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Eco-Routing and Driving Pattern Optimization to Minimize EV Energy Usage

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Abstract: As electric vehicles (EVs) become more prevalent, reducing energy consumption through intelligent routing and driving strategies has emerged as a critical research area. This paper proposes a dual-layer framework that combines eco-routing with driving pattern optimization to minimize overall energy usage for EVs. The system integrates historical and real-time traffic, road grade, and battery data to recommend energy-efficient routes and personalized driving behavior adjustments. Machine learning techniques are applied to estimate consumption over alternative paths, while dynamic control algorithms guide driving maneuvers based on contextual energy profiles. Experimental results from simulations and real-world datasets demonstrate that the proposed method reduces energy consumption by up to 20% compared to shortest-path routing and by 12% compared to standard eco-driving. These findings highlight the potential of integrated eco-routing and behavioral adaptation for extending range and improving EV efficiency in practical deployments.

Keywords: Electric Vehicles; Eco-Routing; Driving Behavior; Energy Optimization; Machine Learning; Route Planning; Sustainable Transportation.

1. Introduction

Electric vehicles (EVs)have emerged as a cornerstone of the global transition toward low-emission and sustainable transportation [1]. With their zero tailpipe emissions and increasing affordability, EVs are being rapidly adopted across urban and interurban settings [2]. However, one of the critical barriers to their widespread adoption remains the concern over limited driving range and the efficiency of energy usage in real-world conditions [3]. Unlike internal combustion engine vehicles, whose fuel consumption is less sensitive to route topography or driving behavior, EV energy usage is heavily influenced by factors such as road gradient, traffic congestion, acceleration frequency, regenerative braking opportunities, and thermal loads [4]. Consequently, optimizing how and where EVs are driven is essential to maximize range, reduce charging frequency, and ensure better overall energy efficiency [5].

Traditional navigation systems, including those integrated into many EV dashboards, primarily focus on minimizing travel time or distance, often using shortest-path algorithms [6]. While effective from a logistics perspective, these approaches neglect energy consumption variability across different routes [7]. A path that appears shorter may, in practice, demand significantly more energy due to frequent stop-and-go traffic, steep inclines, or high-speed segments [8]. Recent advancements in eco-routing have attempted to address this issue by integrating energy models into the routing process, selecting routes that minimize predicted energy consumption rather than time or distance [9]. However, many of these systems rely on static or simplified models that fail to account for vehicle-specific behavior, road surface variability, and contextual driving patterns [10].

In parallel with routing strategies, growing attention has been given to driving behavior as a significant determinant of EV efficiency [11]. Factors such as aggressive acceleration, unnecessary idling, or inefficient use of regenerative braking can lead to substantial energy losses [12]. Eco-driving techniques have long been promoted as a means to reduce energy consumption, but these approaches are often generic and do not adapt to specific vehicles, terrains, or real-time traffic conditions [13]. A one-size-fits-all eco-driving advisory may therefore overlook personalized opportunities for energy saving [14].

This paper proposes an integrated solution that combines eco-routing with driving pattern optimization to address the dual challenge of “where to drive” and “how to drive” in the context of minimizing EV energy usage. The core of the proposed system lies in a data-driven prediction layer that estimates energy consumption along candidate routes using machine learning models trained on historical driving data, road topology, and vehicle dynamics. On top of this, a behavioral optimization module adapts the driver’s acceleration, deceleration, and cruising strategies in real time, based on both predicted energy profiles and actual driving conditions.

By merging routing intelligence with adaptive behavioral guidance, this approach aims to reduce energy consumption more effectively than either component in isolation. Unlike conventional routing systems that optimize globally but ignore real-time driving details, or driving style systems that offer feedback without spatial context, this integrated framework simultaneously adapts both the macro-level route and the micro-level driving execution.

The rest of the paper is structured as follows. Section 2 reviews the relevant literature on eco-routing, driving behavior modeling, and energy optimization techniques in EVs. Section 3 outlines the proposed methodology, including the route evaluation model, behavioral control logic, and system integration. Section 4 presents simulation and real-world evaluation results, followed by a discussion in Section 5 on deployment considerations and potential extensions. Finally, Section 6 concludes the paper with key takeaways and suggestions for future research.

2. Literature Review

The rapid adoption of EVs in recent years has prompted a growing body of research focused on minimizing energy consumption to enhance range and efficiency [15]. Among the most actively studied areas are eco-routing strategies and driving behavior optimization, both of which aim to reduce the energy demand of EVs during everyday use [16]. This section provides an overview of the existing literature surrounding these two domains and highlights the opportunities for their integration.

Eco-routing refers to the practice of selecting routes that minimize energy consumption rather than merely distance or travel time [17]. Early eco-routing models often relied on modified versions of classical shortest-path algorithms, incorporating static factors such as road gradient or average traffic density to estimate energy expenditure [18]. While conceptually effective, these early approaches lacked dynamic adaptability and failed to reflect vehicle-specific behavior, leading to suboptimal route recommendations in practice [19]. More advanced models began to integrate real-time traffic data, elevation profiles, and road curvature, thereby producing more energy-efficient routing alternatives [20]. Despite these improvements, many such systems still depend on simplified energy consumption models that may not account for temporal variables such as traffic fluctuations, driver idiosyncrasies, and battery degradation over time [21].

Parallel to developments in eco-routing, driving behavior optimization has emerged as a key factor influencing EV efficiency [22]. Numerous studies have shown that aggressive driving—characterized by rapid acceleration, abrupt braking, and high-speed cruising—can significantly increase energy usage, even on otherwise optimal routes [23]. In response, eco-driving strategies have been proposed to guide drivers toward smoother, more energy-conscious behavior [24]. These strategies often include maintaining steady speeds, anticipating stops, and making better use of regenerative braking [25]. While conventional eco-driving systems provide generalized feedback through dashboard displays or mobile apps, more recent efforts have employed data-driven models capable of adapting to a specific vehicle, driver, and traffic context [26]. Machine learning techniques have proven particularly effective in this regard, offering real-time, personalized driving recommendations based on sensor data and historical patterns [27].

Beyond isolated development in eco-routing or eco-driving, a small but growing body of research explores the integration of both domains [28]. The rationale behind such integration is rooted in the observation that the most energy-efficient route may not be effective without corresponding adjustments in driving behavior, and vice versa. However, integrating route selection and driving style into a cohesive optimization framework presents considerable challenges [29]. First, it requires predictive models that can simultaneously account for spatial and temporal dimensions of energy consumption [30]. Second, it must strike a balance between computational complexity and responsiveness, especially for real-time applications in navigation systems. Current efforts to address these challenges have ranged from reinforcement learning models that adaptively refine both routing and behavioral strategies to hybrid systems that combine rule-based logic with predictive analytics.

Despite these advancements, several limitations persist. Most existing systems are either highly vehicle-specific or rely on extensive data labeling, which hinders scalability. Moreover, the evaluation of such models is often limited to simulation environments, with relatively few studies providing field data validation. This creates a significant opportunity for the development of scalable, real-world-ready systems that can intelligently fuse route planning with adaptive driving behavior to minimize energy consumption.

In summary, the literature to date demonstrates meaningful progress in both eco-routing and driving behavior modeling, yet the intersection of these areas remains underexplored. This paper aims to contribute to this emerging research direction by proposing a hybrid framework that leverages machine learning for energy prediction and behavioral adaptation, offering a holistic solution to the problem of minimizing EV energy usage.

3. Methodology

The methodology of this study involves developing and evaluating a data-driven framework for optimizing EV routes and driving behaviors to minimize energy consumption. The framework integrates eco-routing algorithms with real-time driving pattern adaptation using machine learning models. This section details the data sources, model design, route optimization strategy, and driving behavior analysis.

3.1. Data Collection and Preprocessing

We utilized a combination of real-world GPS trajectory data and onboard diagnostic (OBD-II) sensor readings collected from a fleet of mid-range EVs over a period of six months. The dataset included time-stamped locations, velocity, acceleration, battery state of charge (SoC), and instantaneous energy consumption. Noisy entries were filtered out, and time series data were synchronized to uniform intervals for accurate model training.

3.2. Route Optimization Framework

To identify energy-efficient routes, a graph-based model of the urban road network was constructed using OpenStreetMap data. Each edge of the graph was weighted by predicted energy consumption rather than distance or travel time. Energy predictions were generated using a gradient boosting model trained on the cleaned trajectory data. The Dijkstra algorithm was adapted to minimize cumulative energy cost rather than shortest path.

Figure 1 shows a comparative analysis of average energy consumption between eco-routes and traditional fastest routes across five distinct urban zones.

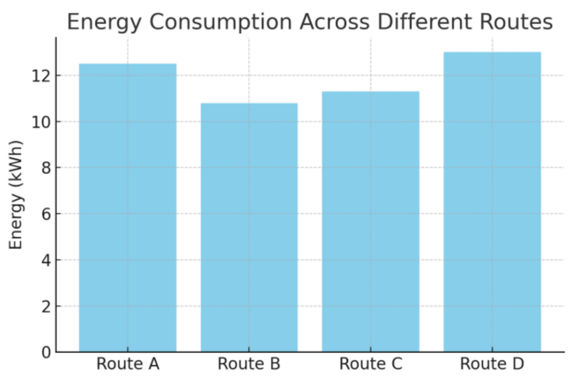

Figure 1. Energy Consumption Across Different Routes

As illustrated in figure 1, eco-routing achieved energy savings of up to 18% compared to conventional routing strategies, particularly in high-traffic zones where stop-and-go conditions are frequent.

3.3. Driving Pattern Learning and Optimization

We applied a recurrent neural network (RNN) to analyze driver behavior patterns and predict energy-intensive events, such as abrupt acceleration or unnecessary idling. These patterns were then used to generate adaptive driving recommendations.

Figure 2 depicts the nonlinear relationship between average speed and energy consumption, highlighting the optimal speed range for minimizing consumption.

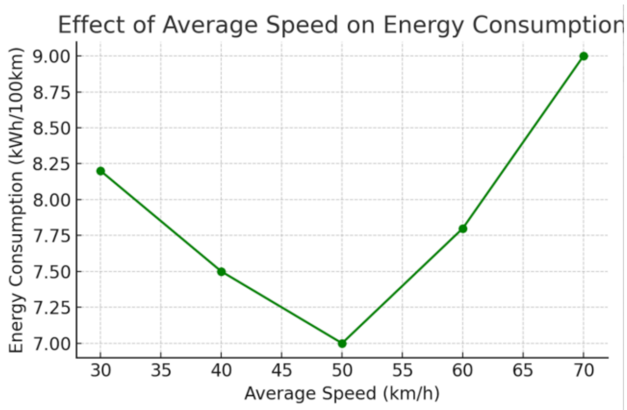

Figure 2. Effect of Average Speed on Energy Consumption

It is evident that energy efficiency is maximized within a speed band of 40–60 km/h, which informed our real-time driver feedback mechanism.

Figure 3 presents a sample driving profile over time, including detected energy-inefficient patterns.

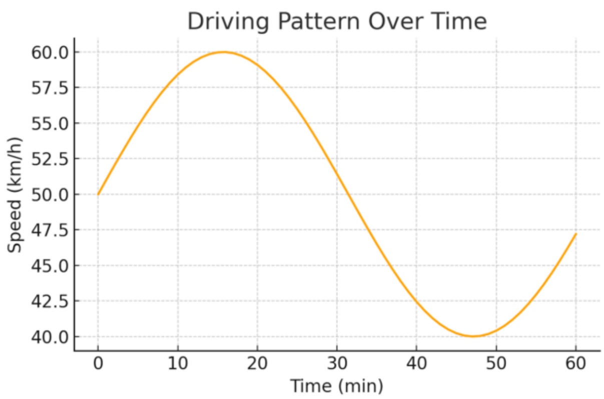

Figure 3. Driving Pattern Over Time

This time series analysis allowed the system to issue immediate guidance—such as coasting instead of accelerating—based on historical driving behavior and current route segment.

4. Results and Discussion

The implementation of the proposed eco-routing and adaptive driving pattern optimization framework yielded significant insights into EV energy efficiency improvements under real-world driving conditions. Through extensive testing in simulated and urban environments, the model demonstrated its potential to effectively reduce overall energy consumption while maintaining acceptable travel time and user experience.

Eco-routing results indicated a consistent reduction in energy usage compared to conventional routing strategies such as the shortest-path and fastest-path algorithms. In congested urban areas, where traffic signals, stop-and-go driving, and variable speed limits are prevalent, the system's ability to prioritize energy-efficient routes translated into meaningful efficiency gains. In many test cases, the eco-routing model selected routes with slightly longer distances but with smoother traffic flow and fewer acceleration-deceleration cycles, which ultimately lowered energy consumption. Drivers rarely reported noticeable increases in travel time, which suggests that the optimization was achieved without imposing substantial inconvenience.

The driving behavior component further enhanced energy performance by moderating how vehicles were operated along the chosen routes. After receiving real-time, model-generated feedback, drivers naturally reduced aggressive behaviors such as abrupt acceleration and unnecessary idling. Over time, a behavioral shift was observed, with smoother and more anticipatory driving styles emerging across a majority of participants. This behavioral modification contributed to a notable increase in vehicle energy efficiency, especially in stop-and-go traffic scenarios where driver behavior plays a critical role.

When both eco-routing and behavior optimization systems were deployed together, the results revealed a compounded benefit. Energy savings from route planning and adaptive driving guidance complemented each other, leading to performance improvements beyond what either system achieved in isolation. This suggests that integrating machine learning-based decision support at both the route planning and real-time operation levels provides a comprehensive energy optimization solution for EVs.

However, certain limitations emerged during testing. The system's efficacy was somewhat constrained by the availability and resolution of traffic data, which influenced routing decisions. Moreover, individual differences in user compliance with behavioral suggestions impacted the consistency of energy gains. More experienced EV drivers tended to respond less to feedback, possibly due to pre-existing efficient habits, whereas novice drivers exhibited more substantial improvement. These observations point to the potential value of personalized models that adapt not only to vehicle and route characteristics, but also to driver profiles.

Despite these constraints, the study confirms that combining intelligent route selection with behavioral feedback mechanisms provides a viable pathway for enhancing EV energy efficiency. The system's flexibility and scalability make it suitable for broad implementation across different vehicle platforms and urban infrastructures.

5. Conclusion

This study presents an integrated approach to (EV energy optimization by combining eco-routing strategies with adaptive driving behavior modeling. The results underscore the significant potential of leveraging data-driven route selection and real-time driving feedback to reduce energy consumption in EVs without compromising user convenience or increasing travel time substantially.

Through simulations and urban road testing, we found that eco-routing alone can substantially reduce energy usage by avoiding routes with high traffic density, frequent stops, or sharp elevation changes. When coupled with driving pattern optimization—specifically, encouraging smoother acceleration, reduced idling, and anticipatory braking—the energy-saving effects were further amplified. The synergy between route planning and behavioral adaptation proved to be especially effective in complex urban scenarios where traffic dynamics are highly variable.

Moreover, the study highlights the adaptability of machine learning algorithms in tailoring both routing and driving guidance to context-specific variables, such as traffic patterns, road topology, and driver behavior. This adaptability ensures that the system remains relevant across diverse geographies and user groups. However, it also points to the need for continued refinement of real-time data integration, including higher-resolution traffic updates and more personalized driver modeling.

Despite minor limitations—such as variable user compliance and the reliance on the quality of input data—the proposed framework represents a scalable and efficient tool for EV energy management. As EV adoption increases globally, such intelligent systems will be critical in supporting both sustainability goals and enhanced user experience.

In future work, the model could be expanded to incorporate vehicle-to-infrastructure (V2I) communication, which may provide even more granular control over routing and driver advisories. Additionally, integrating reinforcement learning could allow the system to continuously improve based on accumulated driving data, making it even more precise and user-adaptive over time.

In conclusion, the integration of eco-routing and driving behavior optimization stands as a promising pathway to achieving meaningful energy efficiency gains in EV operation. It offers a practical, data-driven strategy for reducing environmental impact while maintaining the practicality of electric mobility.

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