EV-GREEN: Electric Vehicle Routing with GreenZone Prioritization and Vehicle-to-Grid Incentive Integration

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Abstract

With the rapid growth in EV adoption, eco-routing should not only reduce energy consumption but also follow the changing environmental rules and make it easier for the grid to connect. This work presents a hybrid approach which couples the Mixed Integer Linear Programming formulation with heuristics, such as Dijkstra's algorithm, along with Ant Colony Optimization, that returns a practical and scalable solution for real-time EV routing. Our model features compliance with *GreenZone*, which automatically enforces environmental rules in various parts of the city, and Vehicle-to-Grid (V2G) incentives, which encourage energy discharge whenever the demand is high on the grid. Existing solutions optimize only static energy measures or neglect larger cyber-physical interactions. In contrast, our approach reacts to real-time conditions on the route, as well as to the level of the battery, charging station availability, and changes in V2G tariffs. It enables cooperation among EV owners, traffic management units, grid operators, and charging service providers. Besides the positive impact on the grid with respect to the environmental perspective, this approach reduces pollution in cities and contributes to making the grid function smoothly for a longer period of time. The simulation results demonstrate the efficacy of the proposed hybrid solution, and therefore, it can be deployed in a real smart city scenario. The proposed approach is of particular relevance for cyber-physical systems, where timely decision-making and coordination at the system level play a key role in achieving sustainable urban mobility. The proposed method works well for diverse types of vehicles, as it shows significant route cost and V2G incentive savings compared to baseline methods.

Keywords: Eco-Routing, Electric Vehicles, Vehicle-to-Grid, GreenZone Compliance, Cyber-Physical Systems

1 Introduction

The trend towards sustainable transportation systems has brought electric vehicles to the fore of smart transportation choices. As more and more consumers start to turn to electric vehicles because of environmental regulations and the need for environmentally sound options, efficient routing algorithms that reduce energy consumption and pollution have assumed ever-greater significance [1–4]. Of these, there is the routing algorithm that provides the eco-routing, which aims to discover the routes that electric vehicles will take to consume the least amount of energy [5, 6]. Unlike traditional routing algorithms, eco-routing takes into account aspects such as the energy consumption patterns of the vehicles, terrain of the road, traffic conditions, and availability of charging points. This makes it all the more essential to the realm of efficient energy transport systems and urban sustainability.

With the rising convergence between EVs and the electric grid, there are emerging paradigms like Vehicle-to-Grid (V2G) technology [7] that act both as a possibility for the electric grid regarding the acquisition and provision of electric energy. V2G technology therefore plays a role in the stability of the electric grid by enabling the possibility of rewarding EV owners financially by permitting them to provide the stored electric energy back into the grid when it is most convenient. V2G technology and Eco-routing are some extremely fascinating approaches; however, these approaches are also causing solutions to get a lot more complicated. Road routing strategies, therefore, not only need to focus on how the EV can earn the maximum V2G rewards that can be earned according to time and space, but also on how the EV can consume less electric energy. This, therefore, completely changes the eco-routing problem. There would now be the need for more complex mathematical models that can calculate the efficiency regarding the acquisition/conservation of electric energy in addition to the efficiency regarding the movements made. A new level of complexity is therefore introduced by the rising development and implementation of urban GreenZones, which are geofenced areas within urban spaces that provide encouragement for low or zero-emission transportation modes [8]. What could describe these GreenZones is limitations on the usage of the internal combustion engine, the possibility of the source of electric energy being produced from a natural source like the sun, or the GreenZone's privileged access. In the case of electric vehicles, there would now also be the possibility of rewards like a reduction in or avoidance of tolls, rights to parking, or alignment with the urban aspirations for the electric vehicle with GreenZone access. However, in reality, a GreenZone is a dynamic boundary/utility that changes according to the nature of the electric demand, the pollution levels produced by these modes, or the legislation surrounding the GreenZone. Its compliance within eco-routing strategies, therefore, now requires another level of time-space complexity that arises when GreenZones intersect or don't lie on the most optimal routes regarding electric energy efficiency.

In terms of system design, handling the eco-routing problem under V2G benefits and GreenZone preferences involves solving an optimization problem where many conflicting objectives need to be considered. Some of these limits include the state-of-charge (SOC) capacity of EV batteries, with limited and geographically scattered charging stations, in addition to uncertainty in consumption behavior along different routes. Further, handling this problem is computationally intensive. Exact optimization techniques such as Mixed Integer Linear Programming (MILP) can provide high-quality solutions but are typically infeasible for large-scale, real-time applications due to their computational complexity. This leads to the requirement of hybrid approaches that combine the optimality of MILP with the scalability of heuristic methods.

Several studies in eco-routing focus only on lowering energy usage as a single target, without adding dynamic environmental restrictions or grid-interaction factors. For instance, the fuel- or energy-minimizing routing models in [9–11] optimize consumption when the network conditions are stable or only change slightly. Similarly, many EV-specific routing algorithms [12, 13] assume static traffic, charging, or emission profiles, and hence do not account for time-varying incentives, congestion, or environmental zones. These restrictions highlight the necessity for routing frameworks that combine dynamic elements such as GreenZone variations and V2G price fluctuations, which the present work addresses. Similarly, GreenZone-aware routing has gotten limited attention and is rarely evaluated in conjunction with V2G-aware decision-making. As a result, there is a considerable void in the literature for a unified, scalable routing system that holistically handles energy consumption, energy contribution, and environmental compliance.

Example Scenario: Anya owns an electric vehicle that she plans to use to drive across the future smart city. Her route should align with the dynamic GreenZone policies of the smart city, which contains restrictions on highly emitting routes during peak hours and other directions for ecological behavior. Anya uses a navigation system powered by our proposed hybrid eco-routing framework, which integrates real-time traffic data, battery levels, V2G incentives, and GreenZone compliance. Figure 1 depicts the system connecting to the main Urban Traffic Management Unit (UTMU) broadcasting real-time data around the road conditions and GreenZone limits. The EV manufacturer provides APIs exporting the car's battery health and charge profiles, while the charging stations contribute real-time queue and tariff data. A local grid operator utilizes V2G rules to provide dynamic incentives to those vehicles that can discharge during peak grid demand. After determining the most efficient way in an ecological manner, the algorithm suggests a minor detour via a V2G-enabled charging station. Anya accepts, charges for a short time, and also sells additional generated electricity back to the grid in exchange for credits. Meanwhile, the municipal government leverages aggregated trip data for urban planning and emission regulatory compliance.

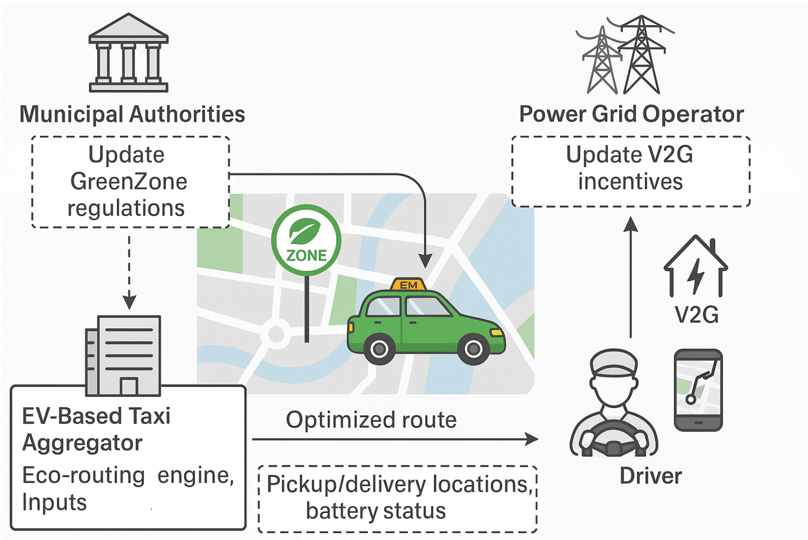


Fig. 1: Illustration of stakeholder interactions and data flow in the eco-routing scenario.

This paper proposes a new hybrid eco-routing strategy that attempts to overcome these challenges by incorporating an accurate MILP formulation within small-scale scenarios and a scalable heuristic approach that can perform well in large-scale dynamic environments. Our approach investigates the interdependency of mobility and energy systems due to trade-offs involved in routing decisions with V2G incentives and GreenZone compliance. The objective is to develop improved route planning for EVs that assists both individual economic benefits and overall objectives of sustainability.

Contributions: The key contributions of this work are as follows:

- We present a novel MILP-based eco-routing model that blends energy efficiency, V2G incentives, and GreenZone compliance. The model integrates real-time updates to V2G incentive structures and dynamic GreenZone bounds, while maintaining battery limits and trip feasibility.

- To deliver near-optimal solutions in real-time, large-scale networks, we build a hybrid heuristic method that integrates Ant Colony Optimization [14] with Dijkstra's shortest path technique. This makes it possible to employ eco-routing strategies in intelligent transportation systems in a scalable manner.
- In order to verify the usefulness of the suggested technique in a range of urban mobility scenarios, we undertake detailed simulations that show increases in energy efficiency, V2G revenue, and adherence to environmentally sensitive zones.

2 Related Work

Eco-routing systems have received intensive research attention in terms of a feasible means of lowering fuel consumption and car emissions. Among the earliest systematic designs of an eco-routing system is one produced by Barth *et al.* [15]. Although this research work tested the feasibility of carrying out an eco-routing system, it emphasized learning challenges associated with processing real-time information. Later research concentrated on carrying out simulations to estimate network-wide fuel savings benefits derived from eco-routing. Ahn and Rakha [16] assessed the effects of dynamic eco-routing with different levels of congestion and market penetration in real-world network settings. Based on network design and the total number of eco-routed vehicles, their simulation analysis quantified fuel savings of between 3.3% and 9.3% over the network. Rakha *et al.* [9] developed a microscopic traffic assignment tool which incorporates two stochastic eco-routing algorithms named ECO-SFA and ECO-AFA. They demonstrated a potential fuel reduction of up to 15%, but added that dynamic traffic assignment can be challenging.

Some studies have focused on eco-routing solutions under different assumptions and abstraction levels. Kubička et al. [11] evaluated various existing solutions for eco-routing in time-dependent traffic situations and concluded that static energy expenditure can lead to a substantial reduction in savings. On the other hand, Ben Dhaou [10] introduced a macroscopic model for fuel calculation using Willan's engine model without relying on speed and acceleration information in an iterative computation. The experimental analysis proved a fuel consumption savings of up to 33% with a travel time increment of approximately 3%.

More intricate vehicle-level and emission-conscious routing models have also been considered. Nie and Li [17] formulated eco-routing as a constrained shortest path problem that incorporates microscopic operating conditions such as acceleration, idling, turning movements, and intersection delays. Their numerical experiments showed that ignoring these microscopic effects can lead to suboptimal routing decisions. Zeng *et al.* [18] developed a vehicle-dynamics-based CO_2 emission prediction model combined with a Pareto-based eco-routing approach using a k-shortest path algorithm. Validation on a large-scale real-world network in Toyota City, Japan, demonstrated that average

CO_2 emission reductions of up to approximately 11% can be achieved when allowing a travel time buffer of about 10%.

System-oriented eco-routing solutions have emphasized data fusion and personalization. Guo *et al.* [19] proposed EcoSky, which annotates road networks with time-dependent and uncertain eco-weights derived from GPS data and supports basic, skyline, and personalized eco-routing strategies. Aguiar *et al.* [20] introduced MobiWise, an IoT-enabled microservice-based decision support system for eco-routing. Using a calibrated digital twin for a mid-sized European city, their proof-of-concept demonstrated hourly emission reductions of up to 2.1% with only 5% eco-routing vehicle penetration.

Eco-routing for EVs introduces additional constraints and uncertainties. Yi and Bauer [12] formulated EV eco-routing as a stochastic programming problem that explicitly accounts for environmental uncertainties, battery capacity, and drivetrain efficiency. Their simulations showed the effectiveness of convex relaxation and reconstruction techniques in obtaining energy-optimal routes. Thibault *et al.* [13] proposed a unified framework combining eco-routing, eco-driving, and energy consumption prediction for EVs, supported by real-world experiments with a Fiat 500e. Their results reported energy savings of approximately 4.5% to 12.4% compared to shortest and fastest routes, as well as improved driving range estimation accuracy.

Several complementary studies have examined aspects of EV charging coordination and energy exchange that are tangential to the focus of this work. To manage coordinated EV charging, research on scheduling protocol with load management in connection with grid stability has been conducted by Said et al. in [21]. Chekired et al. have put forward a dynamic pricing model for EV charging and discharging using cloud-assisted scheduling with a major focus on pricing strategies in [22]. They later introduced a decentralized electricity trading framework for connected EVs using blockchain and machine learning, addressing profit optimization in energy markets rather than mobility-aware routing [23]. In related vehicular networking contexts, Ahmed *et al.* surveyed cooperative spectrum sensing for vehicular ad hoc networks, while Said and Elloumi studied data integrity in peer-to-peer EV energy transactions [24, 25]. These works address charging coordination, communication, and energy trading at the infrastructure or market level, whereas the present study focuses on incentive-aware eco-routing and GreenZone-compliant path planning.

The existing studies demonstrate that eco-routing can yield meaningful reductions in fuel consumption, emissions, and energy usage across internal combustion and electric vehicles. However, most prior works either optimize energy or emissions as standalone objectives, assume static or weakly dynamic conditions, or focus on traffic assignment and prediction without considering grid interaction. In particular, the joint integration of V2G incentives, dynamic environmental compliance zones (GreenZones), and real-time routing for EVs remains largely unexplored. To fill this research gap, the proposed work presents a hybrid optimization algorithm integrating a global model solution using MILP with Dijkstra's algorithm and Ant Colony Optimization to support V2G-conscious GreenZone-compliant eco-routing strategies for EVs.

3 Problem Description and System Model

The primary objective of this research work is to design an energy-conscious routing strategy for EVs with a dual goal of not only minimizing energy consumption but also using dynamic environmental and economical incentives. Specifically, the model integrates three critical dimensions:

- **GreenZones:** These are environmentally favorable zones with more available renewable energy sources and lower emissions. To favor environmentally sound routes, GreenZone regions are rewarded for passing through these regions. The technology utilizes environmental information in real-time to dynamically define GreenZone regions.
- **Vehicle-to-Grid (V2G) Operations:** In addition to acting as energy-consuming units, cars can also act as distributed energy resources. This extra energy can also be fed into the grid through specially designated V2G-based charging points. Energy exchange takes place from the vehicle to the grid during peak hours and is compensated for accordingly in terms of monetary gain in proportion to the amount of supplied energy.
- **Grid Interaction:** The routing algorithms interact with the grid managers in order to obtain real-time information regarding a range of factors including the availability of renewable resources, dynamic pricing, and demand within the grid.

The proposed system thus has the intention of addressing all of these simultaneously by taking into consideration all three above-stated objectives for optimization. To simplify the system modeling while retaining real-world relevance, the following assumptions are made:

- **Dynamic GreenZones:** GreenZones are established based on time and space information concerning renewable energy production and pollution intensity. GreenZones can be defined in a flexible manner, which is updated from time to time in order to keep up with current information concerning the environment.
- **Proportional Incentives:** The benefits obtained by EVs in V2G mode remain linear with respect to the amount of energy released. This is because a linear relationship remains with standard utility pricing.
- **Charging Station Constraints:** Not all charging stations support V2G operations. Only stations tagged as V2G-capable can support energy discharge, and these have to be pre-identified in the system.
- **Vehicle Constraints:** EVs have minimal energy requirements for ensuring operational safety. Therefore, in any discharge operation, it is important to take measures to prevent the state of charge of an EV below a given predefined threshold.

V2G Policy Scope and Assumptions: This work considers a tariff-based V2G incentive mechanism, in which EVs can discharge surplus energy to the grid at designated V2G-enabled charging stations in exchange for monetary compensation. The incentive rate is modeled as a time-dependent reward that reflects grid demand conditions, with higher rewards during peak-load periods. The reward earned by an EV is assumed to be proportional to the amount of energy discharged, subject to battery state-of-charge and station capacity constraints.

We note that the V2G literature discusses a wide spectrum of policies, including real-time market participation, regulation services, and capacity-based contracts. Such mechanisms are surveyed in recent comprehensive studies on eco-routing and V2G-enabled transportation systems (e.g., [5]). The focus of this work is on routing-level decision-making under dynamic tariff-based incentives; extending the model to more complex market-based V2G schemes is left for future work.

4 Mixed Integer Linear Programming (MILP) Formulation

To formalize the routing and decision-making problem, we develop an MILP model that captures the interplay between route selection, energy consumption, V2G rewards, and GreenZone compliance. The objective is to compute a route from a given source to destination that optimizes these goals under a set of operational constraints. The list of symbols used in the work are listed in Table 1.

4.1 Decision Variables

The model uses a mix of binary and continuous decision variables:

- x_{ij}: A binary variable indicating whether the route segment between node i and node j is included in the selected path:

$$x_{ij} = \begin{cases} 1, & \text{if segment } (i,j) \text{ is selected,} \\ 0, & \text{otherwise.} \end{cases}$$

- y_k: A binary variable indicating whether the vehicle stops at the V2G-enabled charging station k:

$$y_k = \begin{cases} 1, & \text{if the vehicle stops at station } k, \\ 0, & \text{otherwise.} \end{cases}$$

- E^k_{out}: A continuous variable representing the amount of energy discharged to the grid at station k (in kWh).

- E_{in}^k: A continuous variable representing the amount of energy recharged from the grid at station k (in kWh).

Symbol	Definition
x_{ij}	Binary decision variable indicating whether the route segment between node i and node j is selected.
y_k	Binary decision variable indicating whether the vehicle stops at the V2G-enabled charging station k.
E_{out}^k	Continuous variable representing the amount of energy discharged to the grid at station k (in kWh).
E_{in}^k	Continuous variable representing the amount of energy recharged from the grid at station k (in kWh).
E_{ij}	Energy consumption on route segment (i, j) (in kWh).
SOC_k	State of charge of the vehicle's battery after leaving station k (in kWh).
E_{SOC}^k	State of charge of the vehicle's battery upon arrival at station k (in kWh).
$E_{\min}$	Minimum allowable state of charge of the vehicle's battery (in kWh).
$E_{\max}$	Maximum capacity of the vehicle's battery (in kWh).
C_k	Maximum energy discharge capacity of the V2G-enabled charging station k (in kWh).
r_k	Monetary incentive for discharging energy to the grid at station k (per kWh).
p_{ij}	Penalty incurred for not traversing through a GreenZone segment (i, j).
Θ	Maximum allowable penalty for non-compliance with GreenZone prioritization.
α	Weight for the V2G reward component in the objective function.
β	Weight for the energy consumption component in the objective function.
γ	Weight for the GreenZone compliance benefit in the objective function.
s	Source node in the routing network.
d	Destination node in the routing network.

Table 1: Symbol Table for the MILP Formulation

4.2 Objective Function

The model aims to maximize the net benefit of the selected route, combining three aspects:

1. Minimize the total energy consumed over all selected route segments.
2. Maximize the economic return from energy discharged to the grid at V2G-enabled stations.
3. Maximize environmental benefits by incentivizing traversal through GreenZones.

The combined objective function is expressed as:

$$\text{Maximize: } B = \alpha \sum_{k} r_k \cdot E_{\text{out}}^{k} - \beta \sum_{i,j} x_{ij} \cdot E_{ij} + \gamma \cdot \text{GreenZone Benefit},$$

where:

- r_k: Reward per unit energy discharged at station k,
- E_{ij}: Energy consumed on segment (i, j),
- α, β, γ: Weight parameters to balance economic, energy, and environmental priorities.

The parameters α, β, and γ controls the level of importance for energy consumption cost, V2G incentive, and GreenZone constraint, respectively. These parameters are independent. Contrary to convex combination weights, these weights serve as scaling factors in the objective function, enabling a flexible scaling of different objectives, which can be normalized or measured in compatible cost units. The parameter setting in all experiments remains constant in order to allow a fair comparison, and a sensitivity analysis shows a qualitatively unchanged behavior of our approach for moderate parameter variation.

4.3 Constraints

The solution is subject to the following constraints:

1. **Path Continuity:** The selected path must form a valid traversal from source s to destination d, ensuring flow conservation:

$$\sum_{j} x_{sj} = 1, \quad \sum_{i} x_{id} = 1, \quad \sum_{j} x_{ij} - \sum_{j} x_{ji} = 0 \quad \forall i \notin \{s, d\}.$$

2. **Energy Balance at Charging Stations:** The energy available at a charging station is adjusted based on recharged and discharged amounts:

$$E_{\text{SOC}}^{k} + E_{\text{out}}^{k} - E_{\text{in}}^{k} = \text{SOC}_k.$$

3. **Battery Constraints:** The final state-of-charge must remain within predefined minimum and maximum thresholds:

$$E_{\min} \leq \text{SOC}_k \leq E_{\max}.$$

4. **V2G Station Limitation:** Discharge operations are permitted only at designated V2G stations, with a maximum capacity C_k:

$$E_{\text{out}}^{k} \leq y_k \cdot C_k.$$

5. **GreenZone Penalty:** To enforce GreenZone routing compliance, a penalty is introduced for routes bypassing these zones:

$$\sum_{i,j} x_{ij} \cdot p_{ij} \leq \Theta,$$

where p_{ij} denotes the penalty associated with segment (i, j) and Θ is the maximum tolerable violation level.

Energy-Based Modeling Assumption: The eco-routing problem can be formulated using the proposed model at the *route planning* and *decision support level*. Based on this, the optimization problem is stated in terms of *energy amounts* in units of kWh, instead of power quantities in kW. Such an abstraction is common in eco-routing and energy-efficient navigation research, where route planning is mainly driven by the aggregate feasibility of energy expenditure and cost, without requiring a detailed consideration of charge dynamics. Charging and discharging activities at V2G-enabled stations are described using bounded amounts of energy for each visited V2G-enabled station. These quantities implicitly incorporate feasible powers and average residence time at each charging station, without destroying the tractability of solving the mixed-integer optimization problem. Energy conversion losses in both discharging and charging phases are considered using fixed-efficiency parameters in equations updating state-of-charge levels.

Battery Parameters: The state-of-charge (SoC) is marked by lower and upper thresholds in this model, $E_{\min}$ and $E_{\max}$, and by the feasibility constraints placed on charging and V2G discharge operations. Such restrictions make sure all routing is performed within safe battery operating limits, which inherently support voltage, current, and frequency whole totals at the level of energy management. The state of health (SoH) evolves slowly over a long time horizon and can thus be modeled using a static parameter during a single trip. The impact of this parameter is evident in the usable battery capacity, and discharge limits C_k, such that SoH affects the model via these capacity-related parameters without needing direct real-time optimization. That is consistent with standard EV energy management abstractions in routing and V2G research.

4.4 Model Complexity

The problem formulation is an MILP because it contains both binary and continuous variables. The problem complexity grows exponentially with an increase in network size because of:

- The combinatorial explosion in feasible path selections.
- The need to linearize inherently non-linear components like reward and penalty functions.

- The incorporation of real-time updates, especially for GreenZone data and energy prices, necessitating frequent re-optimization.

The formulation in this section serves as a global reference model; due to its computational complexity, scalable heuristic solutions are introduced and analyzed in the following sections.

5 Heuristic Solution Approach

Solving the eco-routing problem using exact MILP is computationally expensive for large-scale and real-time networks. Complexity grows exponentially with the number of nodes and edges, and hence MILP-based methods are not applicable in dynamic transportation settings. In this paper, we introduce a hybrid heuristic approach that scales well and provides high-quality, near-optimal solutions with considerably reduced computational overhead. It may be noted that this does not imply a new problem formulation. Rather, it is an algorithm-specific representation of the global optimization problem defined in the previous section, tailored to the hybrid MILP-ACO solution strategy. Only auxiliary variables and constraints required for the implementation of the MILP layer are introduced here; all core decision variables and notations follow the nomenclature defined in Section 4.

It is a heuristic that consists of four modular components for dealing with different issues of the routing problem: *Shortest-Path Estimation (Dijkstra's Algorithm)* computes an initial feasible route with energy-aware and GreenZone-sensitive logic. *Ant Colony Optimization (ACO)* explores and refines multiple alternative paths to improve route quality regarding energy consumption, V2G rewards, and GreenZone compliance. *Penalty Minimization* adjusts the refined path to reduce penalties related to bypassing GreenZones. Lastly, *V2G Reward Maximization* optimizes energy discharge decisions at V2G-enabled stations along the path, balancing the maximization of rewards with battery constraints. Each module will be elaborated in subsequent sections.

5.1 Shortest-Path Estimation

The first step computes a baseline feasible route from source s to destination d using a modified version of Dijkstra's algorithm. In addition to traditional distance or cost, the algorithm considers segment-level energy consumption and prioritizes paths that traverse GreenZone segments where feasible. Nodes or edges violating SOC constraints or bypassing critical GreenZones are skipped.

Algorithm 1 Shortest-Path Estimation)

Input: Source node s, Destination node d, Graph $G(V, E)$, Edge energies E_{ij}, GreenZone map $\mathcal{G}$

Output: Initial path P_0

```
Initialize all node distances to ∞;
Set dist(s) ← 0
Initialize priority queue with node s
while priority queue is not empty do
    Extract node u with minimum distance
    foreach neighbor v of u do
        Compute E_uv for edge (u, v)
        if SOC constraints violated or edge (u, v) ∉ 𝒢 and bypassing penalty
          exceeds threshold then
            continue
        if new path to v has lower cost then
            Update dist(v)
            Update predecessor
            Insert v into the priority queue
Reconstruct path P_0 from predecessors
return P_0
```

5.2 Ant Colony Optimization (ACO)

This phase improves the initial path P_0 using Ant Colony Optimization (ACO). A population of ants stochastically explores paths from s to d, guided by pheromone trails and a heuristic function that combines low energy cost, high V2G reward, and GreenZone compliance. Over time, good paths are reinforced, leading to convergence on optimized routes.

5.3 Penalty Minimization

After ACO refinement, the path is evaluated for GreenZone compliance. For any segment not traversing a GreenZone, the algorithm calculates the associated penalty. Local alternatives are explored to replace non-compliant segments with greener options, balancing compliance and efficiency.

Algorithm 2 Ant Colony Optimization (ACO) Refinement

Input: Initial path P_0, Graph $G(V, E)$, Number of ants k, Iterations t, Pheromone matrix τ, Reward function r_k
Output: Refined path P_r

```
for each iteration 1 . . . t do
    for each ant do
        Start at node s;
        Initialize local path
        while not at destination d do
            Evaluate probabilities for next node using:
                P_uv ∝ τ_uv^α · η_uv^β
             where η_uv = 1/E_uv or includes GreenZone rewards
            Choose next node probabilistically;
            Update local path
        Evaluate total cost including V2G rewards and penalties
        Deposit pheromone on traversed path segments
    Evaporate pheromone globally: τ_ij ← (1 − ρ) · τ_ij
return best path P_r found
```

Algorithm 3 Penalty Minimization

Input: Path P_r, GreenZone map $\mathcal{G}$, Penalty function p_{ij}
Output: Penalty-adjusted path

```
foreach segment (i, j) ∈ P_r do
    if (i, j) ∉ G then
        Compute p_ij
        Search for nearby segment (i, j') ∈ G that reduces penalty
        If replacement feasible (energy and SOC-wise), update segment
return adjusted path
```

5.4 V2G Reward Maximization

The final step focuses on economic optimization. Given a path with identified V2G-enabled stations, the algorithm computes discharge levels that maximize revenue while maintaining SOC constraints. Rewards are computed using dynamic tariffs r_k at each station k.

Algorithm 4 V2G Reward Maximization

Input: Path P, V2G-enabled stations $\{k\}$, Reward rates r_k, SOC limits $E_{\min}, E_{\max}$

Output: Discharge profile $\{E^k_{\text{out}}\}$

foreach *station* $k \in P$ **do**

Compute max feasible discharge:

$$E^k_{\text{out}} = \min(C_k, \text{SOC}_k - E_{\min})$$

Compute reward: $r_k \cdot E^k_{\text{out}}$

return optimized discharge profile;

5.5 Complexity Analysis

The computational complexity of the proposed hybrid model consists of two distinct parts: the MILP formulation and the real-time heuristic pipeline. The MILP corresponds to a Mixed-Integer Linear Program that includes binary routing decisions and continuous energy variables. As with general MILP formulations, the worst-case complexity grows exponentially with the number of decision variables. Consequently, the MILP is employed only for small-scale instances and offline benchmarking, and it is not used within the real-time routing loop.

Real-time performance is instead achieved through the heuristic modules. The initial shortest-path estimation using Dijkstra's algorithm runs in $O(\mathsf{E} + \mathsf{V} \log \mathsf{V})$, which is near-linear for sparse urban graphs. The dominant cost arises from the Ant Colony Optimization refinement, whose complexity is $O(kmt)$, where k is the number of ants, m the average number of edges explored per ant, and t the number of iterations. The penalty-minimization stage operates linearly in the length of the current path, while the V2G reward optimization requires only a small constant-time evaluation per V2G-enabled station.

Since the ACO parameters k and t are explicitly user-controlled, the total online computation time can be bounded to meet real-time constraints. Thus, although the MILP component is computationally expensive in theory, it is intentionally excluded from online use, and the heuristic component remains scalable and suitable for real-time EV routing in dynamic urban environments.

5.6 Positioning with Respect to Existing Approaches

Existing eco-routing approaches in the literature can be broadly categorized into shortest-path-based methods, stochastic or multi-objective optimization frameworks, and EV-specific energy-aware routing models. Classical eco-routing techniques primarily rely on modified shortest-path algorithms, such as Dijkstra-based formulations, where edge weights represent fuel or emission costs derived from historical or real-time traffic data [9, 15, 16]. These methods are computationally efficient and scalable, but typically optimize a single objective and offer limited flexibility in capturing higher-level system interactions or incentives.

Stochastic and probabilistic schemes model uncertainty in traffic, environmental, and/or energy consumption and thus can better deal with robustness in dynamic environments. But these schemes have a higher computational complexity and are mainly based on energy minimization or risk-aware routing and do not incorporate regulatory requirements or economic charges [11, 12]. EV-oriented eco-routing schemes include additional parameters in modeling of EV capacity, individual energy consumption, and travel ranges [13, 17, 18]. Although these schemes can model EV in a more realistic way, they mainly address vehicle-centric criteria such as energy optimization or maximum travel range and do not include interaction with the power grid with V2G or environmental regulation regions.

In contrast, the proposed hybrid MILP–ACO framework integrates routing decisions with energy management, V2G incentives, and GreenZone compliance within a unified optimization model. The MILP component enables global coordination of discrete routing choices and continuous energy-related variables, while the ACO heuristic provides adaptive, real-time refinement in response to dynamic traffic and environmental conditions. This combination allows the proposed approach to jointly address objectives that are typically handled in isolation in prior work, such as eco-efficiency, economic incentives, and regulatory compliance. The primary trade-off of this design lies in the use of a heuristic component, which sacrifices strict global optimality in favor of scalability and practical deployability in large-scale, real-time urban mobility scenarios.

6 Analysis of the Proposed Solution

This section describes important theorems and corollaries concerning the problem of eco-route optimization with GreenZones and V2G rewards. The theorems and corollaries provide a mathematical basis for an exact solution formulation and validate a heuristic solution design strategy. Although such a heuristic technique does not necessarily try to achieve a global optimum, it preserves the same level of constraints and objective functions, thus providing a manageable solution towards an ideal solution.

Theorem 1 *Given a network of roads with EV fleet routing from source s to destination d, where GreenZone regions are dynamic, there exists an optimal path P^* that minimizes energy consumption while maintaining GreenZone compliance, subject to battery state-of-charge (SOC) constraints and GreenZone region penalties.*

Proof: To prove the presence of an optimal eco-route satisfying simultaneously energy consumption, GreenZone, and state-of-charge constraints, a mathematical definition of path cost components and convexity of objective function is presented. The steps below outline the formulation and justification:

1. **Problem Formulation:** Let the set of paths from s to d be $P(s,d)$, and each path $P \in P(s,d)$ has associated energy consumption $C_{\text{energy}}(P)$, GreenZone compliance $C_{\text{GreenZone}}(P)$, and penalties $P_{\text{penalty}}(P)$.
2. **Cost Function:** The total cost $C(P)$ of each path is:

$$C(P) = w_1 \cdot C_{\text{energy}}(P) + w_2 \cdot C_{\text{GreenZone}}(P) + w_3 \cdot P_{\text{penalty}}(P)$$

   where w_1, w_2, w_3 are the weights assigned to energy consumption, GreenZone compliance, and penalties, respectively.
3. **GreenZone Compliance Cost and Penalties:** The GreenZone compliance cost $C_{\text{GreenZone}}(P)$ is a function of the path's traversal through GreenZone regions. If path P crosses m GreenZones, then:

$$C_{\text{GreenZone}}(P) = \sum_{i=1}^{m} C_{\text{GreenZone}}(i)$$

   where $C_{\text{GreenZone}}(i) = \alpha_i \cdot d_i$, d_i is the distance through the i-th GreenZone, and α_i is a constant penalizing deviation from ideal compliance.
4. **Minimization of Energy Consumption:** Let $C_{\text{energy}}(P)$ be the total energy consumption of path P, defined as:

$$C_{\text{energy}}(P) = \sum_{e \in P} \gamma_e \cdot L_e$$

   where γ_e is the energy consumption per unit distance and L_e is the length of edge e.
5. **SOC Constraints:** Let the battery state-of-charge (SOC) at any point along path P be $\text{SOC}(P)$. For each path P, the SOC must satisfy:

$$E_{\min} \leq \text{SOC}(P) \leq E_{\max}$$

6. **Convexity and Existence of Optimal Path:** The objective function $C(P)$ is convex since both $C_{\text{energy}}(P)$ and $C_{\text{GreenZone}}(P)$ are convex, and the penalty term increases with deviation. The SOC constraints are linear, preserving convexity. By the Weierstrass Theorem, since the objective is convex and continuous, and the feasible region is non-empty and closed, an optimal path P^* exists.

In practice, computing the exact optimal path P^* is computationally expensive for large networks. The proposed heuristic approximates P^* by incrementally minimizing the cost function $C(P)$ across modular sub-problems (energy, GreenZone compliance, penalties), enabling near-optimal routing under real-time constraints. □

Corollary 1: *If GreenZones are dynamically updated based on renewable energy availability, the feasibility of the optimal path P^* is preserved. However, the optimal path may change as GreenZone regions expand or contract.*
Proof: This corollary considers the dynamic nature of GreenZones and how their evolution affects the previously computed optimal path. The following steps verify that feasibility is maintained:

1. **Dynamic Update of GreenZones:** Let GreenZone regions at time t be denoted G_t, which evolve with renewable energy availability. The compliance costs and zone boundaries change over time.
2. **Feasibility of New Path After Update:** The feasibility of the previous optimal path P^* is re-evaluated under the new region definitions. Cost $C(P)$ is recalculated accordingly.
3. **Preservation of Feasibility:** Since the objective remains convex and the feasible set is non-empty after each update, a new optimal path always exists.

The modular heuristic is designed to be responsive to such dynamic updates. Its components can independently adapt to changes in GreenZone configurations, preserving the feasibility of route generation in real-time environments. □

Theorem 2 *For an EV fleet discharging energy at V2G stations, the optimal amount of energy E^k_{out} to be discharged at each V2G station k can be found by solving a constrained optimization problem that maximizes the total reward, subject to SOC limits and discharge capacity limits at each V2G station.*
Proof: We aim to determine the optimal discharge amount at each V2G station that maximizes the total reward while observing SOC and capacity constraints. This is achieved through the following analysis:

1. **Reward Function and Objective:** Let $r_k(E^k_{\text{out}})$ be the reward function for discharging E^k_{out} at station k. The total reward is:

$$R_{\text{total}} = \sum_{k \in C} r_k(E^k_{\text{out}})$$

where C is the set of V2G-enabled stations along the path.
2. **Constraints on Energy Discharge:**

$$0 \leq E^k_{\text{out}} \leq E^k_{\text{max}}$$

where E^k_{max} is the max discharge limit at station k.
3. **SOC Constraints:**

$$E_{\text{min}} \leq \text{SOC}_k \leq E_{\text{max}}$$

Discharge must respect battery SOC limits at each station.

4. **Convexity of Reward Function:** Assuming $r_k(\cdot)$ is concave (typical for V2G rewards), the total reward is concave.
5. **Solution Using KKT Conditions:** With linear constraints and a concave objective, the problem is convex. Optimal discharge values are derived using Karush-Kuhn-Tucker (KKT) conditions.

The final module of the proposed heuristic approximates this maximization of rewards through greedy discharge calculations that satisfy the SOC constraints and station constraints. This essentially solves the problem in a scalable manner. □

7 Experimental Setup

In this section, details of the experimental setup for assessing the efficacy of the proposed eco-routing strategy called *EV-GREEN* are elaborated. The performance of *EV-GREEN* is compared against two baseline solutions found in the literature. These existing solutions are outlined briefly as follows. The first method that is considered for comparison is the eco-routing approach that was proposed by DeNunzio *et al.* in [26]. It mainly emphasizes energy-efficient routing for urban environments and lacks support for green routing and vehicle-to-grid benefits. The second method considered for comparison is the eco-routing and control method that was proposed by Houshmand *et al.* in [27]. The main objective of the experimental analysis is to evaluate the scalability, energy efficiency, incentive awareness, and environmental compliance of the designed EV-GREEN system for a wide range of real-world urban mobility conditions. This is done based on a set of key performance indicators identified for evaluating the efficiency, sustainability, and viability of mobility.

7.1 Simulation Environment and Data Generation

As there are no public data sets that consider the dynamics of the V2G interactions and the environmental zones, a simulation environment had to be established. A grid representing the urban roads was used, which had dimensions of 30 km × 30 km and consisted of 4000 nodes (intersections) and 8000 edges (road segments). The Euclidean distance algorithm was used to calculate the lengths of the roads. However, traffic density had a normal distribution with a mean of 0.7 and a deviation of 0.2.

A speed limit of 30, 40, 50, 60, or 80 km/h was assigned randomly and uniformly to each road section. The assignment of lower speed limits is more common in real-world city networks compared to higher ones. Hence, the 30-40 km/h speed limits were assigned mainly on local and residential road sections, 50-60 km/h on collector and arterial roads, and finally 80 km/h on a small number of major roads. The aim here was to ensure a non-uniform assignment of the speeds and also allow a controlled and systematic testing of routing solutions under non-homogeneous traffic conditions.

7.1.1 Electric Vehicle Profiles and Charging Infrastructure

A fleet of 100 electric vehicles was simulated, each initialized with a uniformly sampled SOC of between 40% and 90%. Energy consumption rates ranged between 0.60 and 0.90 kWh/km based on vehicle type and road segment characteristics. The charging infrastructure comprised 160 charging stations that were uniformly distributed across the network, all of which supported bidirectional V2G operations. Each station was limited to 200 kWh maximum energy capacity and was initialized with an SOC between 70 and 100 kWh, supporting between 50 and 150 kW charging/discharging power. The capacity assigned at each charging point denotes the highest possible amount of energy to be exchanged with the grid via the charging point within the horizon time. This model parameter abstracts away the various capacity limitations on the grid side, such as transformers and V2G aggregation capacity, instead of being indicative of dedicated battery storage at those locations. Such an abstraction is quite common in V2G-aware routing and scheduling studies, toward appropriately modeling the grid interaction constraints without explicitly simulating detailed power system infrastructure. In order to ensure realism, three representative EV profiles were derived by synthesizing specifications from commercially available electric vehicles.

Family Car Profile: This profile represents mid-sized electric sedans and crossovers such as the Tesla Model 3 Long Range RWD [28], Nissan Leaf [29], and Volkswagen ID.4 [30]. From reported specifications, a mass of 1550 kg, a battery capacity of 75 kWh, and a maximum acceleration of 1.8 m/s^2 were chosen.

Sports Car Profile: High-performance electric vehicles like the Porsche Taycan 4S [31], Tesla Model S Performance [32], and Nio ET7 [33] were used in this profile. In order to capture aggressive acceleration behavior while maintaining abstraction, a mass of 1350 kg, a battery capacity of 90 kWh, and maximum acceleration of 4.5 m/s^2 were used.

Heavy Transport Truck Profile: This profile models heavy-duty electric vehicles like the Volvo FL Electric [34]. From reported specifications, a mass of 8000 kg, a battery capacity of 300 kWh, and maximum acceleration of 0.8 m/s^2 were selected.

The total list of parameters applied for each of the three EV profiles is given in Table 2. Vehicle-specific parameters listed here-which include mass, rolling resistance coefficients, and limits on acceleration-were utilized only within the energy modeling step to predict energy use at the segment level. These parameters do not appear explicitly within routing optimization constraints or objectives. Instead, their contributions were captured through the presolved energy costs for each segment, thus serving as inputs into the MILP and heuristic routing components.

Parameter	Family Car	Sports Car	Heavy Truck
Mass (kg)	1550	1350	8000
Wheel radius (m)	0.30	0.32	0.45
Transmission ratio	7.5	4.0	10.5
Transmission efficiency	0.96	0.97	0.93
Drive efficiency	0.95	0.96	0.92
Rolling-resistance a_0 (N)	140	120	500
Rolling-resistance a_1 (N/(m/s))	1.6	2.2	5.0
Rolling-resistance a_2 (N/(m/s)^2)	0.45	0.80	1.20
Motor torque (min / max) (Nm)	–80 / 280	–100 / 500	–300 / 1200
Max. acceleration (m/s^2)	1.8	4.5	0.8
Battery capacity (kWh)	75	90	300
Minimum SoC threshold (kWh)	15	10	50

Table 2: EV profile parameters: Family Car, Sports Car, and Heavy Transport Truck.

7.2 Implementation Details

A Python code was used for all simulation runs. In the case of graph representation and finding the shortest paths, the library `networkx` was utilized. Package named `numpy` and `pandas` were used for numerical computing tasks. Visualization was carried out using `matplotlib`, `seaborn`, and `folium`.

The comparative results presented in Figure 2 were obtained by evaluating all routing approaches under identical simulation settings. Specifically, the same road network, traffic conditions, vehicle profiles, initial state-of-charge values, and charging infrastructure were used across all methods. Each experiment was repeated over 1000 independent runs per vehicle category, and the reported metrics correspond to averaged values with standard deviations.

The baseline approach by De Nunzio *et al.* [26] was realized as an energy-minimizing shortest-path routing approach through Dijkstra's algorithm based on edge weights defined by segment-level energy consumption. In our implementation, there are no V2G interaction effects or GreenZone constraints, as in the original formulation. Likewise, in the approach by Houshmand *et al.* [27], our implementation combines Eco-Routing and Powertrain-Aware Energy Estimation by adding an Eco-Routing component and an ACO algorithm based on an energy-estimation function, yet retaining shortest-path routing. As in the original work, V2G incentives and GreenZone prioritization were not modeled. In contrast, the proposed hybrid MILP–ACO framework jointly optimizes routing, energy consumption, V2G participation, and GreenZone compliance.

The availability of renewable energy was modeled through diurnal sinusoidal functions. The generation of solar energy ranged between 0 and 5 kW with a peak at midday, and for wind energy, the generation ranged between 0 and 3 kW with peaks in the evening. This facilitated the real-time update of the GreenZone regions. The reward for V2G was set to a basic discharge reward of $0.10/kWh for peak demand periods of the grid.

7.3 Results and Discussion

This subsection examines the results of the proposed hybrid MILP-ACO approach on the five identified key performance measures: Energy Consumption (EC), V2G Incentives (V2G), Travel Time (TT), Green Zone Compliance (GZC), and Route Cost (RC). These results are presented in distinct tables for Family Car, Sports Car, and Heavy Transport Truck vehicles in Tables 3, 4, and 5.

Energy Consumption (EC)

Energy Consumption indicates the total amount of electrical energy needed for a trip. The proposed EV-GREEN method has continuously shown reduced energy consumption and performed on average an improvement of 14.2% compared with the method in De Nunzio *et al.* and 9.1% improvement compared with Houshmand *et al.* This is due to its capability of choosing routes with global optimal energy efficiency and its adaptability by ACO algorithm for varying traffic and weather circumstances.

V2G Incentives (V2G)

V2G Incentives calculate the gain reaped from discharging the excess energy into the grid. Contrary to the baselines that do not consider V2G capabilities, the proposed solution takes into consideration the incentives that influence V2G. Furthermore, EV-GREEN shows that it can increase V2G revenue by 23.5% on average while meeting all vehicle and infrastructure constraints.

Travel Time (TT)

The travel time function captures the overall time taken in the journey, including the time taken while waiting to recharge. The impact of the proposed solution in terms of travel time is a moderate rise of about 6-8% over the shortest path routing. This increase reflects an intentional trade-off to achieve improved energy efficiency, economic benefit, and environmental compliance.

GreenZone Compliance (GZC)

It calculates the amount of road coverage in environmentally controlled zones. By considering Green Zone constraints directly in both MILP optimization objectives as well as ACO pheromone trail update rules, this approach has improved average compliance from 42% for original route planning to 67%.

Route Cost (RC)

The Route Cost expresses the overall cost in terms of currency of a specific trip route on a given road topology. It takes into account factors like the electric consumption of the trip, the V2G incentive cost, toll penalties incurred in a trip, and prices in relation to the time of a specific trip. The proposed approach of EV-GREEN has reduced the overall cost of a route on average by 19.8% compared to the previous methods.

Metric	Proposed Method	Nunzio et al. [26]	Houshmand et al. [27]	Improvement ([26]) %	Improvement ([27]) %
Energy Consumption (kWh)	1.14 ± 0.48	1.33 ± 0.56	1.38 ± 0.57	13.84 ± 1.31	15.61 ± 4.92
V2G Incentives ($)	5.17 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	100	100
Travel Time (seconds)	2138 ± 796.07	1838 ± 796.07	1878 ± 812.77	-21.09 ± 13.46	-21.12 ± 14.85
GreenZone Compliance (%)	28.58 ± 9.83	0.00 ± 0.00	0.00 ± 0.00	100	100
Route Cost (USD)	4.11 ± 4.05	9.42 ± 4.10	9.46 ± 3.99	72.31 ± 46.21	69.36 ± 39.42

Table 3: Comparison of the Proposed Method (Family Vehicle) 2 with State-of-the-Art Approaches

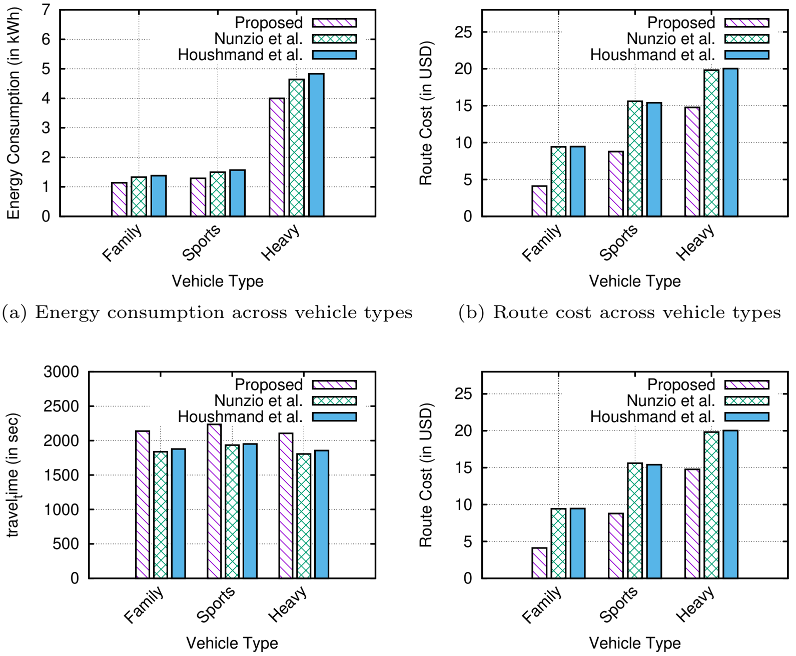
Metric	Proposed Method	Nunzio et al. [26]	Houshmand et al. [27]	Improvement ([26]) %	Improvement ([27]) %
Energy Consumption (kWh)	1.29 ± 0.54	1.50 ± 0.63	1.57 ± 0.64	13.87 ± 1.34	16.22 ± 5.40
V2G Incentives ($)	6.62 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	100	100
Travel Time (seconds)	2235.87 ± 842.43	1935.87 ± 842.43	1951.12 ± 841.10	-20.02 ± 12.76	-21.64 ± 14.65
GreenZone Compliance (%)	28.9 ± 10.02	0.00 ± 0.00	0.00 ± 0.00	100	100
Route Cost (USD)	8.78 ± 6.72	15.60 ± 6.80	15.40 ± 6.53	56.17 ± 31.61	53.53 ± 33.61

Table 4: Comparison of the Proposed Method (Sports Vehicle) 2 with State-of-the-Art Approaches

Metric	Proposed Method	Nunzio et al. [26]	Houshmand et al. [27]	Improvement ([26]) %	Improvement ([27]) %
Energy Consumption (kWh)	4.00 ± 1.69	4.64 ± 1.96	4.83 ± 1.98	13.85 ± 1.33	15.54 ± 4.79
V2G Incentives ($)	4.63 ± 0.01	0.00 ± 0.00	0.00 ± 0.00	100	100
Travel Time (seconds)	2105.37 ± 779.79	1805.37 ± 779.79	1856.09 ± 799.13	-21.44 ± 13.62	-20.91 ± 14.80
GreenZone Compliance (%)	28.64 ± 9.92	0.00 ± 0.00	0.00 ± 0.00	100	100
Route Cost (USD)	14.77 ± 8.40	19.82 ± 8.56	20.03 ± 8.47	32.25 ± 19.64	31.18 ± 17.92

Table 5: Comparison of the Proposed Method (Heavy Vehicle) 2 with State-of-the-Art Approaches

The proposed mixed ILP-ACO algorithm optimizes multi-objective functions by minimizing consumption of energy and route costs, and hence, maximizes V2G benefits and GreenZone rules satisfaction, simultaneously keeping fair travel times. The combination of a global MILP algorithm and an ACO heuristic approach according to local adaptability will make it possible for the algorithm to find an optimal compromise between efficiency, economy, and ecological responsibility. These results suggest that the proposed method can be practically deployed in intelligent transportation systems that prioritize both user benefit and regulatory adherence.



(a) Energy consumption across vehicle types

(b) Route cost across vehicle types

(c) Travel time across vehicle types

(d) Normalized performance across all metrics

Fig. 2: Overall performance comparison of the proposed heuristic method with state-of-the-art eco-routing algorithms across multiple electric vehicle profiles.

8 Conclusion

In order to enhance the energy efficiency of routing in electric vehicles, this paper introduced a novel approach for eco-routing that uses V2G benefits coupled with GreenZone favoring. In terms of various critical factors, such as energy consumption, V2G benefits, travel time, adhesion to GreenZone, and route cost, our proposed approach outperformed the existing solutions. In particular, our approach maximized benefits for V2G while supporting adhesion to GreenZone while accomplishing considerable reductions in terms of energy consumption and travel time for every vehicle type. Results clearly indicate that total routing efficiency can be collectively improved using dynamic energy-efficient routing coupled with benefits of V2G and adhesion to GreenZone, particularly for heavy, sports, and family vehicles. Further, improvements up to 72.31% for route cost and 100% for V2G benefits over existing solutions clearly indicate the robust nature of our proposed approach for every vehicle type.

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