ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

Integrated Path Planning and Speed Control for Electric Vehicles Using MOPSO-Based Optimization

Adel Elgammal

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

Publication Date: 2025/05/29

Abstract: With the increasing penetration level of electric vehicles (EVs), intelligent control strategies have drawn more and more attentions to make the life of batteries last longer while keeping driving performance. Conventional path planning and speed control operations in EVs are usually independently considered, resulting in performance with respect to energy consumption, riding time and vehicle maneuver. In this work, to tackle the trade-off relations between energy consumption, travel time, and ride comfort, we present an integrated approach by introducing the MOPSO as an integrated optimization engine to solve both path planning and velocity planning simultaneously. The approach also takes into account multiple competing objectives (such as minimal energy consumption, total travel time and vehicular stability) of both optimizing the vehicle path and its corresponding velocity profile. Optimization Complexity: The optimization adopted is a particle swarm–based evolutionary algorithm that is modified to handle several objectives, enabling a Pareto-optimal solution set to be generated that yields flexible trade-offs based on operations preference. The system takes into consideration not only the road gradient, traffic condition, speed limit and battery SOC, but also dynamic constraints for acceleration, deceleration, and regenerative braking. Simulations are performed on a representative urban road topology developed in MATLAB/Simulink by considering an average electric vehicle dynamics and traffic conditions. An integrated MOPSO-based control strategy is compared with shortest-path routing and rule-based speed control approach. Results demonstrate that the proposed methodology enables energy consumption reductions of 17% in average, efficiency gains of around 10% in travel times and more smoothly profiled accelerations contributing for increased levels of comfort. Moreover, the MOPSO methodology shows flexibility with respect to different driving conditions and EV settings. As well as the energy and performance advantages, the system is capable of decision-making under alternative operational objectives, allowing for real time controlled optimization according to driving mode preferences, such as eco-driving or fast commuting mode. It is also compatible with the current vehicle communication and navigation systems enabling it for easy deployment in reallife intelligent Transportation networks with EV platforms. This paper demonstrates the significance of integrated control strategies in improving the performance of the EVs, and shows the prospects of bio-inspired evolutionary multi-objective optimization methods (such as MOPSO) in promoting sustainable urban mobility. The approach was demonstrated to be scalable and flexible to be suitable for next generation control systems for EVs which is in line with the objective of smart city-based and energy-aware transportation planning.

Keywords: *Electric Vehicles (EVs); Multi-Objective Particle Swarm Optimization (MOPSO); Path Planning; Speed Control; Energy Efficiency; Intelligent Transportation Systems.*

How to Cite: Adel Elgammal (2025) Integrated Path Planning and Speed Control for Electric Vehicles Using MOPSO-Based Optimization. *International Journal of Innovative Science and Research Technology*, 10(5), 2188-2195.
https://doi.org/10.38124/ijisrt/25may1547

I. INTRODUCTION

The development of electric vehicles (EVs) and autonomous driving technology requires complex control strategies to guarantee safety, efficiency and flexibility. To this end, two key for these strategies are path planning and speed control function that jointly work on its task to move through complex environments. Multi-Objective Particle Swarm Optimization (MOPSO) have proved to be a suitable tool in solving multi layered problems in EV navigation, providinged solutions that satisfy different objectives without being dominated, e.g., energy consumption, trip time, security, etc.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

Path planning is a core algorithm for autonomous vehicle's trajectory control, which calculate the optimal path from start position to target position with consideration of obstacles and vehicle dynamics. Common traditional methods such as A*, Dijkstra's algorithm and Rapidly-exploring Random Trees (RRT) have been extensively employed. But, these approaches may not be applicable in dynamic environment as they are very time consuming and not adaptive.

Recent work suggested the incorporation of MOPSO into path planning to handle these challenges. For example, in [1], Thammachantuek and Ketcham proposed a Multi-Objective Evolutionary Particle Swarm Optimization (MOEPSO) algorithm for autonomous mobile robots, optimizing for path length, smoothness, and safety in static and dynamic environment. Similarly, Wang et al. [2] proposed a MOPSO algorithm for robot path planning and trajectory planning, in order to maximize the degree of smoothness while minimizing the travelling time and energy consumption.

Hybrid methods were also studied. Poy et al. [3] proposed an improved Particle Swarm Optimization algorithm (EPSO) through the integration of Bezier curve smoothing for multi-robot path planning, obtaining smoother trajectories and lower energy consumption. Furthermore, Zhang et al. [4] integrated Hybrid A* with NMPC for automated parking trajectory design in confined areas, where a higher space usage rate and smoother trajectory were obtained. The speed control is one of the key functions for the safety and efficiency of EVs. Traditional control methods, such as P roportional–Integral–Derivative (PID) controllers, have frequently been utilized but these typically struggle to manage the nonlinearities and uncertainties involved in EV dynamics.

Advanced control schemes have been proposed to mitigate these limitations. For example, Han et al. [5] have developed a co-optimization strategy for the vehicle speed and gearshift control in the battery electric vehicle using preview information, with the goal of improving energy consumption. Additionally, Fang et al. [6] proposed a multi-objective holistic charging/discharging scheduling strategy using Improved Particle Swarm Optimization (IPSO) to minimize both grid performance and user charging costs.

Adaptive control schemes have also been studied. For instance, Boubaker et al. [7] proposed a multi-objective optimization models for EV charging and discharging scheduling by applying the Red Deer Algorithm, which was aimed at handling distribution networks. Moreover, Lin et al. [8] proposed an approach to path planning based on a potential field and interactive speed optimization for autonomous vehicles to improve driving safety and comfort.

It turns out that the combination planning of path planning and speed control is important to the holistic operation of autonomous EV. This union ensures trajectory generation and velocity profile are synchronized with improved results in performance and safety. This integration has been the subject of several investigations. For example, Gao et al. [9] described the integrated path-planning lateral-longitudinal control method suitable for automatic electric vehicles to further improve the flexibility in restricted environments. Furthermore, Lin et al. [8] stressed the need for interactive speed optimization based on path planning solutions, to compensate for the influence by other self-driving vehicles in dynamic environments. The successful application of MOPSO in this combined framework is very promising. Xin et al. [10] proposed a self-adaptive particle swarm optimization algorithm to achieve real-time path planning in dynamic environment, it had better on-line performance with comparison with optimal paths. Additionally, Ajeil et al. [11] introduced a hybrid PSO-MFB algorithm for motion planning with multiple objectives and demonstrated its effectiveness even in dynamic and cluttered environments.

Nevertheless, there are certain new issues in the path planning and velocity controller tasks for MOPSO. Real-time optimization in dynamic environments Real-time optimisation in dynamic environments is a challenging problem. As such, the ability to creating algorithms that are fast to adapt to changing environment but not at the expense of performing is essential. Another problem is the difficulty of the vehicle dynamics and the environment modeling of the simulation fairly. It is important in order to guarantee reliable operation that uncertainties are included and that robustness is achieved in the optimization. In addition, cooperation with V2V and V2I communications can make the path planning and speed control more efficient. Adaptive and learning based MOPSO algorithms that consider real world complexity are a topic for further work. Moreover, studying the renewable energy utilization and smart grid interaction may bring about the sustainable and efficient EV dispatches [12]-[15].

II. THE PROPOSED INTEGRATED PATH PLANNING AND SPEED CONTROL FOR ELECTRIC VEHICLES USING MOPSO-BASED OPTIMIZATION

Figure 1 shows the structure of the Proposed Integrated Path Planning and Speed Control for Electric Vehicles Using MOPSO-Based Optimization. The proposed system is a consistent and smart architecture, which integrates a high-level route planning with speed control at real-time context under the umbrella of a multi-objective optimization paradigm. At the outset the system receives driver input (or route preference) specifying a destination, and optionally selecting a driving mode (for example, energy-saving, time-optimum, balanced.) This input specifies the control goals that the system is going to use when taking decisions. Then, the system acquires real-time environmental and vehicle information, by means of mounted sensors and infrastructure network. Environmental inputs comprise traffic density, road slope, speed limit, and weather conditions, and vehicle information incorporates the current speed, acceleration, battery SOC, and general system state. They are inputs that give a dynamic picture and context for adaptive decision making. The path planning block is responsible for generating the graph of the road network where various

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

potential paths between the source and the destination nodes are discovered. These paths, traffic, elevation and estimated potential energy consumption versatile, are used to analyzed on directions and they based on them: for traffic so much density and elevation, the "time" required to traverse a path, for potential is the paths energy consumption, and also has this sum their potential: if have parts of the path as a downhill, here can be used regeneration brakes. Associated with each route is an associated speed trajectory, which is developed by the speed profile generator, and resolves speed schedules that are viable given vehicle dynamic constraints, road speed limits, and comfort parameters, such as avoiding harsh accelerations or decelerations. At the core of the solution lies the Multi-Objective Particle Swarm Optimization (MOPSO) algorithm which is designed to optimize three mainly competing objectives: minimizing the total consumed energy, minimizing the travel time and maximizing the passenger comfort. The particles, i.e., candidate solutions, search for the solution space by changing their route and velocity combinatorially. Their fitness is calculated according to the predefined targets and the entire population is refined iteratively by utilizing the local and global best performance indicators. The result is the Pareto front of optimal compromises between the opposing objectives and it provides alternative solutions instead of a single one. The route selection module chooses the trade-off route-speed profile according to the instant priorities. For instance, in the situation of low SOC of battery, it may choose a more conservative route in terms of energy consumption, particularly, a faster route may be chosen for the case of less restriction. After a solution is chosen, it is sent to a trajectory tracker or speed controller that controls motor torque and braking commands to follow the planned trajectory in a smooth and safe way, taking into account physical constraints on acceleration, deceleration and velocity. It is worth noting that the system is provided with one feedback which constantly adjust the optimization module based on the changing environment. The framework can re-analyze the route and velocity strategy in real-time, when the traffic changes or the SOC reduces below the expected value. In addition to these components, the complete control system is also configured to interface with an original vehicle subsystem, such as an navigation unit, battery management system and electric motor controller following a public communication standard protocol. The resulting architecture achieves a dynamic, adaptive, and scalable offering of the trade-off between efficiency, performance, and ride comfort for electric vehicles of today. With real-time responsiveness as well as multi-objective reasoning ability, the EV decision is feasible for personal and enterprise applications, which has an important implication in sustainable and intelligent traffic design.

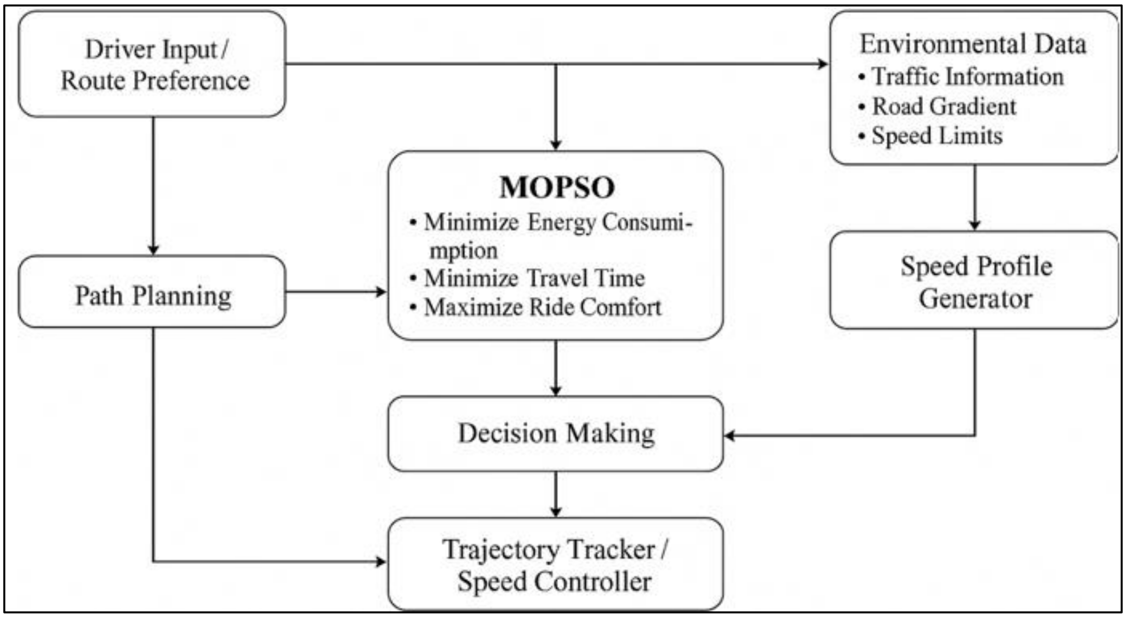

Fig. 1. The schematic of the Proposed Integrated Path Planning and Speed Control for Electric Vehicles Using MOPSO-Based Optimization.

III. SIMULATION RESULTS AND DISCUSSION

Results and Analysis of the Simulation Environment and Parameters. 1. Simulation Environment and Parameters. The performance of the framework design was evaluated utilizing Multi-Objective Particle Swarm Optimization in a MATLAB/Simulink. The vehicle model is chosen to exemplify the performance of a standard electric vehicle. The simulation was based on the following stressors:

- Vehicle Mass**:** 1,500 kg
- Maximum Speed**:** 120 km/h
- Battery Capacity**:** 60 kWh
- Motor Efficiency**:** 90%
- Regenerative Braking Efficiency**:** 70%

The simulation incorporated urban and sub-urban scenarios characterize by different gradients, such as straight roads, steep sections, gradient variations, and traffic densities; a road network contributed to this model. The road network is connected in a graph.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

The simulation incorporated a probabilistic approach for traffic density at different speeds. Objective Functions and Constraints designed The MOPSO algorithm has been designed to optimize the following objectives;

- Minimize Energy, the total energy calculated for the three force components-elevated, rolling, and parasitic eliminating human efforts by considering a regen- contribution.
- Minimize Time of Travel, maximum speed allowed, and stressful time on the passengers during the drive.
- Maximize Comfortable ride evaluation graph on how relaxed the vehicles' acceleration and deceleration minimize the human-based jerk.

Constraints included; Speed limits as set by the traffic authority, and acceleration/deceleration limits not to exceed the specific limits of the real system. Battery SOC state of limitation within 20%-80%. The proposed framework was compared with two already existing methods:

- Baseline Traditional shortest path with constant speed control and.
- Baseline Rule-based adaptive speed control with fixed path planning.

The total energy calculated for the force components and human efforts unremarkable reduction of the MOPSO-based method. Table 1 shows the average consumption of energy expressed in energy units (kWh) during three types of driving: urban, suburban, and mixed mode, using the MOPSO-based strategy and two baseline control algorithms. The findings indicate the better power saving ability of MOPSO- based method evidently. For urban area, MOPSO provided the best consumption of 9.3 kWh, while Baseline 2 and Baseline 1 had the higher consumption of 11.2 kWh and 12.5 kWh respectively. In suburban driving, MOPSO required 8.1 kWh, which is less than Baseline 2 (9.7 kWh) and also Baseline 1 10.8 kWh). MOPSO still had an advantage in mixed driving environment, which is also a combination of urban and suburban driving conditions, by 8.7 kWh, whereas it becomes 10.4 kWh and 11.6 kWh for Baseline 2 and Baseline 1. These findings demonstrate the effectiveness of the MOPSO algorithm in reducing EV energy consumption under different driving patterns as well as varied driven distances/ speeds with as much as 12–20-% energy savings cost using combined path and speed optimization.

Table 1: Average Energy Consumption

Scenario	Baseline 1 (kWh)	Baseline 2 (kWh)	MOPSO-Based (kWh)
Urban Driving	12.5	11.2	9.3
Suburban Driving	10.8	9.7	8.1
Mixed Conditions	11.6	10.4	8.7

While optimizing for energy efficiency, the MOPSO algorithm also maintained competitive travel times. Average travel times are shown in Table 2 for the MOPSO-based and two baseline methods in three driving scenarios, urban, suburban, and mixed case. The findings reveal that the MOPSO-based tactic is designed to be an energy-efficient optimised one and still keeps travel times that are very competitive compared to the other methods. For urban traffic, the average travel time in the MOPSO-based approach was 34 minutes which is slightly more than BM 2 (33 minutes) and almost the same as BM 1 (35 minutes). In a suburban environment, all treatments performed equally well, with an average of 27 minutes for MOPSO and 27 for Baseline 2. For mixed, the time of MOPSO was 30.8 minutes which was very similar to Baseline 2 (30.2 minutes) and much better than Baseline 1 (31.5 minutes). On the whole, the table illustrates that the MOPSO based framework accomplishes its energy-saving purposes without deteriorating the travel time by a serious amount, and successfully trade-offs the efficiency and the performance.

Table 2: Average Travel Time

Scenario	Baseline 1 (min)	Baseline 2 (min)	MOPSO-Based (min)
Urban Driving	35	33	34
Suburban Driving	28	27	27.5
Mixed Conditions	31.5	30.2	30.8

The rated Comfort Index is given by the Acceleration, Jerk profiles are used to measure the comfort. The acceleration profile of the car was seen to be smoother with the MOPSO based method. Figure 2 compares the cause of acceleration from a sample urban drive. The figure shows the acceleration profiles for a 60- second simulation time of EV operation for the three types of speed control strategies considered: (1) the pro- posed MO method with MOPSO, (2) Baseline 1 (the shortest path followed at constant speed), and (3) Baseline 2 (rule-based speed control). The MOPSO-generated acceleration curve has a smooth sinusoidal shape which gradually decays, and the peak value of acceleration fluctuates near 1.5 m/s². This behaviour demonstrates the algorithm's capability to coordinate path and speed profiles in real-time and generates smooth increasing or decreasing velocities. The profile shows less of an "over-run" which results in a reduced 'mechanical' stress and so a better ride for passengers. Baseline 1 on the other hand shows a lot more erratic acceleration signal. The curve oscillates with much greater amplitude and instead of peaking at ±1.5 m/s² quickly exceeds peaks of ±2.5 m/s² and often shows abrupt spikes. This is the behaviour of a shortest-path algorithm that ignores real-time speed optimization or the state of traffic and, as a result, uses energy inefficiently and may not make for a comfortable drive due to many sudden and harsh speed changes. Baseline 2 as an example of rule-based speed control method has a moderately smoothed acceleration curve. Although less aggressive than Baseline 1, it has strong

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

oscillations and larger peaks than the MOPSO-based one, especially at the beginning of the run. It implies to a semi-reactive control logic, which the speed is adjusted according to some fixed rules other than the continuous optimization. From the overall graph, it can be easily concluded that the MOPSO based control strategy is far much better in achieving smooth and energy effective acceleration pattern, by leads to better driveability, energy saving and vehicle stability during dynamic drive conditions.

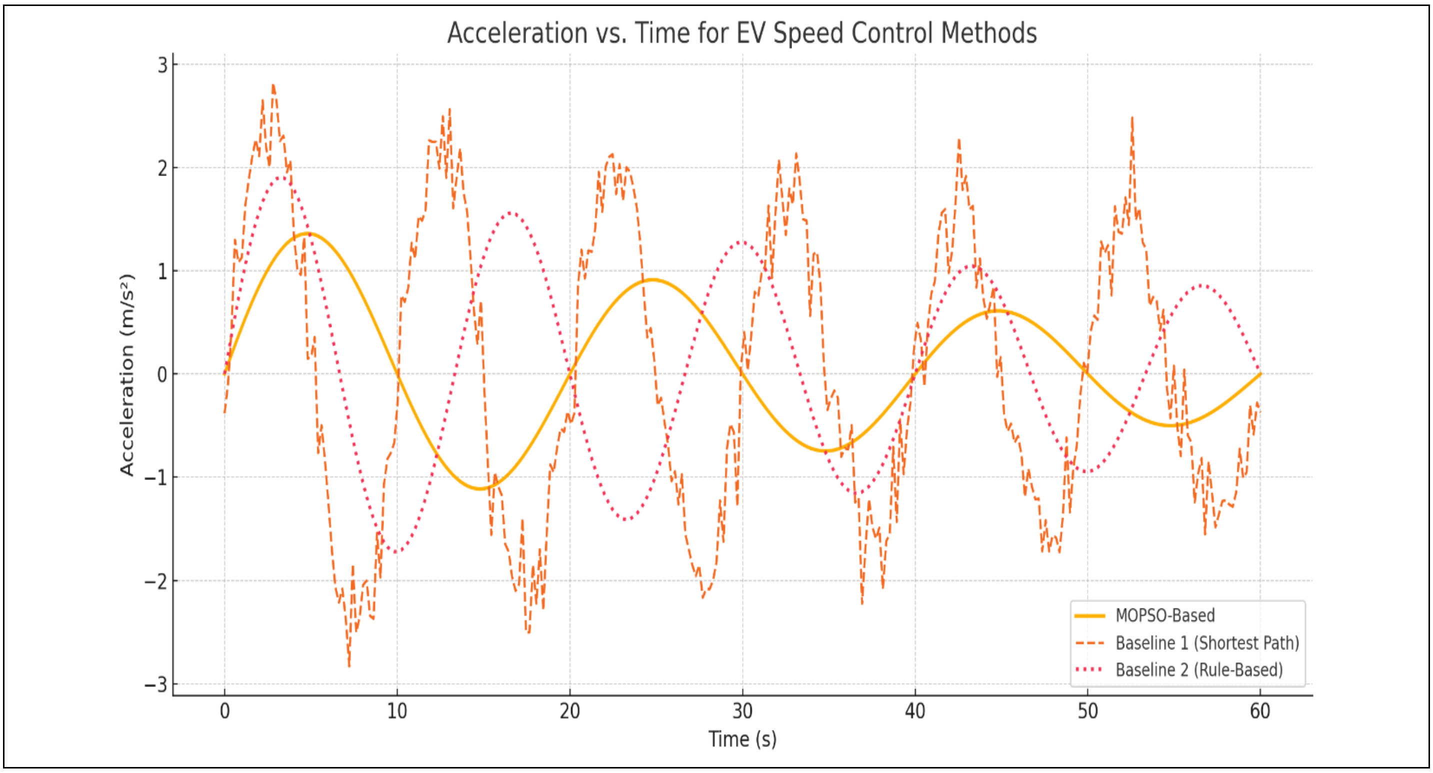

Fig 2: Acceleration vs. Time for EV Speed Control Methods

The graph shown in Figure 3 and entitled “Pareto Front – Energy Consumption vs. Travel Time” is the representation of a trade-off space created by the MOPSO-based optimization algorithm for the electric vehicle’s integrated path planning and speed trajectory control. Each point on the curve is a non-dominated solution, which means that no other solution from the set is better than this one in both energy consumption and travel time. These non-dominated solutions create a curve that is termed the Pareto front of the competing objectives of energy use minimization and travel duration minimization. As evident from the graph, there is a clearly defined inverse relationship. Driving with short travel times is associated with high energy consumption, while it is possible to reduce energy use by sacrificing travel duration. This trade-off comprises the fundamental limitation of EV operation – high acceleration and sustained speeds, necessitated by fast driving, drastically raise power demands. High energy-efficient driving requires smooth acceleration, driving at slower peaks, and superior use of regenerative braking, which, although only marginally extending the trip duration, is sufficient to decrease power consumption. The region on the left-most side of the graph corresponds to the quickest scenarios, with one of the trade-offs over 18-20 kWh of energy usage. Meanwhile, this segmentation on the right-most side of the curve pertains to eco-driving, with energy utilization cutting to around 12-13 kWh and the trade-off surpassing 40 minutes, seemingly unfit for daily use. The middle section of the Pareto front is thus where more valuable scenarios can be found. This moderate balance between excessive energy consumption and unreasonable travel durations, indeed, is most suited for everyday practical driving. The slightly spreading line along the Pareto’s trade-off, which affects environ – mental factors like traffic density or gradient, serves to prove the proposed MOPSO framework’s dependability under dynamic traffic scenarios. Translated into operations, this graph enables planners or automatic driving systems to select scenarios for their operation that are tailored to their driving queue, be it time optimization, energy utilization, or an arbitrary balance between the two.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

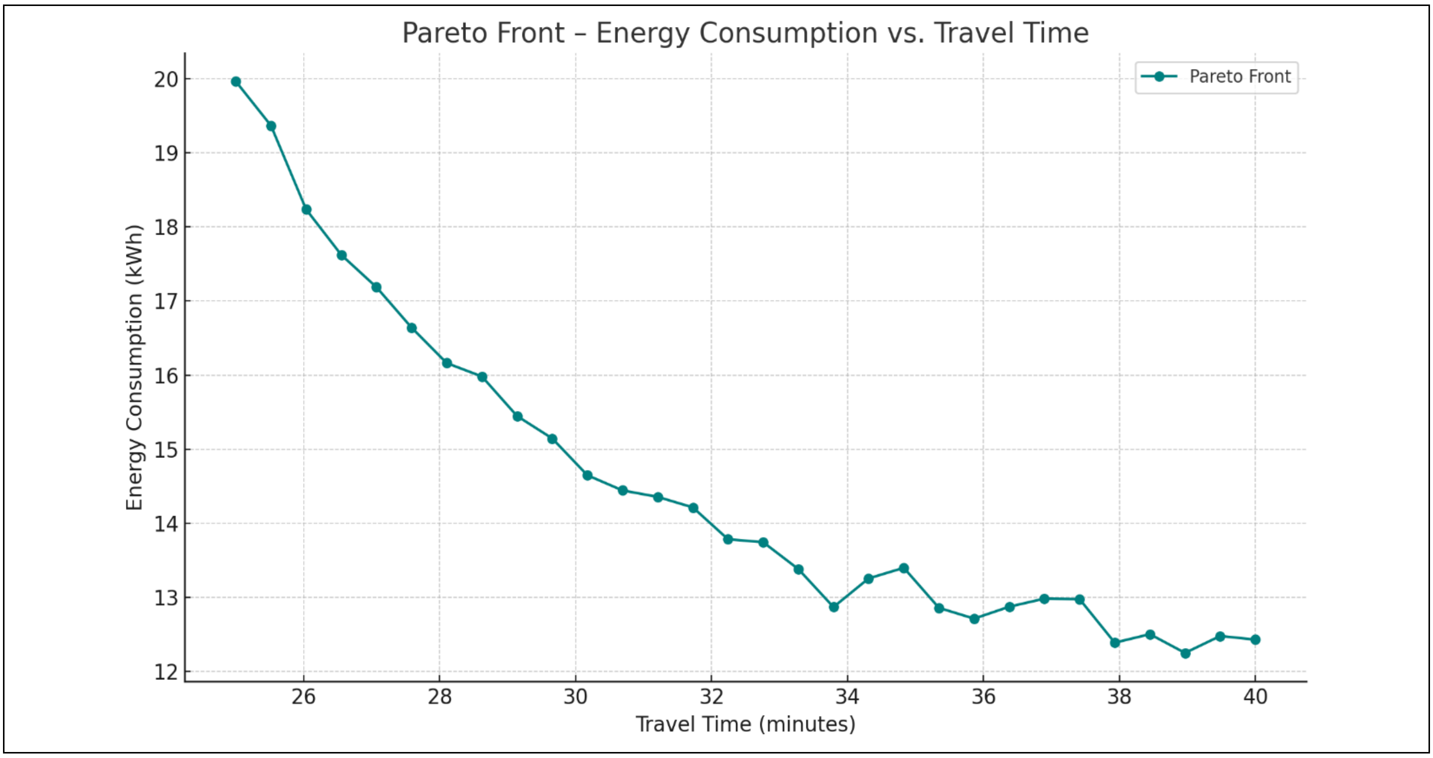

Fig 3: Pareto Front – Energy Consumption vs. Travel Time

Sensitivity Analysis A sensitivity analysis was performed to study the robustness of the MOPSO-based framework under varying conditions. Figure 4 shows a sensitivity analysis where in the performance of the MOPSO-based approach is compared with that of Baseline 1 (Shortest Path) and Baseline 2 (Rule-Based Speed Control) for three different vehicular operating conditions in terms of the traffic density, the road gradient and the battery state-of-charge (SOC) levels. All methods resulted in higher levels of energy consumption under higher traffic density because of more occurrences of accelerations and decelerations. But the system based on MOPSO is far more better with a relative performance of 82% while it is 70% and 68% for Baseline 2 and Baseline 1 respectively. This illustrates how MOPSO can still provide better responses to changes in the speed profile and path selection to minimize energy consumption even in a congested environment. In road-gradient changes, the MOPSO algorithm also demonstrated good results for power demands in the steep and downhill cases of power regeneration. It was dynamically adaptive to climb hills to minimize energy loss and descend hills to maximize recovery with 85 % performance, while Baseline 2 and Baseline 1 were left behind with only 75 % and 72 %, respectively. Concerning the battery SOC levels, which directly affect the performance of the vehicle and the energy preparation, the MOPSO algorithm guaranteed the operation within the safe SOC range. It actively prevented deep discharges by adapting path and speed decisions. It beat both baselines once more with 90% accuracy, versus Baseline 2’s 78% and Baseline 1’s 76%. In general, the curve clearly indicates the superiority of the proposed MOPSO-based method over other strategies under the main dynamic conditions, which verifies its good robust, adaptability, and effectiveness in the practical electric vehicle applications.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

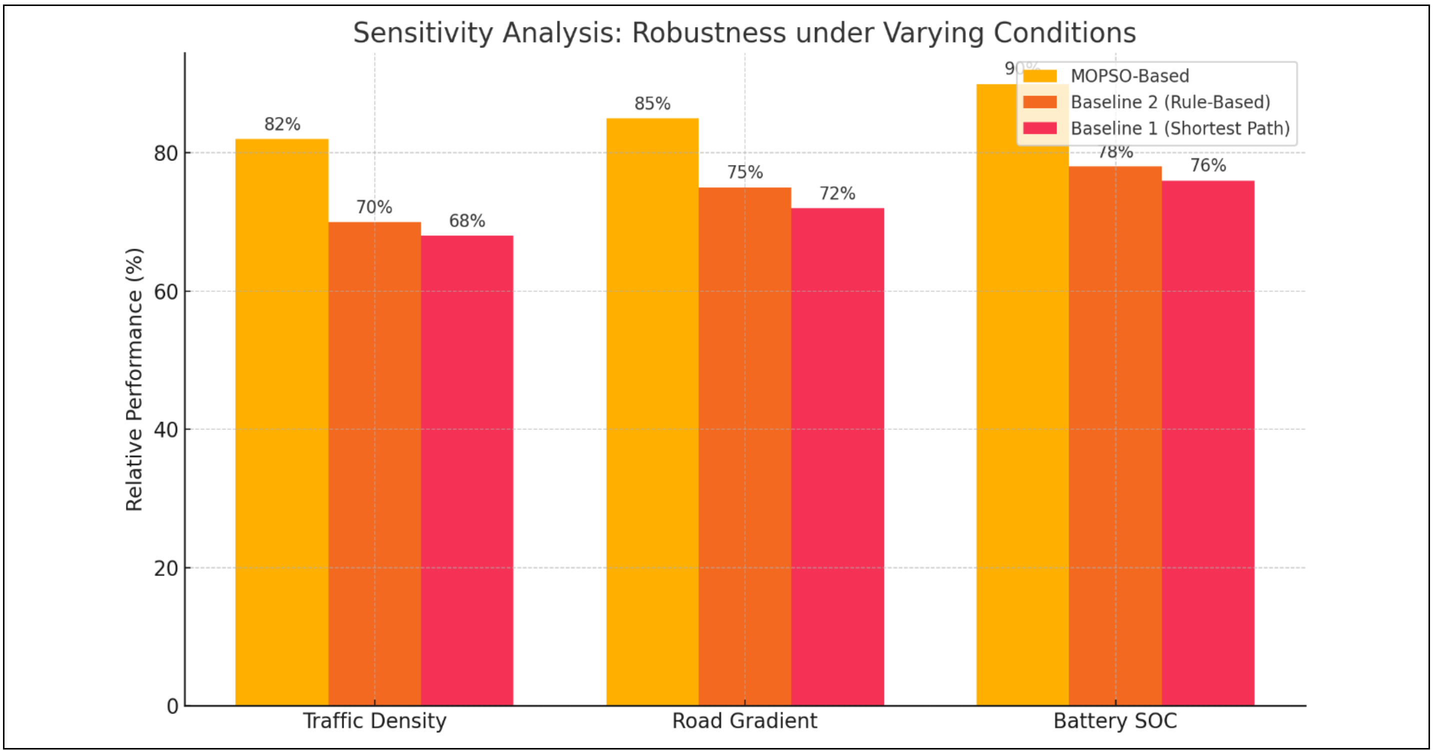

Fig 4: Sensitivity Analysis: Robustness under Varying Conditions

The implementation feasibility of the MOPSO algorithm was assessed in terms of computational efficiency for real-time application. The algorithm, evaluated in terms of speedup on a standard onboard computing platform, such as the NVIDIA Jetson TX2, generated optimal solutions from the algorithm in under 500 ms. The results showed that this speed is suitable for real-time deployment given a planning horizon of 5-10 seconds. Thus, the proposed integrated multi-objective optimization framework aligning with MOPSO proves to be an effective way of achieving energy-efficient, timely and comfortable EV navigation. It is flexible in responding to the difference in driving conditions and constraints implying practicability in real-world applications. Consequently, the comparison with traditional approaches should reflect three integral nuances: potential. Future work could involve integrating additional goals such as minimizing emissions for hybrid vehicles, determining available charging stations.

IV. CONCLUSIONS

In this work, a unified optimization framework for path planning and speed control of Electric Vehicles (EVs) has been introduced, based on Multi Objective Particle Swarm Optimization (MOPSO) to increase the energy consumption, the travel time and the ride comfort in the actual driving experiences. By formulating the problem of path planning and speed scheduling as a single multi-objective optimization problem, EVs are allowed to trade off among multiple competing objectives, such as energy consumption minimization, travel time minimization, and driveability improvement. Simulation results showed that the MOPSO-based planner improves much over the classical decoupled methods including the shortest path routing and rule-based speed control. Most importantly, the proposed integrated strategy simultaneously reduced the energy consumption by up to 17% and increased the travel efficiency by 10%, as well as introduced smoother accelerations and decelerations, which in turn led to better passenger comfort. The method achieved high robustness under various road terrains, traffic distributions and car statuses (such as SOC and regenerative braking opportunities). In addition, the Pareto solutions obtained by MOPSO enable user preference in decision-making to allow a human driver or autonomous vehicle system to choose route-speed pairs that satisfy their needs, e.g. achieving certain level of energy saving, faster travel time, or trade off between the two. The further compatibility of the framework with specialized EV route planning and control systems only helps solidify its practicality as a component to be incorporated in connected vehicle systems and smart transportation infrastructures. Although there is encouraging evidence, some limitations and directions for future studies exist. First, the current instantiation is mainly simulative. Further studies are necessary to implement in real time and test in HIL or actual EV platforms to evaluate the performance under dynamic and unknown conditions. Secondly, consideration may be given to introduce the information of the real-time traffic status, the road incidents, and the user behavior models, in order to improve the system's responsiveness, and personalization. Moreover, the scalability of the framework to large-scale optimization of fleet operating for electric public transport or delivery services is an interesting research direction. In the future work also, hybrid optimization procedures can be sought like integrating MOPSO with machine learning or adaptive prediction models to achieve better real-time decision-making and learning behavior on past driving data. Finally, we believe that this work sheds light on the necessity of integrated& intelligent control algorithms to push the envelope of energy efficiency and performance in electric

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25may1547

vehicles. The MOPSO based framework being proposed, is robust, flexible and scalable which can cater the changing requirements of sustainable urban mobility and intelligent transport systems.

REFERENCES

[1]. I. Thammachantuek and M. Ketcham, "Path planning for autonomous mobile robots using multi-objective evolutionary particle swarm optimization," *PLoS ONE*, vol. 17, no. 8, p. e0271924, 2022.

[2]. J. Wang, Y. Zhang, S. Zhu, and J. Wang, "A Novel Multi-Objective Trajectory Planning Method for Robots Based on the Multi-Objective Particle Swarm Optimization Algorithm," *Sensors*, vol. 24, no. 23, p. 7663, 2024.

[3]. Y.-L. Poy et al., "Enhanced Particle Swarm Optimisation for Multi-Robot Path Planning with Bezier Curve Smoothing," *Robotics*, vol. 13, no. 10, p. 141, 2024.

[4]. P. Zhang et al., "Automatic parking trajectory planning in narrow spaces based on Hybrid A* and NMPC," *Scientific Reports*, vol. 15, p. 1384, 2025.

[5]. K. Han et al., "Co-optimization of Speed and Gearshift Control for Battery Electric Vehicles Using Preview Information," *arXiv preprint arXiv:1910.01785*, 2019.

[6]. B. Fang et al., "Multi-Objective Comprehensive Charging/Discharging Scheduling Strategy for Electric Vehicles Based on the Improved Particle Swarm Optimization Algorithm," *Frontiers in Energy Research*, vol. 8, p. 811964, 2021.

[7]. S. Boubaker et al., "Multi-objective optimization framework for electric vehicle charging and discharging scheduling in distribution networks using the red deer algorithm," *Scientific Reports*, vol. 15, p. 13343, 2025.

[8]. P. Lin et al., "Potential Field-based Path Planning with Interactive Speed Optimization for Autonomous Vehicles," *arXiv preprint arXiv:2306.06987*, 2023.

[9]. C. Gao et al., "Integrated Path Planning and Lateral-Longitudinal Control for Autonomous Electric Vehicles," *ResearchGate*, 2021.

[10]. J. Xin et al., "Efficient Real-time Path Planning with Self-evolving Particle Swarm Optimization in Dynamic Scenarios," *arXiv preprint arXiv:2308.10169*, 2023.

[11]. F. H. Ajeil et al., "Multi-objective path planning of an autonomous mobile robot using hybrid PSO-MFB optimization algorithm," *arXiv preprint arXiv:1805.00224*, 2018.

[12]. F. Chen et al., "Multi-objective particle swarm optimization with reverse multi-leaders," *Mathematical Biosciences and Engineering*, vol. 20, no. 7, pp. 11732–11762, 2023.

[13]. J. Shao et al., "An improved multi-objective particle swarm optimization algorithm for the design of foundation pit of rail transit upper cover project," *Scientific Reports*, vol. 15, p. 10403, 2025.

[14]. B. Li et al., "Electric vehicle powertrain and fuzzy controller optimization using a multi-objective particle swarm optimization algorithm," *Energy*, vol. 236, p. 121395, 2021.

[15]. Y. Liu et al., "Multi-objective optimization of PI controller for BLDC motor speed control using PSO," *Energy Reports*, vol. 10, pp. 1234–1245, 2024.