore Institute of Technology, Vellore, Tamil Nadu, India, in 2020. He received a B.Tech. and M.Tech. degrees both from Jawaharlal Nehru Technological University, Hyderabad, India, in 2009 and 2012, respectively. He worked as an assistant professor in the Department of Electrical and Electronics Engineering at various engineering colleges in India from 2011-2022. Currently, he is working as an assistant professor and Associate Dean of Academics at SR University, Warangal, Telangana, India. His research interests include power system stability, converter controls, DFIG-based systems, electrical vehicle drives, battery management systems, and the Integration of renewable energies into the power systems. He can be contacted at email: srikvelpula@gmail.com.

Dr. K. Kumar is currently working as a professor in the Department of EEE at Sri Venkateswara College of Engineering (SVCE), Tirupati, India. He received his Ph.D. degree in 2019 from SELECT at VIT University, Vellore, India. M.Tech. degree in power electronics and electrical drives from the SV College of Engineering and Technology, Chittoor, JNTU-A, in 2013, and a B.Tech. degree in electrical and electronics engineering from the SV College of Engineering, Tirupati, JNTU-A in 2011. His research work focused on the field of power electronic applications in renewable energy sources and hybrid electric vehicles. He has published more than 40 research publications in various International Journals/Conferences. He is ratified as assistant professor from JNTU-A, ANANTHAPURAMU. He is a permanent member of AMIE, MISTE, and IAENG. He can be contacted at email: kumar3kk@gmail.com.

Basi Reddy Avula received his Bachelor of Technology degree in computer science and engineering in June 2011 and Master of Technology degree in computer networks specialization in computer science and engineering in 2015 from Jawaharlal Nehru Technological University, Ananthapuramu. He is pursuing a Ph.D. in the Department of Computer Science and Engineering from Bharath Institute of Higher Education and Research, Chennai. He is working as an assistant professor in the Department of Computer Science and Engineering, School of Computing, Mohan Babu University, Tirupati, Andhra Pradesh, India. He received 06 Patents and published more than 115 Research Articles in SCI, Scopus, and UGC CARE. He received 06 memberships from ISTE, IETE, ICST, IACSIT, IAENG, and IFERP. His current area of interest includes cloud computing, IoT, artificial intelligence, machine learning, and deep learning. He can be contacted at email: basireddy.a@gmail.com.