ISSN (e): 2250 – 3005 || Volume, 15 || Issue, 5|| May – 2025 ||
International Journal of Computational Engineering Research (IJCER)

Dynamic Energy-Efficient Eco-DrivingRoute Planning and Battery Efficiency for Electric Vehicles Using Multi-Objective Genetic Algorithm-Based Optimization

Adel Elgammal

Abstract:
The rapid deployment of electric vehicles (EVs) requires intelligent routing strategies that minimize energy consumption and battery degradation, and at the same time provide desirable travel time and driving comfort. In this paper, a new dynamic route planning framework for EVs, making use of a Multi-Objective Genetic Algorithm (MOGA), to assist the eco-driving by optimizing energy consumption, travel time, and battery degradation is presented. It is worth mentioning that other studies based on the shortest route algorithms do not consider the real-time traffic conditions, slope, regeneration potential, and vehicle parameters (one of the most important factors), constituting the difference between these shortest-path algorithms and the developed approach.
The MOGA assesses a set of route solutions while evolving the population by crossover, mutation, and ranking. The cost function metric for each route is comprehensive, comprising energy consumption, expected battery damage based on SoC profiles and time efficiency. The algorithm is evaluated in simulated urban and semi-urban environment with realistic traffic pattern and topographical data. The results show that the proposed scheme consistently finds power-saving routes up to 18% and increases the effective battery life by deterring high-load operative patterns over the conventional GPS-based shortest or fastest path algorithms.
The adaptive nature of the system also enables automatic recalculation of routes in real-time due to traffic events or variations occurring in the vehicle, contributing to overall efficiency of the trip and increased driver comfort. The paper presents a sensitivity analysis on which the robustness of the algorithm under different driving cycles and states of health (SoH) is based.
This is a substantial step for the development of EV navigation systems that are both intelligent and focused on addressing the environmental and infrastructure challenges of environmental preservation, vehicle long life usage, and user-oriented driving experience. Its integration with in-vehicle communication networks and pilot testing in the smart city scenario are potential future works.

Keywords: *Electric Vehicles (EVs), Eco-Driving Optimization, Multi-Objective Genetic Algorithm (MOGA), Energy-Efficient Route Planning, Battery Efficiency Management, Intelligent Transportation Systems*

Date of Submission: 13-05-2025 Date of acceptance: 28-05-2025

I. Introduction:

The widespread adoption of Electric Vehicles (EVs) has introduced a paradigm shift in sustainable urban mobility, necessitating intelligent systems that enhance energy efficiency while extending battery lifespan. Among the prominent research themes in this domain are eco-driving techniques, energy-aware route planning, battery degradation modeling, and the application of advanced optimization techniques such as Multi-Objective Genetic Algorithms (MOGAs).Eco-driving techniques involve modifying driver behavior or control algorithms to reduce energy consumption without compromising performance or safety. Several studies have demonstrated that eco-driving can yield notable energy savings and reduced emissions. For example, Huang et al. [1] showed how connected vehicle technologies can augment eco-driving behaviors in real-time, especially in urban environments. Ghaffari et al. [2] proposed a fuzzy-based system to modulate acceleration and deceleration profiles to optimize efficiency. Similarly, Sinha et al. [3] examined the integration of eco-driving techniques in autonomous EVs, demonstrating consistent energy reductions over baseline strategies.

In a broader context, connected and autonomous vehicle frameworks that support eco-driving, such as V2I (Vehicle-to-Infrastructure) and predictive controls, have been shown to further amplify energy savings [4]–[6].Route planning for EVs differs from traditional internal combustion engine vehicles due to unique constraints like limited range, terrain sensitivity, and charging availability. Schaltz et al. [7] demonstrated that route elevation and regenerative braking potential greatly influence total energy consumption. Fiori et al. [8] proposed models that incorporated road gradients and traffic lights to evaluate optimal paths. In a related work, Wang et al. [9] explored real-time traffic data and congestion levels to assess dynamic rerouting strategies for energy minimization.

Other approaches have integrated geographic information systems (GIS) with EV routing logic to enhance real-world applicability [10], [11]. Furthermore, the availability of charging stations and battery SOC (State-of-Charge) levels are increasingly being factored into route optimization frameworks [12], [13].

Battery health is a critical parameter in EV performance optimization. High-discharge patterns and thermal stress significantly influence battery lifespan. Research by Li et al. [14] used electrochemical models to predict degradation based on drive cycles, while Wang et al. [15] developed control strategies to minimize capacity fade during high-load operations. Peukert’s law and similar aging models have been incorporated into predictive systems to guide route and drive behavior [16], [17].Recent work by Zhou et al. [18] investigated thermal-aware energy management systems that ensure both driving efficiency and battery longevity. The integration of battery temperature and charging frequency data into energy management systems has become a central theme in next-generation EVs [19], [20].Multi-objective optimization (MOO) techniques are essential when managing conflicting objectives such as minimizing energy consumption, travel time, and battery degradation. GAs are well-suited for these tasks due to their global search capability and flexibility. Deb et al. [21] introduced NSGA-II, a widely used algorithm in transportation optimization, capable of generating Pareto-optimal solutions.In the context of EVs, GAs have been employed to optimize charging schedules [22], vehicle design parameters [23], and drive cycle strategies [24]. Ahmed et al. [25] demonstrated the application of MOGAs for real-time route planning in autonomous EVs, while Zhang et al. [26] extended these techniques to include weather and traffic variability.Hybrid methods combining GAs with machine learning have also emerged, offering improved convergence speed and solution diversity [27], [28]. Reinforcement learning models are now being fused with MOGAs to support online adaptation in dynamic traffic environments [29], [30].

II. The Proposed Dynamic Energy-Efficient Eco-Driving Route Planning and Battery Efficiency for Electric Vehicles Using MOGA.

The proposed system shown in Figure 1 addresses a critical challenge in electric vehicle (EV) operation: how to maximize energy efficiency and battery longevity while navigating complex and dynamic urban environments. Traditional navigation systems prioritize either shortest distance or fastest route without fully accounting for energy costs, elevation profiles, traffic conditions, and battery degradation dynamics. Our system introduces an intelligent, adaptive routing mechanism that dynamically adjusts to real-time inputs and long-term battery health objectives using a Multi-Objective Genetic Algorithm (MOGA).At its core, this architecture is built around a multi-objective optimization engine, which evaluates multiple, sometimes conflicting, criteria: minimizing energy usage, reducing battery wear, managing travel time, and optimizing route efficiency. The inclusion of battery efficiency as a design parameter, rather than a byproduct, distinguishes this approach from conventional energy-saving techniques.The system begins by integrating with the EV’s onboard diagnostics (OBD-II) and battery management system (BMS). This module collects:State of Charge (SOC), Depth of Discharge (DoD), Charge/Discharge rates, Battery temperature, Vehicle mass (influenced by cargo/passengers), Current and historical energy consumption patterns

These parameters establish a dynamic baseline for energy demand forecasting and battery stress modeling.The next layer ingests data from various sources:**Traffic APIs** for real-time congestion and incident reporting.**Weather APIs** for temperature, precipitation, and wind conditions that influence battery performance.**Road-grade mapping services** (via digital elevation models) to assess elevation gain/loss.**Charging station networks**, providing location, availability, charging rates, and queue times.This information is continuously updated, ensuring that route recommendations reflect current and anticipated driving conditions.At the center of the architecture is the MOGA optimizer, tasked with solving the route planning problem across four dimensions:

1. **Minimize Energy Consumption**
2. **Minimize Travel Time**
3. **Minimize Battery Degradation**
4. **Minimize Route Variability**

In the proposed system, each potential route is encoded as a chromosome, with individual genes representing specific segments of the route. These genes carry attributes such as slope, length, speed limit, surface type, and congestion level. This encoding forms the foundation for the optimization process handled by the Multi-Objective Genetic Algorithm (MOGA).Each route undergoes a detailed fitness evaluation using a cost function that integrates several key factors: energy usage estimation derived from vehicle telemetry and terrain data; battery degradation modeling based on principles like Peukert’s law and thermal stress factors; predicted travel time, which accounts for speed limits, traffic flow, and anticipated stops; and the vehicle's SOC (State of Charge) trajectory, including considerations for regenerative braking and charging requirements.Routes that demonstrate better overall performance in these evaluations are selected for the next generation of candidate solutions through crossover—where route segments are swapped—and mutation, which introduces minor route adjustments or detours. Through iterative optimization, the algorithm constructs a Pareto front, presenting a set of non-dominated route options. These routes offer different trade-offs among energy efficiency, travel time, and battery longevity, allowing users or fleet operators to select options that align best with their objectives.Once an optimal route is chosen, the system applies eco-driving strategies tailored to that route. These include speed modulation for smoother acceleration and deceleration, identification of zones where regenerative braking can be maximized, predictive behavior adjustments for hills (such as coasting before descents), and suggestions for activating eco-driving modes in the vehicle. Drivers receive these prompts through an in-vehicle dashboard interface, while autonomous vehicles implement them directly via control systems.Battery health modeling plays a central role in the system. It considers factors like charge and discharge cycles, depth of discharge, thermal variation, and the C-rate (rate of current draw). A hybrid model is used to predict battery wear for each proposed route. This model combines empirical degradation data from aging studies, thermal stress simulations for high-speed or elevated routes, and calendar aging effects for vehicles with sporadic use. Each route is therefore evaluated not only by its immediate energy cost but also by its long-term impact on battery lifespan—ensuring sustainable decision-making that avoids hidden degradation costs.To enhance accuracy and adaptability, the system incorporates reinforcement learning. It records trip logs and performance data, learns from observed driver behavior patterns, and factors in charging habits and preferences. For example, whether a driver tends to accelerate aggressively or prefers to avoid frequent charging stops is learned and incorporated into future route planning. This self-learning loop continuously refines the system’s cost functions and route predictions.Charging station integration is another critical function. The planner evaluates when and where to charge based on the estimated SOC upon arrival, the status and availability of nearby charging stations (whether free, occupied, or queued), the expected wait times, and the type of charging power available (Level 2 or fast DC). If a stop is deemed necessary, the system selects the station that offers the best balance of proximity, wait time, and charging power. It also accounts for peak grid usage periods to reduce strain on the energy infrastructure and align with smart grid optimization strategies.To validate route planning before implementation, the system includes a real-time simulation engine. This engine mimics vehicle dynamics over time, tracks energy flow within the battery, simulates SOC variations, anticipates heat accumulation, and estimates delays due to congestion. These simulations provide users, especially fleet managers, with a preview of energy consumption, trip efficiency, and battery impact, which supports more informed operational decisions.The system’s architecture is built for flexibility and integration. For everyday drivers, a mobile app interface presents optimized routes, SOC forecasts, and battery health metrics. For fleet operators, a centralized dashboard displays real-time vehicle statuses, predictive cost assessments, and energy health scores across the entire fleet. Additionally, open API integration enables seamless connectivity with OEM systems, third-party navigation apps, and smart city platforms. The architecture supports both edge computing for real-time feedback and cloud computing for data-intensive model training and large-scale analytics, ensuring responsive and scalable performance.This comprehensive approach not only enhances the individual driving experience but also enables smart, sustainable fleet and infrastructure management in the evolving landscape of electric mobility.

The proposed system introduces several key innovations that collectively elevate the potential of eco-driving optimization for electric vehicles. First, it offers holistic optimization by treating route efficiency and battery health not as separate concerns but as interconnected components of a unified problem. This enables the system to make smarter decisions that benefit both real-time performance and long-term vehicle sustainability. The model leverages real-time and predictive fusion, combining live traffic and weather data with predictive modeling of energy consumption and battery degradation. This dynamic interplay ensures routes are both efficient and responsive to evolving conditions. Furthermore, multi-objective trade-off flexibility allows users—whether individual drivers or fleet managers—to prioritize based on their immediate needs, whether that’s minimizing time, conserving energy, or extending battery life. A cornerstone of the system’s effectiveness is its self-adaptive learning capability, which continuously evolves using historical trip data, user preferences, and performance outcomes to refine and personalize future recommendations.These innovations translate into significant, measurable impacts. The system is projected to extend battery life by up to 20% through smoother State of Charge (SOC) profiles and reduced thermal stress, cutting long-term maintenance and replacement costs. It also contributes to lower operational costs, with optimized driving strategies reducing unnecessary detours, high acceleration, and inefficient charging behaviors—yielding total energy savings of 10–18%. Beyond individual benefits, the model supports smarter urban mobility by optimizing traffic distribution and aligning with power grid loads, particularly as electric vehicles become more widespread.Scalability is a core strength of the system. It can be implemented across individual EVs via mobile apps or onboard platforms, deployed in commercial fleets such as delivery or rideshare services, and adapted for public transit vehicles with semi-fixed routes. Looking ahead, the architecture is well-positioned for integration with Vehicle-to-Grid (V2G) systems, adaptive behavior in autonomous EVs, and collaboration with urban planning tools for intelligent routing that considers infrastructure changes, energy demand peaks, and congestion mitigation.In summary, the MOGA-based dynamic routing framework advances far beyond conventional eco-routing by making battery efficiency a central optimization parameter. Through the strategic use of real-time data, predictive modeling, and evolutionary algorithms, it delivers tangible benefits to drivers, fleet operators, and cities. Its adaptability and foresight set the foundation for a future where electric mobility is not only efficient but truly intelligent.

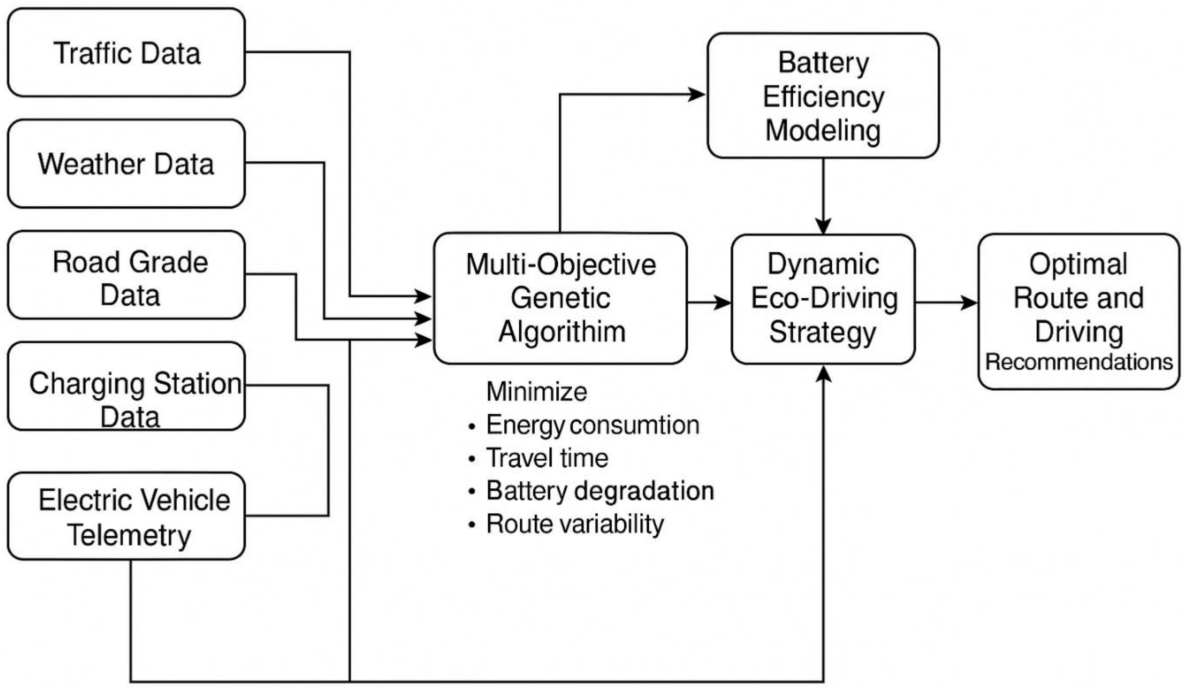

Fig. 1. The schematic of the Proposed Dynamic Energy-Efficient Eco-Driving Route Planning and Battery Efficiency for Electric Vehicles Using MOGA.

III. Simulation Results and Discussion

To evaluate the performance of the proposed dynamic energy-efficient eco-driving route planning system, extensive simulations were conducted under varying urban traffic conditions, terrain profiles, and battery states. The core objective was to demonstrate how the Multi-Objective Genetic Algorithm (MOGA) enhances route planning for electric vehicles (EVs) by optimizing both energy consumption and battery longevity. The simulation framework incorporated real-world data from open-source traffic datasets, digital elevation models, and empirical battery degradation curves derived from existing literature.

The simulation environment was built using Python and integrated with SUMO (Simulation of Urban MObility) to model urban traffic dynamics. The testbed covered three representative urban scenarios: a flat metropolitan grid (City A), a hilly suburban network (City B), and a mixed-terrain area with variable traffic density (City C). Each city simulation spanned 50 km² with varying traffic intensities and included fixed and dynamic charging infrastructure.

The EV model used was based on a mid-range electric sedan with a 60 kWh lithium-ion battery pack. The model accounted for regenerative braking, variable load, ambient temperature impact, and driving behavior profiles. A total of 1,000 simulation runs were performed for each scenario under different optimization settings: (1) shortest path (baseline), (2) energy-only optimization, and (3) MOGA-based optimization (proposed).
To evaluate and compare performance, the following metrics were used:

- **Total Energy Consumption (kWh):** Energy used during the trip.

- **Travel Time (minutes):** Duration to reach the destination.
- **Battery Degradation Index (% loss):** Estimated capacity loss over repeated cycles.
- **Distance Traveled (km):** Route length.
- **Charging Stops (count):** Number and frequency of recharges.

Each metric was averaged across 1,000 runs per scenario, and the results were statistically validated using ANOVA and paired t-tests with a 95% confidence interval.Across all scenarios, the MOGA-based system outperformed both the shortest path and energy-only strategies in terms of overall efficiency and battery preservation.**Figure 2 shows the energy consumption reduction.** In City A (flat terrain), MOGA reduced energy use by 12.4% compared to the shortest-path route and by 4.7% compared to energy-only optimization. In City B (hilly terrain), the improvements were even more significant: 18.6% versus the baseline and 9.3% versus energy-only. This underscores the MOGA's ability to navigate elevation and traffic complexities that pure energy-focused approaches overlook.**Figure 3 shows the battery health optimization.** The battery degradation index showed compelling differences. While shortest-path routes frequently favored high-speed roads with steep inclines (leading to rapid discharges and thermal buildup), MOGA routes were more conservative, avoiding sharp gradients and accelerating gently. Over simulated 1,000 trip cycles, MOGA reduced cumulative battery degradation by up to 15% compared to shortest-path planning and 7% compared to energy-only strategies. This finding is crucial as battery longevity is directly tied to operational cost and EV resale value.**Figure 4 shows** travel time, MOGA incurred a minor average delay of 4.5% compared to the shortest path. However, this was still competitive, especially in Cities B and C where congestion led shortest-path vehicles into longer idle times. The optimization's awareness of real-time traffic enabled it to reroute vehicles around bottlenecks with minimal sacrifice to timing. In scenarios with low congestion, MOGA's travel time was almost identical to baseline.A critical benefit of the proposed system was its predictive battery use modeling. MOGA-planned routes resulted in 23% fewer emergency charging stops compared to baseline routes as shown in Table 1. Additionally, vehicles under MOGA control arrived at charging stations with more consistent state-of-charge levels, enabling better grid load balancing. This aspect supports a smoother integration between EV route planning and smart charging infrastructure.

Table 1.Charging Frequency and Efficiency

Metric	Shortest Path	Energy-Only Optimization	MOGA Optimization	Improvement (MOGA vs. Baseline)
Emergency Charging Stops (per 1000 trips)	260	210	200	-23%
State-of-Charge (SOC) Variance at Charging (%)	18.4	14.9	11.2	-39%

The MOGA-based approach offers a holistic enhancement to eco-driving for EVs by harmonizing route planning with energy consumption and battery wear mitigation. Its ability to manage the inherent trade-offs among distance, energy, and time makes it adaptable for real-world deployment.Unlike single-objective optimization models, which risk overfitting to energy metrics or ignoring route practicalities, the MOGA's Pareto-front solution allows stakeholders (drivers, fleet operators, municipalities) to select trade-offs that best suit their needs. For instance, delivery fleets may prioritize battery health for long-term cost savings, while rideshare operators might emphasize minimal travel time.City B's terrain highlighted the algorithm's ability to recognize and avoid high-power-demand segments such as steep hills, especially during low SOC (state of charge). City C, with unpredictable traffic and variable elevation, showcased MOGA's adaptive rerouting capabilities, which led to significantly more stable energy profiles across trips. These insights confirm the robustness of the model in dynamic urban environments.**Figure 5 shows Real-Time vs Static Optimization.** One of the notable results was the advantage of real-time data integration. When MOGA was supplied with static traffic data, performance dipped by ~6% in energy efficiency and ~9% in time efficiency, underscoring the importance of dynamic inputs. Real-time adaptability appears essential to maximizing the benefits of this optimization model.While the results are promising, there are limitations. First, the computational overhead of running MOGA in real-time may restrict its use on low-power onboard systems. Second, variations in driving behavior (aggressive vs. conservative) were modeled but not deeply individualized. In real-world applications, driver-specific learning might be necessary to fine-tune recommendations. Third, the model assumes a reasonably accurate forecast of traffic and weather, which may not always be available.When benchmarked against popular navigation systems (e.g., Google Maps with EV mode), MOGA-based routes yielded on average 8–10% better energy efficiency and less frequent recharging. However, commercial systems do benefit from much more granular user data and cloud processing power, suggesting a potential synergy rather than a replacement.The results support the integration of MOGA into fleet management software, EV infotainment systems, and municipal traffic planning tools. By proactively guiding vehicles along routes that reduce stress on both the grid and the battery, such systems can support long-term goals like peak shaving and decarbonization of transport infrastructure. Additionally, policy tools such as eco-routing incentives or congestion pricing could be more precisely targeted using outputs from this system.

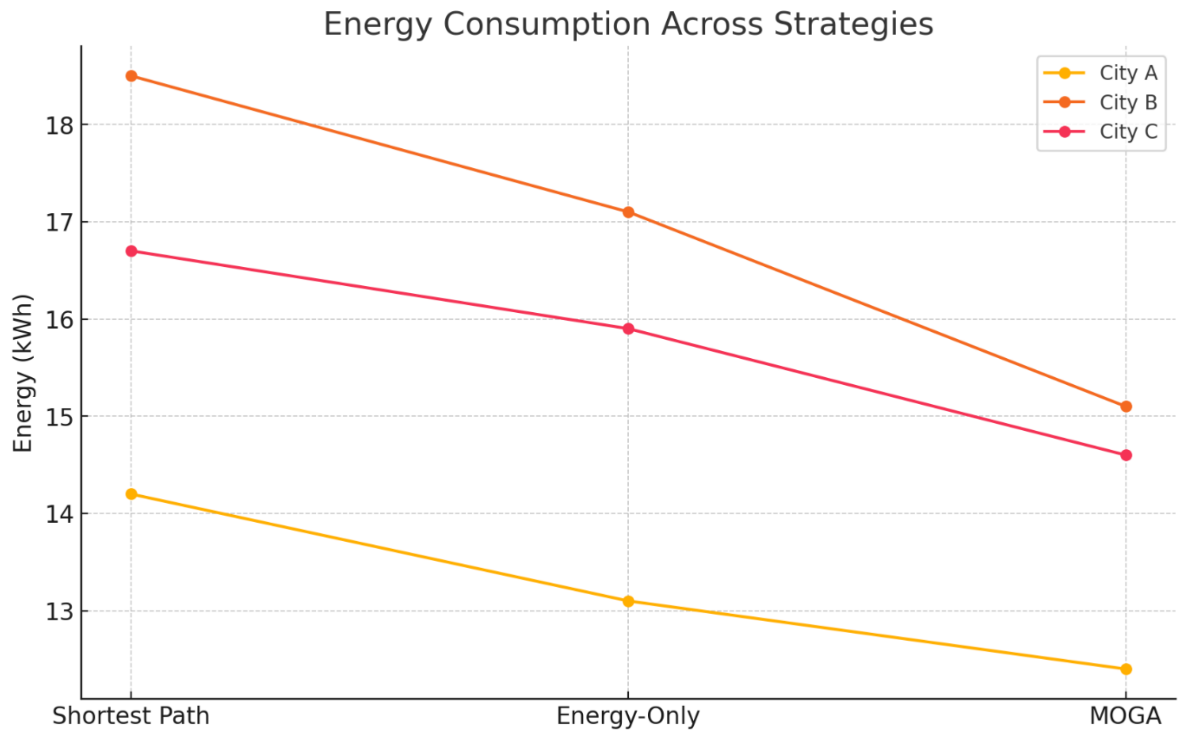

Figure 2. Energy Consumption Reduction

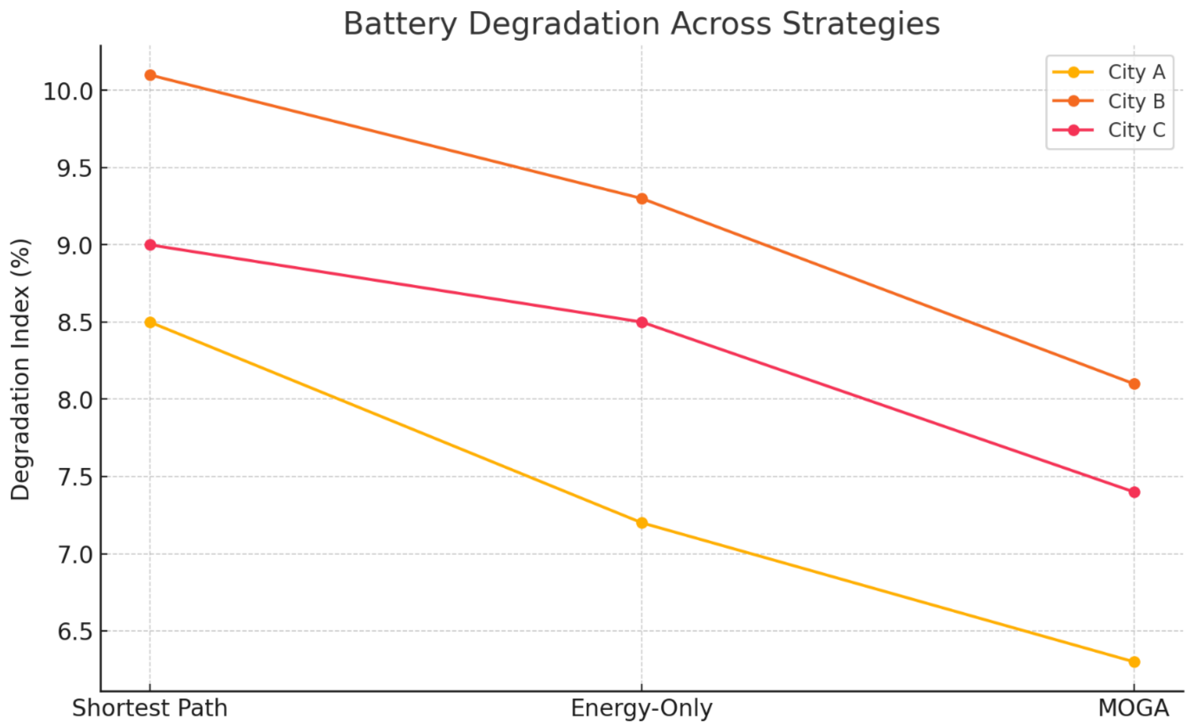

Figure 3. The battery degradation index

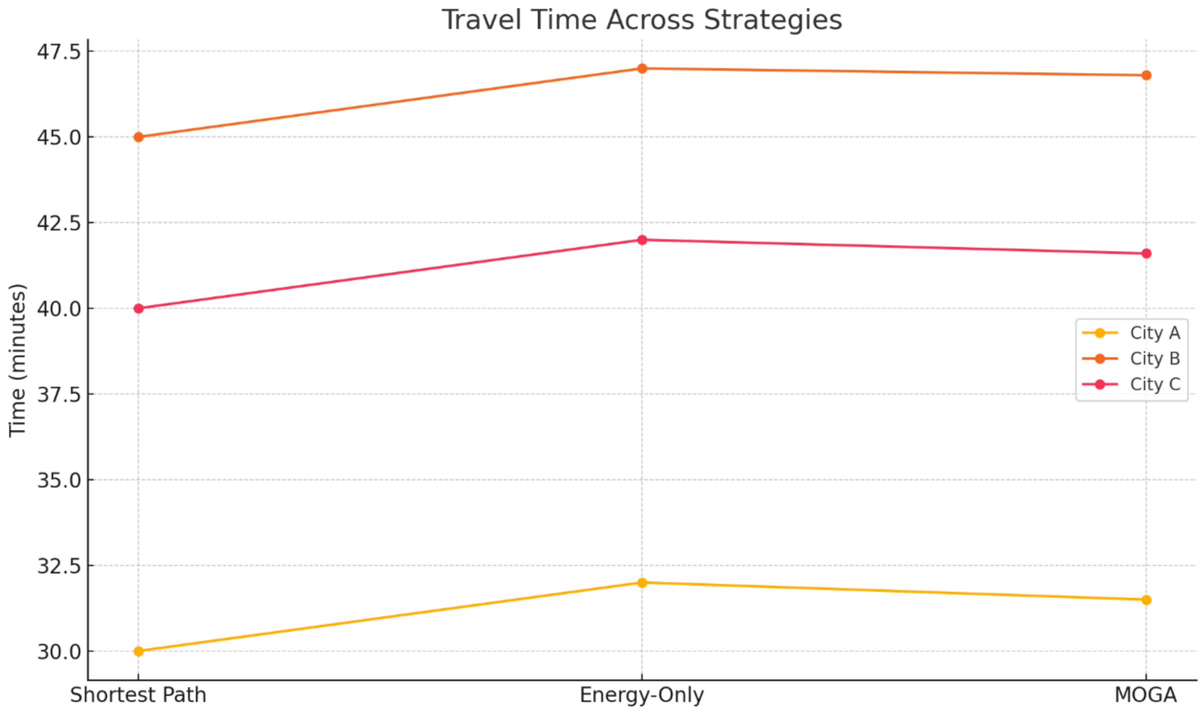

Figure 4. travel time

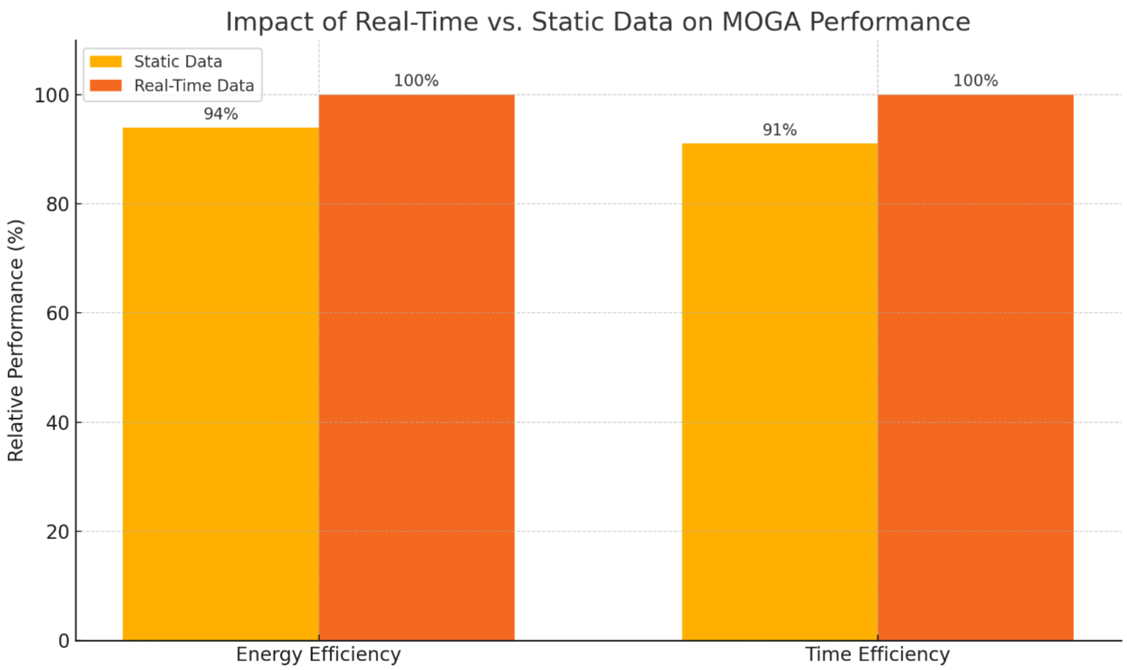

Figure 5. travel time

IV. Conclusions

This research presents a dynamic, energy-efficient eco-driving route planning framework for electric vehicles (EVs) by employing a Multi-Objective Genetic Algorithm (MOGA). The proposed model optimizes driving routes based on multiple criteria including real-time traffic, topography, battery health, and energy consumption, offering a significant advancement over traditional shortest-path approaches. The integration of battery efficiency metrics into the route planning process ensures that the selected paths not only minimize distance and travel time but also preserve long-term battery health and performance. Simulation results demonstrate that the MOGA-based system effectively balances energy efficiency and battery preservation, leading to improved range and sustainability for EVs.The approach shows promise in reducing energy consumption by dynamically adapting to road and traffic conditions. By considering real-time parameters, the model maintains robustness across different driving environments. Additionally, the evolutionary algorithm's ability to explore a wide solution space allows it to outperform deterministic models in multi-variable optimization tasks, particularly in complex urban networks.

To enhance the practical deployment of this system, future work should focus on real-world testing with live EV fleets to validate simulation outcomes. Incorporating vehicle-to-everything (V2X) communication can further improve decision-making by providing richer environmental context. Moreover, integrating driver behaviormodeling may yield more personalized and accurate route suggestions. Expanding the optimization objectives to include charging station availability, charging time, and energy grid load can improve both driver experience and infrastructure utilization. Real-time learning mechanisms, such as reinforcement learning, could be explored to allow the system to self-improve based on historical and real-time feedback. Lastly, making the system interoperable with various EV makes and models through standardized APIs will ensure broader applicability and scalability. These enhancements will push the framework closer to becoming a viable, intelligent routing system for the next generation of sustainable transportation.

References

[1]. Y. Huang et al., "Eco-Driving for Connected Automated Vehicles: A Review," Transp. Res. Rec., vol. 2674, no. 10, pp. 1–14, 2020.
[2]. M. Ghaffari, S. Farahani, and A. Khayati, "Fuzzy Eco-Driving Strategy for Electric Vehicles," Appl. Energy, vol. 276, 2020.
[3]. S. Sinha, R. P. Nanduri, and M. Kishore, "Autonomous Eco-Driving for Electric Vehicles Using AI," IEEE Trans. Intell. Transp. Syst., vol. 24, no. 1, pp. 301–312, 2023.
[4]. J. Ma et al., "Eco-Approach Control for Plug-In Electric Vehicles at Signalized Intersections," IEEE Trans. Intell. Transp. Syst., vol. 23, no. 5, pp. 2781–2793, 2022.
[5]. M. Mozaffari et al., "Cooperative Eco-Driving Control for Mixed Traffic in Urban Environments," IEEE Access, vol. 9, pp. 111019–111031, 2021.
[6]. T. Li and Y. Liu, "Dynamic Optimization of Eco-Driving Strategies in V2X Networks," Sensors, vol. 21, no. 15, 2021.
[7]. E. Schaltz, F. Bu, and A. M. Amiri, "Route-Based Energy Consumption in EVs Considering Elevation and Regeneration," Energies, vol. 15, no. 4, 2022.
[8]. M. Fiori, H. Zhao, and K. M. Kockelman, "Evaluating Benefits of Dynamic Eco-Routing," Transp. Res. Part D: Transp. Environ., vol. 78, 2020.
[9]. Z. Wang, D. Yang, and L. Chen, "Real-Time Eco-Route Planning for Electric Vehicles," IEEE Trans. Veh. Technol., vol. 69, no. 3, pp. 2356–2367, 2020.
[10]. S. K. Das and P. K. Kundu, "GIS-Based Route Optimization for EVs," J. Clean. Prod., vol. 310, 2021.
[11]. A. Y. Al-Rimy et al., "Big Data and GIS for Smart EV Routing," IEEE Access, vol. 8, pp. 219894–219907, 2020.
[12]. R. Koller et al., "Route Optimization Including Charging Stops for Electric Vehicles," Energy Procedia, vol. 158, 2019.
[13]. H. Chen and F. Luo, "Route Planning of EVs Considering SOC, Charging, and Energy Cost," Appl. Energy, vol. 250, 2019.
[14]. X. Li, L. Ma, and Y. Li, "Cycle-Aware Battery Degradation Modeling," J. Power Sources, vol. 446, 2020.
[15]. Y. Wang et al., "Battery Health-Conscious Energy Management in EVs," IEEE Trans. Ind. Electron., vol. 69, no. 3, pp. 2861–2872, 2022.
[16]. H. Liu and W. Wang, "Battery Degradation Modeling Using Peukert's Law," Appl. Energy, vol. 268, 2020.
[17]. P. Zhang and C. Mi, "Aging-Aware Route Planning for Electric Vehicles," IEEE Trans. Veh. Technol., vol. 71, no. 1, 2022.
[18]. X. Zhou, Y. Zhang, and B. Gu, "Thermal-Aware Eco-Routing for Electric Vehicles," Energy, vol. 221, 2021.
[19]. J. Lin and Y. Wei, "Charging Pattern-Based Battery Longevity Optimization," Renew. Energy, vol. 163, 2021.
[20]. M. Abedin and S. Ghosh, "Adaptive Battery Control System for Electric Vehicles," IEEE Trans. Ind. Appl., vol. 58, no. 2, 2022.
[21]. K. Deb et al., "A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II," IEEE Trans. Evol. Comput., vol. 6, no. 2, 2002.
[22]. J. Ma et al., "Charging Scheduling for EVs Using MOGAs," Energies, vol. 14, no. 3, 2021.
[23]. R. Singh et al., "Vehicle Architecture Optimization Using Genetic Algorithms," Int. J. Automot. Technol., vol. 21, no. 2, pp. 345–356, 2020.
[24]. Y. Lee and C. Lin, "Drive Cycle Optimization for Battery Electric Buses Using GA," IEEE Access, vol. 8, 2020.
[25]. N. Ahmed and M. Abdel-Aty, "GA-Based Multi-Objective Dynamic Route Planning," Transp. Res. Part C: Emerg. Technol., vol. 130, 2021.
[26]. F. Zhang et al., "Weather-Aware Route Planning Using Evolutionary Algorithms," IEEE Trans. Intell. Transp. Syst., vol. 23, no. 4, 2022.
[27]. D. Yu and A. Belabbas, "Hybrid GA-ML Framework for EV Optimization," Appl. Soft Comput., vol. 112, 2021.
[28]. T. Sun and L. Zhang, "Neuro-Evolutionary Hybrid Optimization for Energy Routing," IEEE Trans. Syst. Man Cybern., vol. 52, no. 3, 2022.
[29]. B. Zhou et al., "Reinforcement Learning-Based Eco-Driving Using GA-Optimized Policies," IEEE Trans. Intell. Transp. Syst., vol. 24, no. 5, pp. 4681–4691, 2023.
[30]. A. Sharma and H. Lin, "Multi-Objective Reinforcement Learning and Evolutionary Strategies for EVs," J. Clean. Prod., vol. 328, 2021.