A Review of Hybrid Optimization Approaches for Eco-Friendly Vehicle Routing in Smart Cities

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Abstract. The rising demand for sustainable urban transportation has led to the growth of Eco-Friendly Vehicle Routing Problems, which aim to minimize environmental impacts while optimizing routing decisions. In smart cities, the integration of hybrid optimization techniques has recognized to be a promising solution to address the complex nature of vehicle routing, where multiple objectives, such as minimizing fuel consumption, energy use, and emissions, must be balanced with real-time constraints like traffic and weather conditions. This paper reviews hybrid optimization approaches for EVRP, focusing on the amalgamation of metaheuristic algorithms (e.g., GA, PSO, ACO) with ML techniques, like reinforcement learning and deep learning. These hybrid techniques enhance the flexibility and adaptability of vehicle routing systems, making them fit for the dynamic and evolving environment of smart cities. Also, the paper explores recent trends, including the use of real-time data from IoT sensors and the challenges posed by the scalability of these methods in large urban areas. While noteworthy improvements have been made, several research gaps remain, particularly in improving the scalability of hybrid algorithms, incorporating multi-modal transportation systems, and addressing the integration of emerging technologies like autonomous vehicles. Forthcoming research is central to enhance the effectiveness and sustainability of smart city transportation systems.

Keywords: Hybrid Optimization, Eco-Friendly Vehicle Routing, Smart Cities, Metaheuristic Algorithms, Multi-Objective Optimization, CO2 Emissions Reduction

1 Introduction

As cities expand, transportation must reduce its environmental impact. Increased congestion leads to inefficient vehicle use, higher fuel consumption, and more emissions, worsening climate change and air quality. Eco-friendly vehicle routing optimizes routes for both efficiency and sustainability, particularly with the rise of EVs, where careful route planning ensures energy efficiency and cost reduction[1-6].

In smart cities, optimization is essential for managing complex transportation systems. Real-time monitoring & data analytics aid real-time adjustments in vehicle routing, fleet management and traffic control[2]. ML algorithms help balance goals like reducing travel time, fuel use, and improving traffic flow, while eco-friendly routing

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minimizes emissions and supports sustainability[3]. Hybrid optimization methods combine different algorithms to tackle eco-friendly routing challenges[4]. These methods enhance solution quality and efficiency, and by incorporating machine learning, they adapt to rapidly changing conditions in smart cities[5, 6].

Fig 1 shows how eco-friendly vehicle routing is integrated into smart cities, addressing urban challenges and using hybrid optimization to reduce fuel use and emissions[7]. The remainder of the paper is as follows: Section 2, covers Eco-Friendly Vehicle Routing Problems, variants, environmental constraints, and the role of smart cities. Section 3 discusses hybrid optimization methods, including metaheuristics like GA, PSO, ACO, and their integration with machine learning techniques. Section 4 explores emerging trends such as real-time data integration, electric vehicle routing, and challenges related to scalability in smart cities. Section 5 concludes by identifying research gaps and suggesting future directions in eco-friendly vehicle routing optimization.

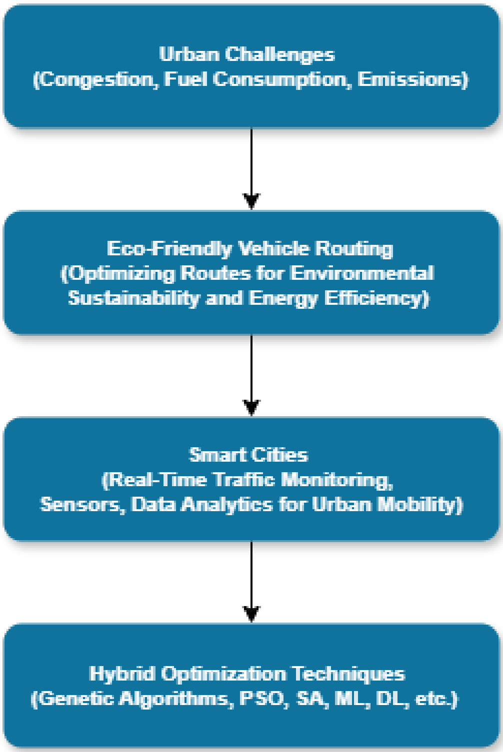

Fig. 1. Conceptual Framework for Eco-Friendly Vehicle-Routing in Smart Cities

2 Overview of Eco-Friendly Vehicle-Routing-Problems

VRP is a common problem in logistics, it finds the best routes to assist customers. Each vehicle starts and ends at a depot. It must visit many locations while reducing travel distance, time, or cost[8-15]. The problem is described by a set of vehicles, a set of customers, and a cost-function that needs to be minimized. The VRP is typically formulated as follows:

$$min \sum_{k=1}^{V} \sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij} \cdot x_{ijk} \qquad --- (1)$$

Where d_{ij} is the distance/cost between locations i and j; x_{ijk} is a binary variable indicating whether vehicle k travels from location i to location j; V is no of vehicles, and N is the no of customers or locations. The goal of VRP is to find the routes that minimize total distance or travel time while satisfying constraints such as vehicle capacity and time windows.

The Eco-Friendly VRP is a variant of the VRP where the objective is to minimize not only the total travel distance or time but also the environmental impact, such as fuel consumption and CO_2 emissions. In Eco-Friendly VRP, additional factors such as vehicle energy consumption, battery limits (for electric vehicles), and emissions are integrated into the optimization model to make it more environmentally conscious[1, 16].

2.1 Evolution and Variants of Eco Friendly VRP

Over time, the standard VRP has evolved to solve real-world problems, leading to several variants. Among them, the Eco-Friendly VRP has become important due to environmental concerns and the need for sustainable transport. The main difference between traditional VRP and its eco-friendly versions is the focus on environmental goals[5, 8, 9].

The Green Vehicle Routing Problem (GVRP) aims to reduce environmental impact by minimizing fuel consumption and CO_2 emissions. GVRP assumes electric or hybrid vehicles and focuses on energy efficiency, with constraints on energy use and emissions[9].

The Electric Vehicle Routing Problem (EVRP) deals specifically with electric vehicles (EVs) and their unique challenges like battery limitations and charging station locations. The goal of EVRP is not just minimizing distance or time, but also ensuring vehicles don't run out of energy during the route[10]. The mathematical formulation for EVRP typically includes energy consumption as a constraint:

$$\sum_{j=1}^{N} Energy_{ij} \cdot x_{ijk} \leq Battery_k \; \forall k \qquad --- (2)$$

Where, $Energy_{ij}$ represents the energy consumption between nodes i and j; $Battery_k$ is the maximum battery capacity for vehicle k.

In real scenarios, many goals must be managed together. In eco-friendly vehicle routing, the focus is on saving fuel, reducing travel time, and cutting emissions. Multi-objective methods merge these goals into one smart optimization model[11,17]. A typical formulation might look like:

$$\min(\alpha \cdot \text{Cost} + \beta \cdot \text{Emission} + \gamma \cdot \text{Time}) \qquad ---(3)$$

Here, α, β, and γ are weights for cost, emissions, and time. Cost, Emission, and Time show total expenses, pollution, and travel duration. Hybrid algorithms like GA[12, 13], PSO[14], and ACO[15] help solve these multi-objective problems by using the best features of different optimization methods.

2.2 Environmental Constraints in Eco-Friendly Routing

EVRP is different from normal VRP because it includes environmental rules. These rules cover emissions, fuel use, energy, and battery limits for EVs. This makes route planning more complex[15-22].

Emissions: Reducing CO2 is a key goal in eco-friendly routing. Models include emissions in the objective function and try to minimize them while planning routes. Emissions depend on distance and vehicle type[1],[23-29]. EVs have almost no emissions while running, but charging may still cause pollution. The formula for emissions can be written as:

$$Emissions = \sum_{k=1}^{V}\sum_{i=1}^{N}\sum_{j=1}^{N} Emission_{ij} \cdot x_{ijk} \qquad ---(4)$$

Where, $Emission_{ij}$ represents the emission factor between nodes i and j.

Fuel Consumption and Energy Usage: For conventional vehicles, fuel consumption is a major factor in eco-friendly routing. The fuel consumed depends on the distance traveled, the vehicle's fuel efficiency, and the driving conditions (e.g., road type, traffic). For electric vehicles, energy consumption is the key constraint, and it is modeled similarly but in terms of energy used rather than fuel[16,30]. The energy consumption for an electric vehicle can be modeled as:

$$Energy_{ij} = Energy_{ij}^{dist} + Energy_{ij}^{traffic} \ \forall i, j \qquad ---(5)$$

Where, $Energy_{ij}^{dist}$ denotes energy consumed per-unit distance between nodes i and j; $Energy_{ij}^{traffic}$ accounts for additional energy usage due to traffic conditions.

Battery Limitations: In EVRP, battery limitations play a crucial role in route optimization. A vehicle's battery must be sufficient to cover the distance between charging stations or its depot[17]. The battery capacity is often modeled as a constraint in the optimization shown in equation (2).

Environmental constraints in eco-friendly vehicle routing, including emissions, fuel consumption, energy usage, and battery limitations. These environmental constraints force optimization algorithms to make trade-offs between operational efficiency and ecological impact, often requiring a multi-objective approach[1], [31-35].

2.3 Importance of Smart Cities in Eco-Friendly Routing

Smart cities use live data to plan eco-friendly routes. Traffic sensors and weather updates help save fuel and cut pollution [7]. Smart routing avoids traffic jams[18]. EV charging stations give real-time battery info[19]. Vehicles change routes based on air quality and weather. Smart tricks make transport clean and smooth[20].

3 Hybrid Optimization Techniques

3.1 Metaheuristic-Optimization Algorithms

These algorithms help solve VRP problems, particularly for eco-friendly vehicle routes. GA, PSO & ACO is good for EVRPs. It searches big and complex solution spaces and calculate good solutions quickly[22].

GAs are optimization methods inspired by natural evolution. They improve a population of solutions over generations using genetic operators like selection, crossover, and mutation. For eco-friendly vehicle routing, GAs help reduce emissions, energy use, and travel distance, which are crucial for electric or hybrid vehicles. In GA, a solution is represented as a string (chromosome) and improved through evolutionary steps. The fitness function combines objectives like minimizing fuel use, cutting emissions, and reducing travel distance[13]. A general form of the fitness function might look like:

$$\text{Fitness} = \alpha \cdot \text{Distance} + \beta \cdot \text{Fuel Consumption} + \gamma \cdot \text{Emissions} \qquad --- (6)$$

Where, α, β, and γ are weight factors assigned to each of the objectives. The primary advantage of GA lies in its ability to handle multiple conflicting objectives and constraints, making it ideal for multi-objective EVRPs, where trade-offs need to be balanced between environmental sustainability and operational efficiency.

PSO works like birds flying together. Each solution is a "particle." Particles move by following their own best spot (personal best) and the group's best spot (global best)[14]. The movement of particles is ruled by the equations (7 &8):

$$\mathrm{v}_i(\mathrm{t}+1) = \mathrm{w} \cdot \mathrm{v}_i(\mathrm{t}) + \mathrm{c}_1 \cdot \mathrm{r}_1 \cdot (\mathrm{p}_i - \mathrm{x}_i(\mathrm{t})) + \mathrm{c}_2 \cdot \mathrm{r}_2 \cdot (\mathrm{g}_i - \mathrm{x}_i(\mathrm{t})) \qquad --- (7)$$

$$\mathrm{x}_i(\mathrm{t}+1) = \mathrm{x}_i(\mathrm{t}) + \mathrm{v}_i(\mathrm{t}+1) \qquad --- (8)$$

Where, $\mathrm{v}_i(\mathrm{t})$:velocity of the ith particle at time t; $\mathrm{x}_i(\mathrm{t})$:position of the i-th particle at time t, p_i:personal best position of the ith particle; g_i:global best position; w:inertia weight; c_1 and c_2 are acceleration constants; r_1 and r_2 are random values between 0 and 1. PSO is great for continuous optimization problems like reducing fuel use and emissions in vehicle routing. But for EVRP, it needs some tweaks as routing is a combinatorial problem. Even so, PSO has shown good results in finding efficient solutions while balancing environmental and operational needs of EVRP.

Ant-Colony Optimization is inspired by how ants leave pheromones to mark paths to food. Over time, shorter paths get more pheromones, making them more efficient. In EVRP, vehicles are treated as ants that follow routes, with pheromones updated based on distance, fuel use, and emissions[15]. The pheromone update rule is expressed as:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t) \qquad --- (9)$$

Based on the above, it is established that the three algorithms successfully contribute to solving eco-friendly VRP. GA is on top with 40%, PSO at 35%, and ACO at 25%[1, 6, 22].

3.2 Hybridizing Metaheuristics Algorithm with ML Techniques

Traditional metaheuristics work well for VRPs like EVRP but struggle to adapt to changing conditions or learn from past experiences. That's where ML techniques help. Mixing metaheuristics with ML supports algorithms adjust fast and make smarter adoptions.

L is a type of ML where a system learns by trying things and getting feedback[23]. RL can be used as a Markov Decision Process (MDP)[24], where the State (s) represents the vehicle's current location, Action (A) represents the next destination or route choice, and Reward (R) represents the reduction in emissions or fuel consumption. The system learns the best way by updating Q-values. Q-values show the expected reward for choosing an action in a given situation:

$$Q(s,a) = Q(s,a) + \alpha\left(R(s,a) + \gamma \max_{a} Q(s',a) - Q(s,a)\right) \qquad --- (10)$$

where, α:learning rate, γ :discount-factor, $R(s,a)$: immediate-reward for taking action a in state s, s': next state. By learning from experience, RL can guide the optimization process in dynamic, real-world environments, making it a valuable addition to hybrid metaheuristics in EVRP.

Deep learning techniques, particularly Deep Q-Learning (DQL), have gained attention in the field of optimization, as they can handle high-dimensional state spaces and complex routing problems. DQL uses deep neural networks to approximate the Q-values and has shown promising results in dynamic and large-scale routing problems like EVRP[25].

In EVRP, deep learning models can guess variables such as travel time, energy consumption, or emissions between nodes, and these predictions can be unified into a metaheuristic algorithm like ACO, PSO, or GA[6]. By leveraging large datasets and historical routing data, deep-learning models can provide better accurate estimates of real-world conditions, thus improving the optimization process.

3.3 Applications and Challenges of Hybrid Optimization

Hybrid optimization is useful for eco-friendly vehicle routing in cities. It helps EVs find the best routes, saving fuel and cutting emissions. It is used for EV delivery, electric buses, and waste collection trucks. But these hybrid methods, mixing metaheuristics and ML, have some issues. They need a lot of computing power and can be slow for big problems. Training ML models takes time and resources. As problem size grows, performance drops. To fix this, methods like parallel computing and cloud solutions can speed up processing[1].

4 Emergent Trends and Challenges

4.1 Integration of Real-Time Data (IoT, Traffic, Weather)

Real-time data integration is becoming crucial in eco-friendly vehicle routing. In smart cities, IoT devices like traffic sensors, GPS, weather stations, and energy monitors collect data to improve vehicle routing by providing live updates on traffic, road conditions, energy use, and weather[3].

Real-Time Traffic Data

Traffic jams waste fuel and increase pollution. Real-time data from sensors and GPS helps avoid congestion. Routes adjust dynamically to save energy and cut emissions[26]. Traffic conditions update travel time in routing models for better planning.

$$\mathrm{Travel\ Time_{ij}(t) = Base\ Time_{ij} + \Delta Time_{ij}(t)} \qquad --- (11)$$

Where, $\mathrm{Travel\ Time_{ij}(t)}$ is the time required to travel between nodes i and j at time t, $\mathrm{Base\ Time_{ij}}$ is the default time based on the shortest path, $\mathrm{\Delta Time_{ij}(t)}$ represents the increase in travel time due to traffic congestion.

Weather Data Integration

Bad weather like rain, heat, or strong wind affects energy use in electric vehicles[27]. More drag or heating increases power consumption. Using weather forecasts in EV routing helps save energy. A simple model can use a factor θ to adjust energy use based on weather impact:

$$\mathrm{E_{route}} = \sum_{i=1}^{n} \left(\mathrm{Energy_{ij}} + \theta \cdot \mathrm{Weather\ Factor_{ij}}\right) \qquad --- (12)$$

Where, $\mathrm{E_{route}}$:total-energy consumption for the route, $\mathrm{Energy_{ij}}$:energy required to travel between nodes i and j, θ is a coefficient that represents the sensitivity of the vehicle to weather conditions, $\mathrm{Weather\ Factor_{ij}}$ is the impact of weather conditions (like wind, rain, etc.) on energy consumption between i and j. Integrating real-time weather and traffic data into hybrid optimization algorithms improves the overall efficiency of eco-friendly vehicle routing by ensuring the routes are dynamically adjusted to match real-world conditions[28].

4.2 Hybrid Approaches for Electric Vehicle Routing

Electric vehicles (EVs) present unique challenges compared to traditional fuel-powered vehicles, particularly in terms of range limitations, charging requirements, and battery performance. Hybrid optimization approaches that combine metaheuristics and machine learning techniques are particularly effective for addressing these challenges[5].

Range and Charging Constraints

In EV routing, it's crucial to ensure the vehicle doesn't run out of charge. Hybrid optimization techniques can optimize the placement of charging stations in the city. Charging stations are treated as nodes, and the distance between them is calculated, considering the vehicle's range limits[29]. Let's assume the battery capacity is B and the energy consumption per unit of distance is α. The maximum distance that a vehicle can travel without recharging is:

$$D_{max} = \frac{B}{\alpha} \qquad --- (13)$$

When many charging stations are there the aim is to save energy and keep the vehicle charged. A smart method can use an algorithm to choose the best charging stops based on vehicle energy use[11].

Routing with Multiple Charging Stops

For longer trips that exceed the maximum range of an EV, hybrid optimization algorithms can help find the optimal placement and sequencing of charging stops. In these cases, the goal is to minimize detours, reducing time and energy consumption spent at charging stations[30]. The route is thus a combination of travel between regular nodes (cities or delivery points) and charging stations. The total route cost C_{total} could be expressed as:

$$C_{total} = \sum_{i=1}^{k} Cost_{i,i+1} + \sum_{j=1}^{m} Cost_{charging} \qquad --- (14)$$

Where, $Cost_{i,i+1}$ represents the cost of traveling between consecutive nodes in the route (whether a city or charging station), $Cost_{charging}$ represents the additional cost (in time or energy) associated with stopping for charging at each station.

4.3 Scalability and Practical Considerations in Smart Cities

As smart cities grow, scalability and practical challenges increase in using hybrid optimization for eco-friendly vehicle routing. The complexity of hybrid algorithms rises with network size and vehicle numbers[7]. In large cities, real-time computation needs to be handled by distributed computing, cloud, or edge computing. Besides, practical factors like traffic laws, road closures, and vehicle maintenance schedules must also be considered, adding complexity to routing solutions[31]. These real-world constraints require dynamic adaptation to uncertainties, like travel times or vehicle status[1]. For instance, a stochastic cost function might look like:

$$C_{route}(t) = E\left[\sum_{i=1}^{k} Cost_{i,j}(t)\right] \qquad --- (15)$$

Where, E represents the expected value, $Cost_{i,j}(t)$ is the time or energy cost for traveling between nodes i and j at time t, which could vary due to uncertainties in traffic or road conditions.

4.4 Addressing Algorithmic Limitations for Dynamic Environments

The dynamic nature of real-world environments, especially in smart cities, presents a significant challenge to traditional optimization algorithms. Conditions such as traffic, road closures, and vehicle breakdowns can change randomly, needing constant re-optimization of routes in real time[32].

To tackle these challenges, dynamic re-optimization is used in hybrid methods. This means recalculating routes regularly based on new data or changes, balancing cost and solution quality. Online optimization and adaptive algorithms work well in such changing environments[33].

Hybrid optimization methods should handle changes in input data, like roadblocks or breakdowns. Robust optimization techniques focus on finding solutions that work despite such uncertainties. The problem is often framed as robust optimization, considering worst-case scenarios:

$$\text{Minimize} \max_{t \in T} \left(\sum_{i=1}^{k} \text{Cost}_{i,j}(t) \right) \qquad ---(16)$$

T is the set of possible states of the system (including disruptions), the optimization lessens the maximum cost incurred across all possible states. Emerging trends in eco-friendly vehicle routing include real-time data integration, hybrid techniques, scalability challenges, and adapting to smart cities[34, 35]. These are shown in Table 1.

Table 1. Emergent Trends and Challenges in Eco-Friendly Vehicle Routing

Emergent Trends/ Challenges	**Description**	**Mathematical Modeling**
Integration of Real-Time Data [36]	Real-time data from sensors and GPS helps make better route decisions.	Stochastic Modeling
Real-Time Traffic Data[37]	Traffic info helps avoid jams, saving fuel and time.	Dynamic Routing Function
Weather Data Integration[38]	Weather affects energy use, so routes change according to weather.	Weather Adjustment Function
Hybrid Approaches for EVR [10]	Combines methods to handle EV range and charging needs.	Hybrid Optimization Algorithm
Routing with Multiple Charging Stops[39]	Finds best places to stop for charging to save energy and time.	Multi-Objective Optimization

Scalability in Smart Cities[40]	Smart cities need powerful computing to handle large data.	Scalable Distributed Algorithms
Real-World Constraints[41]	Real-world issues like roadblocks and breakdowns must be considered.	Constraint-Based Optimization
Dynamic Re-Optimization[33]	Routes change in real-time due to unexpected events.	Dynamic Re-Optimization Function
Robustness and Flexibility[42]	Solutions should work even with unexpected disruptions.	Robust Optimization Techniques

5 Conclusion and Research Gaps

Hybrid optimization methods have emerged as a promising solution for addressing the complex Eco-Friendly Vehicle Routing Problem in smart cities. Traditional optimization techniques such as meta-heuristics (GA, PSO, ACO) can be combined with modern ML and reinforcement learning models to address the dynamic and multifaceted nature of urban transportation networks. The incorporation of real-time data, such as traffic and weather information, improves the adaptability and efficiency of routing algorithms, which are required for smart cities' ever-changing environments.

However, significant research gaps must be addressed in order to advance the field. These challenges include the scalability of hybrid algorithms in large-scale urban environments, the integration of emerging technologies such as self-driving cars, and the use of multi-source data to optimize routing decisions. Furthermore, user-centric models that account for preferences and constraints are underdeveloped. By focusing on these areas, future research could significantly improve the sustainability and efficiency of vehicle routing systems, thereby contributing to the realization of greener, more intelligent cities. Addressing these gaps will pave the way for the development of environmentally friendly smart transportation systems that can adapt to the changing nature of urban environments.

Disclosure of Interests. The authors declare that there is no potential conflict of interests.

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