Eco-Friendly Route Planning Algorithms: Taxonomies, Literature Review and Future Directions

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Eco-friendly navigation (aka eco-routing) finds a route from A to B in a road network that minimizes the greenhouse gas (GHG) emission or fuel/energy consumption of the traveling vehicle. As road transport is a major contributor to GHG emissions, eco-routing has received considerable research attention in the past decade, mainly on two research themes: 1) developing models to estimate emissions or fuel/energy consumption of vehicles; and 2) developing algorithms to find eco-friendly routes for a vehicle. There are some excellent literature reviews that cover the existing estimation models. However, there is no literature review on eco-friendly route planning algorithms. This paper fills this gap and provides a systematic literature review in this area. From mainstream online databases, we obtained 2,494 articles and shortlisted 76 articles using our exclusion criteria. Accordingly, we establish a holistic view of eco-routing systems and define five taxonomies of estimation models, eco-routing problems and algorithms, vehicle types, traffic, and road network characteristics. Concerning the taxonomies, we categorize and review the shortlisted articles. Finally, we highlight research challenges and outline future directions in this important area.

Additional Key Words and Phrases: Eco-routing, Navigation systems, Intelligent transportation systems, Taxonomy, Systematic literature review

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1 INTRODUCTION

Road transport has contributed significantly to greenhouse gas (GHG) emissions, causing global warming in the past decades. Reports from various countries show that road transport accounts for 16% to 20% of the total global GHG emissions [40]. Thus, reducing the GHG emission from road transport has received significant attention from academia and industries [49, 126, 165, 212]. Among many other initiatives like replacing gasoline-based vehicles with electric vehicles, intelligent routing strategies that optimize fuel consumption, commonly known as eco-friendly navigation (aka eco-routing), have shown significant promise in reducing GHG emissions [2]. According to Google, one of the most popular navigation service providers, the eco-routing service provided by the company in the last year has the potential to allow users to avoid over 1 million tons of carbon emissions per year [112]. In addition to reducing carbon emissions, eco-routing has the potential to save millions of dollars by reducing the increased fuel costs of commuters [196]. Note that fuel consumption is directly proportional to GHG emissions, and we can easily extend the techniques designed to minimize fuel consumption to minimize GHG emissions, and vice versa [152]. Similarly, energy consumption directly contributes to GHG emissions for electric vehicles, assuming that the vehicle is charged using dirty energy sources such as electricity produced using fossil fuels. In this paper, we focus on minimizing fuel/energy consumption. Note that we can directly apply the existing techniques to minimize emissions by using emission models instead of fuel/energy consumption models. For simplicity, in the rest of the paper, we use the term "energy consumption" instead of "fuel/energy consumption".

Eco-routing finds the most energy-efficient path for a vehicle from a given origin to a given destination. More specifically, given a road network and the energy consumption costs of every link of the network, the eco-routing algorithm finds the route (sequence of road network segments) that minimizes the energy consumption for traveling from the origin to the destination [30]. Thus, an eco-routing system has two major components: (i) an energy consumption model to estimate the energy consumption for a given road segment/route; and (ii) a routing algorithm that finds the most energy-efficient route from the origin to the destination.

As the energy consumption of a vehicle traveling on a route depends on various factors that include traffic dynamics (e.g., average speed, traffic flow, and traffic signaling), road properties (e.g., roadway grade, surface roughness, and horizontal curvature), vehicle properties (e.g., engine, loading, vehicle speed, and acceleration), driving behaviors, etc., the research on the transportation area mainly focuses on developing different energy consumption models utilizing various aspects of these factors. Though most of the earlier models were based on physics or rules [228], data-driven models [112, 116] have shown a great promise recently. As vehicle properties play a vital role in the process, different energy models have been proposed for different types of vehicles, e.g., gasoline vehicles [172], hybrid vehicles [61, 155], and electric vehicles [39, 96].

Though significant attention has been given to developing appropriate energy consumption models, the proposed eco-routing approaches adopt a wide variety of routing algorithms for finding the eco-route. The path returned by eco-routing can be very different from the paths produced by the conventional routing approaches that find the fastest or shortest route from the origin to the destination [9, 88]. For example, according to a case study [128], on average, the eco-route takes 9% longer distance to travel than the shortest route. Another study [10] shows that by sacrificing 4.3 minutes of travel time for a longer route for the same origin-destination pair, drivers may save around 18–23% of energy. Thus, the eco-routing strategy also optimizes energy consumption while imposing travel time/distance constraints to make the path more practical and convenient for users. Existing eco-routing approaches adopt a wide variety of algorithms ranging from optimization algorithms [218] to simple search-based techniques [224] to advanced AI-driven search techniques [117] under different environments and user-defined constraints.

Eco-routing has received huge research attention in the past decade or so. Most of the existing works can be categorised in two major themes: 1) developing models to accurately estimate energy consumption of vehicles; and 2) developing algorithms to find eco-friendly routes. There has been several literature reviews [18, 58, 93, 228] covering the former. For example, earlier works by Faris et al. [93] and Zhou et al. [228] provide a comprehensive review of state-of-the-art energy consumption models and classify them into different categories. Chen et al. [58] provide a review of energy consumption estimation of electric vehicles (EVs) and how to support the improvement of models and development of emerging EV applications. Although there are also some literature reviews related to eco-routing, these existing surveys have a different focus than our work. For instance, Almalki et al. [19] present a survey on eco-friendliness in smart cities, but their primary focus is on the development of Internet of Thing (IoT) techniques. Lin et al. [140] and Ferreira et al. [95] present comprehensive surveys on minimizing energy consumption in logistics. However, their focus is primarily on the Vehicle Routing Problem (VRP). Unlike eco-routing, which focuses on finding eco-friendly routes, VRP focuses on assigning orders to a group of vehicles to minimize a given objective function (such as driving distance or fuel consumption). These surveys do not address the computation of eco-friendly routes between a start and a target location, which is the specific focus of this survey. Instead, they concentrate on the assignment of orders to the vehicles. Alfaseeh et al. [18] focus on a three-factor taxonomy where eco-routing models are classified at a more disaggregated level. The taxonomy is based on the level of aggregation of traffic flow and emission models, scalability, and the number of objectives optimized simultaneously. Our survey is unique in that it primarily focuses on algorithms for finding eco-friendly routes while also covering a variety of taxonomies to classify different works.

Despite a large body of existing works on developing algorithms to find eco-friendly routes, there is no existing literature review that critically analyses these works. We fill this gap and present a systematic literature review of the eco-routing algorithms. We present several important and original taxonomies and categorize the existing research based on different dimensions. We make the following key contributions in this paper.

- We identify major aspects of eco-routing systems, mainly focusing on routing algorithms. We conduct a systematic literature review of the existing research on eco-routing approaches and critically review the influential papers collected from well-known research databases.
- We provide five major taxonomies to categorize the existing eco-routing approaches: (i) an energy consumption model taxonomy to categorize different types of energy consumption estimation strategies; (ii) a taxonomy to group existing works based on the types of problems studied and the types of algorithms employed to solve the problems; (iii) a taxonomy to differentiate existing works based on the vehicle types (e.g., electric vehicle or internal combustion vehicle); (iv) a taxonomy based on the traffic conditions; and (v) a taxonomy to show the scalability of the proposed approaches.
- We review relevant existing works on eco-routing under two major categories of routing algorithms: unconstrained and constrained routing algorithms. We critically analyze each of the works from the perspective of our defined taxonomies.
- We discuss prominent challenges hindering the research in eco-routing algorithms adapted in different eco-routing systems and outline important future research directions.

The rest of this paper is organized as follows. Section 2 presents different taxonomies that incorporate the key aspects of eco-routing approaches. Section 3 explains the state-of-the-art eco-friendly navigation approaches and categorises them based on the defined taxonomies. Section 4 highlights the major research challenges and future research directions. We conclude the paper in Section 5. Furthermore, Section A.1 in the Supplementary Material provides the scope and structure of this literature review, and Section A.2 presents our methodology for a systematic literature review.

2 TAXONOMIES

The existing literature on eco-routing considers a variety of different aspects important for eco-routing. In this section, we discuss some of the major aspects and present taxonomies for these aspects. These taxonomies are then used in our literature review to discuss the existing work. Figure 1 depicts five crucial aspects of eco-routing discussed in this paper. When categorizing existing literature, it is essential to evaluate each aspect independently. However, these aspects often intersect and exhibit interdependencies. In Figure 8, we present an overview of the eco-routing system, illustrating how each aspect interacts with the others. For example, energy consumption models rely on vehicle parameters, traffic information, and road network characteristics. Similarly, road network characteristics, such as travel time, are influenced by traffic data. It is important to note that these aspects offer different frameworks for classifying existing works, and these classification methods may not always be directly comparable. Different readers may prefer classifications based on specific taxonomies depending on their interests and preferences. For example, a reader primarily interested in energy consumption models in eco-routing may prefer a classification based on those models. Given that our work focuses on algorithms for various eco-routing problems, we primarily categorize existing works based on the eco-routing problems studied in these papers and the proposed algorithms. Nevertheless, we also provide two tables (Table 1 and Table 2) that classify these works according to other taxonomies for readers with different interests. These tables can be particularly useful for readers interested in classifications by a different taxonomy. For example, a reader may be looking for works that use mesoscopic energy consumption models. They can refer to these tables to identify relevant works in that category.

The rest of this section is structured as follow. We present taxonomies for each aspect illustrated in Fig.1, including: i) fuel/energy consumption models (Section 2.1); ii) type of routing problems studied and the algorithms used (Section 2.2); iii) vehicle parameters (Section 2.3); iv) traffic (Section 2.4); and v) road network characteristics (Section 2.5).

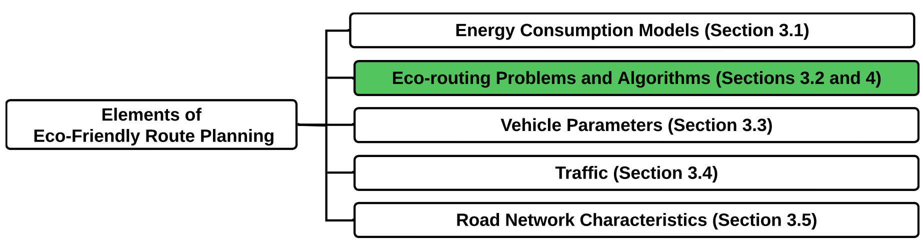

Fig. 1. Elements of eco-friendly route planning.

2.1 Energy Consumption Models

The energy consumption models that estimate the overall energy consumption of a vehicle during navigation on roads have an enormous impact on eco-routing. As the energy consumption depends on a variety of factors, we will first summarize these factors in Section 2.1.1, and then present two different paradigms of taxonomies for energy consumption models. Specifically, we discuss existing energy consumption models from the perspective of transparency in Section 2.1.2 and from the standpoint of granularity of input data in Section 2.1.3.

2.1.1 Factors affecting energy consumption. A large number of factors affect a vehicle's energy consumption and emission while navigating on a road. Ahn et al. [13] categorized these into six main categories: travel-, weather-, vehicle-, traffic-, roadway-, and driver-related factors. Table 3 in the Supplementary Material is an enriched and more informative version of a table presented in a previous survey paper [228]. In particular, Table 3 shows some examples of each factor influencing energy consumption as previously noted in [228] and shows the percentage effects of each factor in the first column on the energy consumption.

Researchers have discovered that some factors are more important than others in developing various energy consumption models. The engine is the major fuel economy determinant, and thus most energy consumption models consider different vehicle-specific parameters [82, 87, 123]. The size, power, and speed of an engine, the type of energy used, and whether or not an exhaust after-treatment system is installed directly affect engine energy usage [35]. However, using these variables are ineffective if the vehicle type is unknown to the system or if we want to find eco-routes for a new type of vehicle. Thus, many works only consider a subset of these factor while designing their energy models. Apart from the vehicle and engine specific factors, driving behaviors [28, 125, 129] and roadway-related factors (roadway grade, surface roughness, and horizontal curvature) [226] significantly impact the energy usage. The road grade affects fuel consumption and emissions [63, 154]. For example, if one route has major hills and another is somewhat longer but less hilly, the longer route may be more environmentally friendly.

Developing a new energy consumption model should prioritize roadway and driver variables, followed by travel and weather. Finally, we can incorporate traffic-related aspects by addressing communication between the driver, vehicle, and traffic signals [228].

2.1.2 Transparency based classification. The level of physical knowledge about the model and how the user could interpret the model differ among models. Thus, existing literature often classifies the models based on transparency, representing how transparent (or easy) it is to perceive a model's structure, equations, parameter values, and assumptions for an outsider. Existing fuel consumption models are divided into three categories based on the degree of transparency they provide: *white-box*, *black-box*, and *grey-box*. White-box models rely on mathematical formulation and physics to develop equations to represent the influential sub-processes of the energy consumption and thus require a complete understanding of the system. In contrast to white-box models, black-box models lack physics in their model structure and rely solely on the system's input-output mapping based on data (e.g., data-driven machine-learning models). Grey-box models are hybrid models that work in-between, i.e., their transparency level falls between white and black-box models. A grey-box model is based on insights into the system considered and experimental data. Fig. 11 in the Supplementary Material illustrates the properties of these three types of models.

White-box fuel consumption models [43] are based on engine's physical or chemical processes, i.e., they use mathematical formulas to describe the processes of engine intake, compression, combustion, and exhaust. The number of parameters that need to be determined in a white-box fuel consumption models is typically large [109]. A black-box fuel consumption model [12, 48, 155, 158, 167, 171, 220] is usually based on experimental data and data processing methods. Such a model is mainly mathematical because it provides little physical explanation. Furthermore, black-box fuel consumption modeling has several disadvantages: it is a entirely data-driven model that must be calculated using various linear or nonlinear regression methods based on a significant amount of data. A grey-box fuel consumption model [157] is a hybrid of a white-box and a black-box model. Unlike a white-box model, a grey-box fuel consumption model does not require detailed engine knowledge, making it easier to create. Researchers have experimented with combining multiple modeling methods to model fuel consumption because each has its own unique properties. For example, Chiara et al.[61] designed a hybrid instantaneous fuel consumption model for diesel engines that includes white-box and grey-box models.

White box models require the lowest amount of experimental data. Their accuracy is relatively high; however, their structures are highly complex, increasing the computation time if used in eco-routing systems. Saerens et al. [171] suggested that the black-box fuel consumption model is suitable for use in complex applications such as eco-driving and eco-routing systems where the engine seems like a black box. The prediction accuracy of grey-box models is believed to be higher [228] than that of black-box models, although there are exceptions. A recent review [227] shows that there are many data-driven models that achieve high accuracy although they often lack explainability or generalizability.

Energy consumption models are essential for eco-routing, and the accuracy of the energy consumption models vary with the types of model that is used. In the next section, we present a taxonomy of consumption models based on the input data used by different models.

2.1.3 Input-Data based Classification. The level of input needed by the system is a differentiating factor for energy consumption models. Some models require more detailed instantaneous information, e.g., instantaneous speed, whereas others calculate energy based on aggregate data, e.g., total distance, average speed, etc. Based on the input data required for the model, energy consumption models can be divided into three categories: *Macroscopic Models*, *Mesoscopic Models*, and *Microscopic Models* (see Fig. 2).

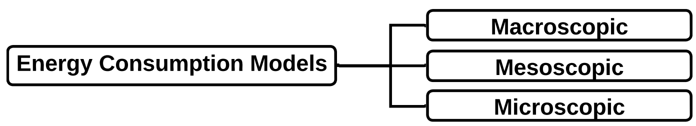

Fig. 2. Taxonomy based on input data.

Macroscopic models [134] typically estimate energy consumption based on total route mileage or aggregate route distance. These models provide a high-level overview by considering overall distances traveled but fail to account for driving heterogeneity, such as variations in traffic conditions, road types, and individual driving styles. This lack of granularity makes them generally unsuitable for solving the eco-routing problem, which requires a more detailed analysis of fuel efficiency based on specific driving conditions [116]. However, due to their simplicity and computational efficiency, macroscopic models can be beneficial for preliminary route planning where a quick estimation of energy consumption is needed without delving into the complexities of driving behavior.

In contrast, microscopic models [29, 97, 153, 157, 167, 169] usually offer the highest accuracy in computing energy or fuel consumption. These models simulate the vehicle's behavior at a detailed level, considering a range of parameters including engine idling induced by traffic signals, instantaneous acceleration, deceleration, and speed variations within each link of the road network [59]. By capturing these detailed dynamics, microscopic models can accurately predict fuel consumption and emissions under various driving conditions. However, this high level of detail requires extensive real-time data inputs, such as precise traffic signal timings, real-time speed, and acceleration data, which are often challenging to obtain before the trip begins. The need for such detailed and dynamic data can limit the practical applicability of microscopic models, especially for real-time applications.

To address these challenges, mesoscopic fuel consumption models [15, 132, 219] offer a compromise between macroscopic and microscopic approaches. Mesoscopic models estimate energy consumption by calculating link costs based on average speeds and other predictable parameters for each link in the road network. They do not require detailed transient driving behaviors as inputs, making them more feasible for real-time eco-routing applications compared to microscopic models. By averaging traffic conditions and simplifying driving dynamics, mesoscopic models can provide reasonably accurate estimates of energy consumption with less computational complexity and data requirements. However, the simplification inherent in mesoscopic models can lead to less precise estimates in scenarios with significant traffic variations or complex road conditions, where detailed driving behavior plays a crucial role in determining fuel consumption [10, 89].

2.2 Eco-routing Problems and Algorithms

Existing works on eco-routing can be classified considering the following aspects: i) eco-routing problem formulation; ii) the algorithms they employ to solve the problem; and iii) whether or not they consider rerouting (in case better routes become available). Next, we discuss these in details.

2.2.1 Problem Formulation. Research shows that eco-routes can take longer time as well as longer distance to travel than the fastest or shortest route. Thus users may want to impose additional constraints on route length, travel time, or other vehicle specific constraints such as refueling and battery recharging facilities along the way. As shown in Fig. 3, the existing research can be categorised into two main types of problem formulation for eco-routing: unconstrained eco-routing and constrained eco-routing.

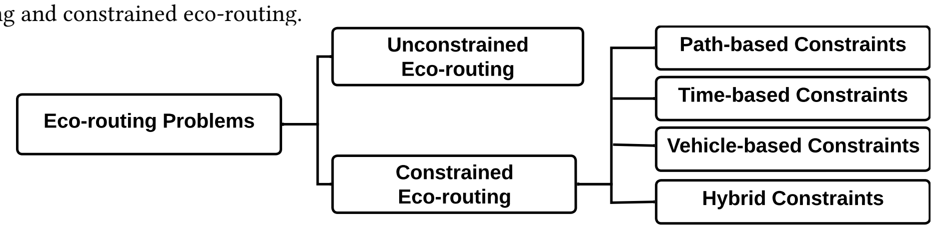

Fig. 3. Taxonomy based on problem formulations.

Unconstrained Eco-routing. In unconstrained eco-routing [20, 75, 89, 135, 170], one is only interested in finding the path that has the minimum energy consumption from the origin to the destination, disregarding all other constraints such as travel time, distance, etc. We formally define the unconstrained eco-routing problem as follows. Given a directed road network graph $G(V, E)$ consisting of a set V of nodes and a set E of edges/links. A link $e = (i, j) \in E$ is a directed edge from node i to node j and has an associated cost c_{ij} referring to the cost to travel on the edge from i to j, such as edge length, travel time, or energy consumption. A path from an origin o to a destination d may be defined as a sequential list of links: $(o, j), \dots, (i, d)$ and the energy consumption cost of the path is the total energy consumption of the vehicle if it takes this path. The unconstrained eco-routing problem is to find the path that has the minimum energy consumption cost from the origin o to the destination d.

Constrained Eco-routing. As discussed earlier, the most eco-friendly route may have higher travel distance or travel time. A user may choose not to travel on a path that significantly increases the traveling time or distance regardless of the saving of associated energy consumption or emissions. Therefore, users may want to define additional constraints to find the most eco-friendly path among all paths. In constrained eco-routing, additional constraints are defined and the goal is to find the most eco-friendly route that satisfies these constraints. As shown in Fig. 3, these constraints may be based on path, time, vehicle, or a combination of these (i.e., hybrid constraints). In path-based constraints, drivers can set their preferences about the route, e.g., preferring freeways or stopping for charging/fuelling along the route. Time-based constrained eco-routing tries to find the most eco-friendly route such that the traveling time on this route is at most $(t \cdot \epsilon)$ where t is the traveling time on the fastest route, and $\epsilon \geq 1$ is a user-defined parameter. In vehicle-based constraints, users can have preferences about the vehicle's initial charge level, battery capacity, desired charge level after the trip, etc. Generally speaking, these problems are the Constrained Shortest Path (CSP) problems, an extension of shortest path algorithms [122]. The path computed using CSP is the shortest path fulfilling a set of constraints. A generic CSP algorithm has been covered in previous studies [60, 99].

2.2.2 Solution Types. Many different types of solutions have been proposed for different types of eco-routing problems. The existing solutions can be broadly categorized into two sub-domains: *search-based solution* and *optimization-based solution* (see Fig. 4). Generally, in a search-based approach, the algorithm conducts a search on the road network (e.g., by incrementally exploring nearby edges) to find the required solution. On the other hand, an optimization-based solution typically uses mathematical optimization to optimize the given objective function while taking into account the defined constraints.

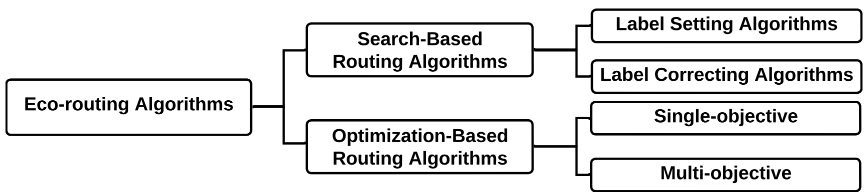

Fig. 4. Taxonomy based on algorithms.

Search-Based Solution. Search-based path-finding approaches have been extensively studied [104]. Search-based algorithms can be classified into two main classes: label-setting and label-correcting [60, 224]. Both approaches are iterative and employ the labeling method [100, 224] in computing one-to-all optimal paths. However, the two groups of algorithms differ in how they update the estimate of the optimal weight associated with each node at each iteration and in how they converge to the final optimal one-to-all optimal paths. In label-setting algorithms, the final optimal weight from the source node to the destination node is determined once the destination node is scanned and permanently labeled. For example, Dijkstra's algorithm and A* algorithm are two well-known label-setting algorithms. In contrast, a label-correcting algorithm treats the weights of all nodes as temporary, and the shortest paths to the nodes are not determined until the algorithm terminates [225]. For example, Bellman-Ford algorithm is a label-correcting algorithm. Some variations of Dijkstra's algorithm (e.g., when multiple criteria are to be considered) are also label-correcting.

Optimization-Based Solution. Optimization-based solutions include all relevant factors while determining the most energy-efficient route [86]. Based on the number of objectives to be optimized, we may further divide it into two categories (i.e., single-objective vs. multi-objective). A single-objective optimization problem aims to find the best solution for a specific criterion or metric. On the contrary, multi-objective optimization refers to locating the optimal route for more than one desired goal [73]. A standard solution to such problems is combining multiple objectives into one single-objective scalar function. This approach is generally known as the weighted-sum, or scalarization method [127]. The weighted-sum method is commonly used because of its simplicity, ease of use, and direct translation of weights into the relative importance of the objectives [146].

2.2.3 Rerouting. Traffic and other road conditions are usually highly dynamic and the optimal route choice may change as the traffic and/or other conditions change. Therefore, it is important to offer drivers feasible detours when their typical route is highly crowded as a result of accidents, events, or other unusual traffic patterns [90]. In some application scenarios, a user may be interested in keeping track of the optimal route (e.g., most eco-friendly route) as the network changes dynamically. This is called rerouting. In some other applications, the user may only be interested in obtaining the optimal route at the start of their journey and does not need to update the route continuously (e.g., ignoring the underlying dynamic network conditions). Therefore, we categorize the existing works based on whether they consider rerouting or not.

2.3 Vehicle Parameters

For a given origin-destination pair, the routes returned by an eco-routing algorithm may differ significantly based on various parameters of the vehicles [8, 168]. Therefore, it is essential to investigate and compare the effects of diverse eco-routing strategies across different vehicle parameters. In Fig. 5, we introduce a taxonomy classifying these vehicle parameters. The existing research considers vehicles from two aspects: how the type of vehicle affects its energy consumption (aka. vehicle type); and how the power system supports the travel of vehicles (aka. vehicle propulsion).

Vehicle Type. Focusing on vehicle size, we can categorize vehicles into two main groups: light-weight and heavy-weight. The light-weight category includes various types of cars, while the heavy-weight category comprises larger vehicles such as buses and trucks. This classification aims to provide a clear distinction between smaller vehicles typically used for personal use and larger vehicles typically used for commercial purposes or for public transport. While there are extra lightweight vehicles, like e-bikes and e-scooters, existing literature on eco-routing often overlooks this category mainly because of their lower carbon footprint, prompting us to omit them for the same reason. Note that heavy-weight vehicles can be further classified based on their Gross Vehicle Weight Rating (GVWR), e.g., in the United States, these classes are numbered 1 through 8. However, such detailed classifications may vary by region and most of the eco-routing techniques are not affected by such detailed classification. Therefore, we limit our classification to light-weight and heavy-weight vehicles.

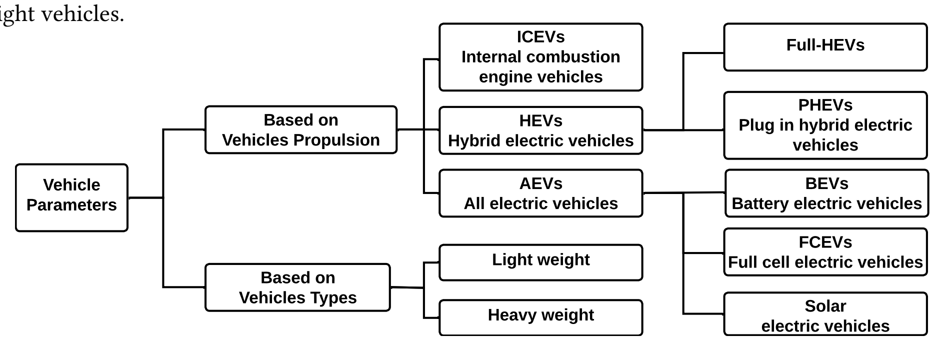

Fig. 5. Taxonomy based on vehicles.

Vehicle Propulsion. The vehicle propulsion or powertrain system supplies the power necessary for a vehicle to travel, with energy consumption varying depending on the type of propulsion system used. There are three main types of propulsion system: *ICEVs* (internal combustion engine vehicles), *HEVs* (hybrid electric vehicles), and *AEVs* (all-electric vehicles). HEVs can be further classified into two categories: Full-HEVs and PHEVs (plug-in hybrid electric vehicles) [110]. While both Full-HEVs and PHEVs utilize internal combustion engines and electric powertrains, the main difference lies in the battery capacities and charging capabilities. Compared to Full-HEVs, PHEVs typically boast larger battery capacities and ability to charge them by connecting to external power sources such as wall chargers and charging stations [200]. AEVs can be further classified into BEVs (battery electric vehicles), FCEVs (fuel cell electric vehicles), and solar electric vehicles [72]. BEVs use the electricity stored in their battery to run the electric motor. FECVs also run an electric motor. However, instead of recharging a battery, an FCEV combines hydrogen with oxygen from the air to produce electricity to run the vehicle's motor [193]. Lastly, solar electric vehicles use self-contained solar cells to power themselves fully or partially from sunlight [64].

The impacts of propulsion system can be seen from two different angles: 1) Some additional constraints may be introduced by a particular vehicle propulsion system directly impacting the routing algorithm. For example, we may have negative edge costs for electric vehicles because of regenerative braking. In such cases, some traditional routing algorithms may become inapplicable. 2) Some energy consumption models are vehicle-specific. For example, the Virginia Tech Comprehensive Power-based Fuel consumption Model (VT-CPFM) [167] is used to model conventional gasoline/diesel vehicles, while the electric vehicle energy consumption model (VT-CPEM) [96] is developed to estimate electric vehicle energy consumption.

2.4 Traffic

Traffic conditions significantly affect the energy consumption of vehicles, e.g., traffic jams or slow-moving vehicles can dramatically increase energy consumption. Some existing works consider the effect of traffic while planning the eco-route, whereas others ignore the impact of traffic. The existing works that consider traffic typically considers two main aspects: how the traffic is assigned to the road network (a.k.a. *traffic assignment*); and how much detailed information was considered (a.k.a. *traffic flow*).

Traffic Assignment. Traffic assignment models are used to estimate the traffic flows on a network. There are two types of traffic assignment models: *dynamic traffic assignment* (DTA) and *static traffic assignment* (STA), as shown in Fig. 6. The STA models ignore congestion and assume an equal inflow and outflow from a link, which is usually unrealistic [62]. Average speed, traffic volume, traffic composition, and level of service are the significant outputs of STA models [189]. On the other hand, DTA models are based on a direct relationship between congestion and traffic flow [205]. DTA represents the real-world scenario more accurately by considering the traffic flow that changes with time. The traffic demand in DTA models may fluctuate over time, but the traffic demand in STA models remains constant. Therefore, a more reliable estimation of weights reflecting traffic characteristics is achieved in DTA.

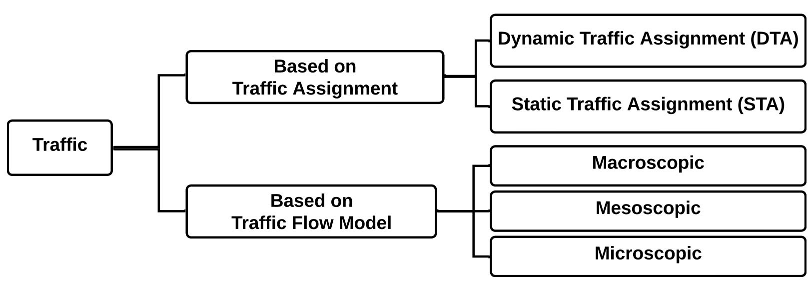

Fig. 6. Taxonomy based on traffic.

Traffic Flow. According to traffic flow models, there is a correlation between the distance between vehicles and their velocities [76, 199]. There are three types of traffic flow models [145]: *microscopic*, *mesoscopic*, and *macroscopic* (as shown in Fig. 6). The microscopic models describe the behavior of individual vehicles taking into account detailed temporal characteristics, as well as the drivers' behavior [162]. The output contains each vehicle's position, speed, and acceleration at each time step. The mesoscopic model [25] lies between the microscopic and macroscopic flow models. It captures the overall flow of vehicles as a probability distribution (typically) and how they should behave. Lastly, the macroscopic models [36, 156, 194] consider the aggregate behavior of traffic flow. The main disadvantage is that it does not reflect reality or certain traffic incidents such as queues [18].

2.5 Road Network Characteristics

Typically, a road network is a graph representing road segments and their interconnections. Existing approaches of eco-routing consider road networks of varying sizes when designing their energy consumption models and routing algorithms. However, the models' outcome and the routing algorithms' applicability largely depend on the road network's size. For example, some routing approaches may not scale to city-scale or country-scale road networks, e.g., due to computational complexity and unavailability of data. We will discuss the limitations in detail in Section 4.

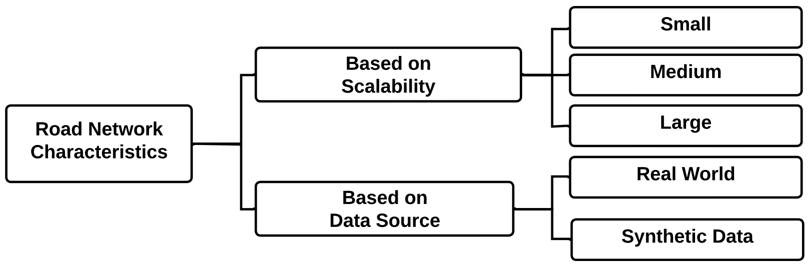

Fig. 7. Taxonomy based on road network characteristics.

In Fig. 7, we present a taxonomy based on the road networks used in the existing studies. Considering the scalability of the road networks, we classify it into three categories. Small-sized road networks consist of a few roads, a small part of a highway, or a zone with a limited number of intersections. A medium-sized road network typically covers an entire metropolitan area, whereas a large road network covers multiple regions. We also consider whether the existing approaches used real-world data or synthetic data. Note that while road networks can be further classified based on the complexity of their topological structure, this study does not include such classification because no existing research has focused on differentiating network complexity.

3 REVIEW OF ECO-ROUTING ALGORITHMS

In this section, we provide a review of the selected papers using the taxonomies presented in the previous sections. First, in Section 3.1, we discuss the existing works that focus on finding the eco-routes ignoring all constraints (i.e., unconstrained eco-routing). Then, in Section 3.2, we present the existing studies on constrained eco-routing. Finally, in Section 3.3, we analyze the advantages and disadvantages of various existing techniques for both constrained eco-routing and unconstrained eco-routing.

3.1 Unconstrained Eco-Routing

Table 1 summarizes the related works on the unconstrained eco-routing using the taxonomies we present in Section 2. Specifically, for each paper, we highlight the details of the energy consumption model used, vehicle types considered, experimental setup, and the type of routing algorithms used to solve the problem. In some of the works, the authors focus only on improving the routing algorithm. Here they do not explicitly mention different factors but assume that the energy consumption cost for each edge of the network is given/known. In Table 1, we mark those as "Cost was provided as input to the Algorithm". For the "Based on Type" column, we have assigned "L" for Light weight vehicles, "H" for Heavy weight vehicles, and "B" for models applicable to Both types. Similarly, in the "Scalability" column, "S", "M", and "L" denote small, medium, and large size datasets, respectively. Given that the main focus of this work is on eco-routing algorithms, next we review these works mainly focusing on the routing algorithm used to solve the problem.

Table 1. Summary of the exiting approaches for unconstrained eco-routing. In the “Based on Type” column: “L” is for Light-weight vehicles; “H” for Heavy-weight vehicles, and “B” for Both types. In the “Scalability” column, “S”, “M”, and “L” represent small, medium, and large datasets, respectively.

Paper	Year	Energy Consumption Model							Vehicle		Experimental Setup					Eco-Routing	
		Influential Variables															
		Vehicle Component	Vehicle Dynamic	Traffic Condition	Environment Related	Driver Related	Based on Model Transparency	Based on Model Input	Based on Propulsion	Based on Type	Traffic Assignment	Traffic Flow Model	Data Source	Scalability	Dataset Availability	Re-routing	Routing Algorithm
Chen et al. [53]	2010		✓	✓			Black	Micro	ICEVs	B	STA	Macro	Syn.	M		✓	Dijkstra
Dhaou [75]	2011	✓	✓				White	Macro	ICEVs	B	Not Discussed		Real	S			A* or Dijkstra
Sachenbacher et al. [170]	2011	✓			✓		White	Marco	BEVs	L	Not Discussed		Real	L			A*
Minett et al. [148]	2011	✓			✓		White	Marco	BEVs	B	Not Discussed		Real	L			A*
Rakha et al.[166]	2012	✓	✓				Black	Micro	ICEVs	B	DTA	Micro	Syn.	S			Feedback Based
Yao and Song [215]	2013	✓	✓		✓		Black	Meso	ICEVs	B	DTA	Micro	Real	M		✓	Dijkstra
Ahn and Rakha [11]	2013	✓	✓				Black	Micro	ICEVs	B	DTA	Micro	Real	L			Feedback Based
Andersen et al. [20]	2013	Cost was provided as input to the Algorithm							All	B	DTA	Marco	Real	L	✓		Dijkstra
Guo et al. [108]	2013	✓	✓				Black	Meso	ICEVs	B	DTA	Micro	Real	M	✓	✓	Feedback Based
Abousleiman and Rawashdeh [5]	2014	Cost was provided as input to the Algorithm							AEVs	L	Not Discussed		Syn.	S			Optimization
Yang et al. [213]	2014	Cost was provided as input to the Algorithm							All	B	STA	Marco	Real	L			Dijkstra
Saremi et al. [176]	2015	✓	✓	✓	✓		Black	Meso	ICVEs	B	DTA	Marco	Real	M		✓	A*
Elbery et al. [84]	2015		✓				Black	Micro	All	B	DTA	Micro	Syn.	S		✓	Feedback Based
Van De Hoef et al. [197]	2015		✓				Black	Meso	ICEVs	H	Not Discussed		Syn.	S			Optimization
Guo et al.[106]	2015	Cost was provided as input to the Algorithm							All	B	STA	Marco	Real	L			Dijkstra
Scora et al. [178]	2015	✓	✓	✓	✓		Black	Meso	ICEVs	H	DTA	Meso	Real	M			Optimization
Qiao and Karabasoglu [163]	2016	✓	✓	✓	✓		Black	Meso	All	B	DTA	Marco	Real	S		✓	Dijkstra

Continued on next page

Table 1 – *Continued from previous page*

Paper	Year	Energy Consumption Model							Vehicle		Experimental Setup					Eco-Routing	
		Influential Variables															
		Vehicle Component	Vehicle Dynamic	Traffic Condition	Environment Related	Driver Related	Based on Model Transparency	Based on Model Input	Based on Propulsion	Based on Type	Traffic Assignment	Traffic Flow Model	Data Source	Scalability	Data Availability	Re-routing	Routing Algorithm
Elbery et al. [85]	2016		✓				Black	Micro	All	B	DTA	Micro	Syn.	S		✓	Feedback Based
Sun and Zhou [187]	2016	Cost was provided as input to the Algorithm							PHEVs	L	Not Discussed		Real	S			Dynamic Programming
Chen et al. [57]	2017	✓	✓	✓	✓		Black	Micro	ICEVs	B	DTA	Micro	Real	S	✓	✓	Dijkstra
De Nunzio et al. [71]	2017	✓	✓	✓	✓		White	Macro	AEVs	L	DTA	Marco	Real	M		✓	Bellman Ford
Yi et al. [217]	2018	✓	✓	✓	✓		Black	Meso	AEVs	L	DTA	Macro	Real	M	✓		Optimization
Hu et al. [115]	2018	✓	✓				Black	Micro	All	B	Not Discussed		Syn.	S			A*
Houshman and Cassandras [113]	2018	Cost was provided as input to the Algorithm							PHEVs	L	DTA	Macro	Real	S	✓		Linear Programming
Bandeira et al. [26]	2018	✓	✓				Black	Micro	ICEVs	H	DTA	Micro	Real	L	✓	✓	Optimization
Wang et al. [202]	2019	✓	✓		✓		Black	Micro	All	B	DTA	Micro	Syn.	S	✓	✓	Dijkstra
Guo et al. [107]	2019	✓	✓		✓		Grey	Meso	ICEVs	B	DTA	Marco	Syn.	M		✓	Modified Dijkstra
Salazar et al. [173]	2019	✓	✓		✓		Black	Meso	PHEVs	L	STA	Marco	Real	S	✓		Linear Programming
Elbery and Rakha [83]	2019	✓	✓				Black	Micro	ICEVs	B	DTA	Mirco	Real	M	✓		Feedback Based
Le Rhun et al. [135]	2020	✓	✓	✓			Black	Meso	HEVs	L	STA	Marco	Syn.	S			A*
Wu et al. [208]	2020	Cost was provided as input to the Algorithm							AEVs	L	DTA	Marco	Real	M		✓	Dijkstra
Ku et al. [131]	2021	✓	✓		✓		Black	Macro	AEVs	L	STA	Macro	Real	M			A*
Chakraborty et al. [47]	2021	✓	✓				Black	Macro	AEVs	L	N/A	N/A	Real	M	✓		A*
Fanti et al. [91]	2021	✓	✓	✓	✓		Black	Mirco	ICEVs	H	DTA	Micro	Real	L		✓	Dijkstra

Continued on next page

Table 1 – *Continued from previous page*

Paper	Year	Energy Consumption Model							Vehicle		Experimental Setup					Eco-Routing	
		Influential Variables					Based on Model Transparency	Based on Model Input	Based on Propulsion	Based on Type	Traffic Assignment	Traffic Flow Model	Data Source	Scalability	Data Availability	Re-routing	Routing Algorithm
		Vehicle Component	Vehicle Dynamic	Traffic Condition	Environment Related	Driver Related											
Chen et al. [51]	2021	✓	✓	✓	✓	✓	Black	Mirco	ICEVs	L	DTA	Micro	Real	M		✓	Dijkstra
Fahmin et al.[89]	2022	✓	✓			✓	Black	Micro	ICEVs	B	Not Discussed		Real	L			Dijkstra
Chen et al. [55]	2022	Cost was provided as input to the Algorithm							AEVs	L	STA	Macro	Real	S		✓	Learning Based
Liu and Zhang [142]	2022	Cost was provided as input to the Algorithm							All	B	Not Discussed		Real	S			A*
Jayol et al. [119]	2022	✓	✓				Black	Marco	ICEVs	B	DTA	Macro	Real	L	✓	✓	Dijkstra
Caspari et al. [45]	2022	✓	✓	✓	✓		Black	Mirco	HEVs	L	STA	Macro	Real	S	✓		Optimization
Farag and Rakha [92]	2023	✓	✓		✓		Black	Micro	All	B	DTA	Micro	Real	S		✓	Dijkstra
Xu et al. [211]	2023	✓	✓		✓		Black	Mirco	HEVs	L	DTA	Micro	Real	M		✓	Reinforcement learning

3.1.1 Dijkstra's Algorithm. Majority of the existing eco-routing works (e.g., [20, 51, 53, 57, 89, 106, 107, 163, 202, 208, 213, 215]) use the well-known Dijkstra's algorithm [77] for finding the most energy-efficient route. The application of Dijkstra's algorithm is straightforward for the cases where the traffic is assumed to be static (e.g., [20, 53, 106, 213]). However, the other group of works (e.g., [57, 107, 215]) use special mechanisms to handle the dynamic traffic scenario. Chen et al. [57] propose a dynamic algorithm where each vehicle receives real-time navigation information at traffic intersections. The real-time traffic information of the system is monitored by the sensing devices mounted on public transport facilities. The proposed algorithm recomputes the eco-route at each intersection.

Yao and Song [215] estimate emissions and fuel consumption for each link based on traffic data updated every 5 minutes. They use the least heap structure [136] to make the algorithm more efficient and practical. Guo et al. [107] execute optimal route planning using dynamic traffic information and an updated Dijkstra's algorithm. The traditional Dijkstra's algorithm is a blind search algorithm, where the resulting search area is too wide, and there are too many discovered nodes [98, 229]. The proposed algorithm limits the search area of the Dijkstra's algorithm. Compared to the standard Dijkstra's algorithm, the modified Dijkstra's algorithm avoids congestion promptly and can re-plan the vehicle path based on real-time traffic intelligence, reducing travel time by 25%. Unlike other works, Fanti et al. [91] consider the heavy-weight vehicle and propose an eco-route planner consisting of two main modules: the data manager and the cloud optimizer. The data manager handles the processing of extensive data from external devices, while the cloud optimizer is tasked with constructing both the route network graph and the admissible state graph. The algorithm apply Dijkstra's algorithm to these graphs to determine the optimal eco-route, including associated optimal velocity and gear profiles. Simliarly, Wang et al. [202] capture the impacts of vehicle type, vehicle transient behavior, and the timeliness of road information in the routing solutions. Their approach ensures that the optimum routes are tailored for each vehicle type, meaning that vehicles of different types may be assigned different routes. It also allows real-time vehicle rerouting by calling the algorithm again, when a vehicle reaches an intersection, to find the most eco-friendly route based on the current traffic information. They deal with the negative weights by assigning zero weights on negative links and thus can use Dijkstra's algorithm. The application of the proposed eco-routing method requires real-time vehicle communication to and from the cloud. Similar to this work, Jayol et al. [119] also utilize a time-dependent Dijkstra algorithm in their model. Instead of relying on connected vehicles environment, Fahmin et al. [89] propose an algorithm to create the mobility profile (e.g., instantaneous speed, acceleration/deceleration, idling time) of a vehicle on-the-fly by considering the maximum possible speed, traffic lights, vehicle type, and driving behavior. Similarly, Chen et al. [51] introduce a framework that incorporates personalized fuel consumption modeling for eco-routing. The framework employs Dijkstra's algorithm to identify the shortest path, which is then partitioned into sub-routes. Subsequently, these sub-routes are evaluated based on both fuel consumption and travel time, aiming to recommend the sub-route with the shortest travel time and minimal potential fuel consumption.

3.1.2 A Algorithm.* Another large group of research works on eco-routing (e.g., [47, 75, 115, 131, 135, 142, 148, 170, 176]) use A* algorithm [111] to find the most energy-efficient route. Compared to Dijkstra's algorithm, A* is an informed algorithm guided by a heuristic which assigns, for each explored vertex, a lower bound cost to reach the target vertex. A* algorithm is more efficient than the Dijkstra's algorithm as it explores a smaller area of the road network due to the heuristic employed. Before applying the A* algorithm, Saremi et al. [176] multiply the distance by an inverse mile-per-gallon (mpg) metric that results in lower weights for fuel-optimal ways. Most eco-routing approaches ignore the signalized intersection's idling time and energy usage. A vehicle traveling through a signalized intersection may accelerate/decelerate following the traffic light phase, resulting in increased energy usage. It may also need to stop and wait. These factors have critical impact on overall energy consumption [13]. Hu et al. [115] extend the A* algorithm to find the optimal route considering the influence of traffic lights. The system can effectively avoid roads with too many signalized intersections that are closely located to each other. The instantaneous fuel consumption model [210] used in this study uses acceleration and vehicle speed. The method is suited to urban roads with dense traffic signals. Recently, electric vehicles (EVs) have attracted much research interest due to their adoption worldwide and future perspectives. One of the EVs' challenging aspects is their poor climbing ability due to limitations associated with battery efficiency [201, 214]. Ku et al. [131] investigate the routing of an EV on a terrain. This study determines the optimal route using 3D spatial data and the slope of each link in the route. The algorithm encourages EVs to use a different route in mountainous areas where there are many slopes, even if the route is slightly longer. Most existing works use cost on distinct edges. However, Le Rhun et al.[135] provide a framework in which eco-routes are computed on a weighted graph with nodes representing (position, state of charge) pairs for the vehicle. They apply the conventional A* algorithm with a heuristic based on a lower bound on the energy required to complete the journey. All the above works that use the A* algorithm have a single objective heuristic. Chakraborty et al. [47] present an intelligent Multi-Objective Heuristic Algorithm (MoHA), a graph-based scheduling strategy that uses the multi-objective A* search algorithm. They describe four MoHA variants: energy-aware, time-aware, random, and weighted, each of which utilizes different techniques to break ties among numerous non-dominated solutions. Liu and Zhang [142] introduce an enhanced A* algorithm where they utilize a novel fuel consumption calculation method, taking into account the fuel consumption and proportions of different vehicles. While they integrate traffic lights to simulate natural traffic conditions, their approach does not explicitly address traffic congestion.

3.1.3 Bellman-Ford Algorithm. Regenerative braking is an energy recovery mechanism typically used in hybrid and electric vehicles. When regenerative braking is considered, the energy consumption can be negative [133, 188]. Therefore the eco-routing algorithm must address the issue of negative weights along edges. Bellman-Ford algorithm [33] can work with negative weights and detect negative cycles. However, compared to Dijkstra's algorithm, it has several drawbacks, such as a higher run-time. De Nunzio et al. [71] propose a novel macroscopic energy consumption model and a novel eco-routing strategy based on Bellman-Ford algorithm.

3.1.4 Optimization-based Approach. So far, we have presented search-based routing approaches. Another class of routing algorithms is optimization-based where the problem is first formulated using mathematical equations and then, by solving those equations, the optimal route is obtained. In [26, 173, 197], authors use different optimization techniques to discover the lowest energy route. Van De Hoef et al. [197] address the issue of coordinating track platoon formation and breakup in an energy-efficient manner. They create an optimization problem that considers routing, energy usage based on speed, and platooning decisions. Bandeira et al. [26] formulate the eco-routing problem as a non-linear and non-convex optimization problem and solve it using the Premium Solver Platform [65]. Sun and Zhou [187] propose a cost-optimal algorithm (COA) for plug-in hybrid electric vehicles (PHEVs) routing against the conventional minimum traveling time routing (shortest path). The problem is solved using dynamic programming [34]. Houshman and Cassandras [113] present a Combined Routing and Power-train Control (CRPTC) eco-routing algorithm for PHEVs. They use a mixed-integer non-linear programming (MINLP) approach to describe the eco-routing problem. Although it is possible to tackle this problem by utilizing Dijkstra's algorithm as demonstrated previously [163]. They present an alternative solution called Hybrid-LP Relaxation. They solve the MINLP problem using a combination of linear programming (LP) and a simple dynamic programming-like algorithm, ensuring global convergence. Likewise, Salazar et al. [173] frame the eco-routing problem as a Mixed-Integer Linear Program (MILP) that can be solved quickly using commercial optimization methods. Abousleiman and Rawashdeh [5] use two metaheuristic optimization methods (Ant Colony Optimization (ACO) [174] and Particle Swarm Optimization (PSO) [181]) to find the most energy-efficient route for EVs. Similarly, Caspari et al. [45] formulate the routing problem as a MILP problem and solve it utilizing the off-the-shelf solver, Gurobi. Scora et al. [178] present eco-routing for heavy-duty trucks incorporating a truck energy and emission model that considers factors such as vehicle weight, real-time traffic speed, and road grade. They compute all possible route combinations between the source and destination, then pick the optimal one for heavy-duty trucks. These approaches are typically unsuitable for large road networks due to their high computational complexity.

3.1.5 Miscellaneous Approaches. Another group of eco-routing systems adopts feedback-based eco-routing (FB-ECO) strategies [11, 83–85, 108, 166, 202]. To compute the route, the FB-ECO utilizes Vehicular Ad Hoc Network (VANET) communication to update link costs in real time based on the experiences of other vehicles in the system. These approaches work as follows. First, upon traveling a road link, a vehicle submits its energy consumption on that link. It then queries to determine which link it should travel next to reach its ultimate destination most efficiently. The FB-ECO navigation system assumes that some vehicles, often called sensor vehicles or probe vehicles, can calculate the amount of energy used on each road link that is traveled. These probe cars are also expected to be connected to the traffic management center, which reports the estimated energy consumption on the relevant road links. Therefore, dynamic route guidance can be sent to all vehicles as needed.

Recently, there have been a few works that use a learning-based approach for eco-routing. Chen et al. [55] propose a novel online eco-routing model for electric vehicles (EVs) to efficiently identify real-time energy-efficient routes for multiple source-destination pairs. The model uses link-level energy consumption information collected from historical EV trajectories and formulates the problem as a combinatorial multi-arm bandit problem [54]. Focusing on reinforcement learning, Xu et al. [211] propose an eco-routing solution based on the Q-learning algorithm. The agent, representing the eco-routing method, is trained using a Q-table that continuously updates during exploration. The environment is modeled as a directed graph with road arc costs. The agent's exploration is guided by the Q-table, introducing a certain amount of noise. The state is defined as the node where the vehicle is located at a given moment, and the action is the forward direction taken at the next moment. This approach aims to learn and select actions that lead to the most eco-friendly route, considering cumulative rewards and environmental factors.

3.2 Constrained Eco-Routing

As discussed in Section 2.2, eco-routing can have multiple types of constraints based on the desired objectives. Here we group relevant works based on different constraint types and discuss the adopted routing strategies. It is essential to highlight that constrained eco-routing problems are required to be formulated as a resource-constrained shortest-path problem (RCSPP) [32, 161], which are NP-complete [14, 37, 44]. Table 2 provides a summary of the major works on the constrained eco-routing problem by highlighting and contrasting each of these works in several crucial dimensions. Similar to unconstrained eco-routing (cf. Section 3.1), these dimensions include the energy consumption models, vehicle types, experimental setups, and routing algorithms. For the "Types of Constraints" column, we have assigned "P" for Path-based constraints, "T" for Time-based constraints, "V" for Vehicle-based constraints and "H" for Hybrid constraints.

3.2.1 Path-based Constraints. In path-based constraints, drivers can set their preferences about the route, e.g., preferring freeways, avoiding tolls or stopping for charging/fuelling. Boriboonsomsin et al. [41] use Dijkstra's algorithm with the binary heap priority queue to calculate the routes for their eco-routing navigation system. Users' route preferences,

Table 2. Summary of the exiting approaches for constrained eco-routing. In the “Based on Type” column: “L” is for Light-weight vehicles; “H” for Heavy-weight vehicles, and “B” for Both types. In the “Scalability” column, “S”, “M”, and “L” represent small, medium, and large datasets, respectively. In the “Types of Constraints” column, “P” stands for Path-based constraints, “T” for Time-based constraints, “V” for Vehicle-based constraints, and “H” for Hybrid constraints.

Paper	Year	Energy Consumption Model							Vehicle		Experimental Setup					Eco-Routing		
		Influential Variables																
		Vehicle Component	Vehicle Dynamic	Traffic Condition	Environment Related	Driver Related	Based on Model Transparency	Based on Model Input	Based on Propulsion	Based on Type	Traffic Assignment	Traffic Flow Model	Data Source	Scalability	Dataset Availability	Types of Constraints	Re-routing	Routing Algorithm
Artmeier et al. [23] Artmeier et al. [22]	2010	Cost was provided as input to the Algorithm							AEVs	L	Not Discussed		Real	L		V		Different Strategies
Boriboonsomsin et al. [41]	2012	✓	✓	✓			Black	Micro	ICEVs	B	STA	Marco	Real	M		P		Dijkstra
Sweda and Klabjan [188]	2012	Cost was provided as input to the Algorithm							AEVs	L	Not Discussed					P		Dynamic Programming
Aziz and Ukkusuri [25]	2012	✓	✓				Black	Macro	ICEVs	B	DTA	Meso	Syn.	S		T		Optimization
Wang et al. [204]	2013	✓	✓	✓	✓		Black	Marco	AEVs	L	DTA	Marco	Real	M		V	✓	A*
Nie and Li[152]	2013	✓	✓				Black	Micro	All	B	Not Discussed		Syn.	S		H		Dynamic Programming
Wang et al. [203] Pourazarm and Cassandras [159] Pourazarm et al. [160]	2014	Cost was provided as input to the Algorithm							AEVs	L	STA	Macro	Syn.	S		V		Dynamic Programming
Cela et al. [46]	2014	✓	✓	✓	✓		Black	Marco	HEVs	L	DTA	Marco	Real	M		T		A*
Arslan et al. [21]	2015	Cost was provided as input to the Algorithm							PHEVs	L	Not Discussed		Real	S		P		Dynamic Programming
Sun and Liu [185]	2015	Cost was provided as input to the Algorithm							All	B	DTA	Micro	Real	M		T		Linear Programming
Zeng et al. [221]	2016	✓	✓		✓		Black	Meso	ICEVs	B	Not Discussed		Real	M		T		K-Shortest Path
Luo et al. [145]	2016	✓	✓				Black	Macro	ICEVs	B	DTA	Macro	Syn.	S		H		Optimization
De Nunzio et al. [70]	2017	✓	✓				Black	Meso	HEVs	L	DTA	Macro	Real	M		T		Modified Bellman-ford

Continued on next page

Table 2 – *Continued from previous page*

Paper	Year	Energy Consumption Model							Vehicle		Experimental Setup					Eco-Routing		
		Influential Variables																
		Vehicle Component	Vehicle Dynamic	Traffic Condition	Environment Related	Driver Related	Based on Model Transparency	Based on Model Input	Based on Propulsion	Based on Type	Traffic Assignment	Traffic Flow Model	Data Source	Scalability	Dataset Availability	Types of Constraints	Re-routing	Routing Algorithm
Zeng et al. [222]	2017	✓	✓	✓	✓		Black	Meso	All	B	DTA	Marco	Real	S		T	✓	K-Shortest Path
Huang and Peng[116]	2018	✓	✓		✓		Black	Meso	All	B	Not Discussed		Real	M		T		Dynamic Programming
Long et al.[143]	2018	✓	✓				Black	Macro	ICEVs	B	DTA	Meso	Syn.	S	✓	T		Optimization
De Nunzio et al. [69]	2018	✓	✓				Black	Meso	HEVs	L	DTA	Macro	Real	M		T		Modified Bellman-ford
Yi and Bauer [216]	2018	✓	✓		✓		Black	Marco	AEVs	L	Not Discussed		Real	M		V		Optimization
Guanetti et al. [105]	2019	✓	✓				Black	Mirco	PHEVs	L	DTA	Micro	Real	S		T	✓	Optimization
Zeng et al. [223]	2020	✓	✓	✓	✓		Black	Micro	ICEVs	B	DTA	Macro	Real	M		T	✓	Optimization
Li et al. [137]	2020	✓	✓		✓		Black	Micro	PHEVs	L	Not Discussed		Real	L		T	✓	Optimization
Alfaseeh and Farooq [17]	2020	✓	✓				Black	Micro	ICEVs	B	DTA	Micro	Real	S		H	✓	Optimization
Djavadian et al. [79]	2020	Cost was provided as input to the Algorithm							All	B	DTA	Micro	Real	S		H		Optimization
De Nunzio et al. [68]	2021	✓	✓	✓			Black	Micro	HEVs	L	DTA	Macro	Real	M		V		Different Strategies
Chen et al. [56]	2021	✓	✓	✓	✓		Black	Micro	BEVs	L	DTA	Micro	Real	S	✓	T		Optimization
Ahn et al. [8]	2021	✓	✓		✓		Black	Micro	All	L	DTA	Micro	Real	S		T		Dijkatra
Houshmand et al. [114]	2021	✓	✓		✓		Black	Micro	PHEVs	L	Not Discussed		Real	M	✓	T		Optimization
Aguiar et al. [7]	2022	Cost was provided as input to the Algorithm							All	B	DTA	Micro	Real	M		T	✓	Optimization
Teng et al. [191] Teng et al. [192]	2023	✓	✓	✓	✓		Black	Micro	ICEVs	B	DTA	Micro	Real	S	✓	T		K-Shortest Path
Wu and Dong [207]	2023	✓	✓	✓			Black	Macro	All	L	Not Discussed		Real	S		T		Optimization

such as favoring freeways or avoiding toll roads, are considered in their path-building approach. It can also use the number of passengers to determine whether a vehicle is eligible to use high-occupancy vehicle lanes.

If the traveling distance is long, EVs need to plan a route that includes charging stations [67, 186]. Traditional route-planning softwares for gasoline-powered vehicles ignore refuelling because gas stations are widespread and easy to use. Sweda and Klabjan [188] propose a dynamic programming-based algorithm for an EV when the vehicle must recharge along the way. Similarly, Arslan et al. [21] propose finding the minimum cost path for PHEVs in a road network with refueling and charging stations. They formulate the routing problem as a mixed integer quadratically constrained problem [38]. They solve it using a discrete approximation dynamic programming heuristic and a shortest path-based heuristic.

3.2.2 Time-based Constraints. As we have discussed earlier, the most eco-friendly route may be quite time-consuming and/or lengthy compared to the shortest path. Therefore, in many eco-routing approaches, the authors impose a constraint on the maximum allowed travel time for the route. A travel-time-constrained eco-routing algorithm is developed to find the most eco-friendly route among the routes that have travel time not much larger than the route with the least travel time, e.g., the travel time must not be more than 1.25 times of the travel time of the route with the least travel time. Cela et al. [46] propose a new algorithm that finds a path whose energy cost is optimal and the time cost is at most β times the cost of the time optimal path. The algorithm is based on a combination of the ideas proposed elsewhere [141, 170, 198]. The core algorithm is based on the algorithms proposed in[141] and [198], which modify Dijkstra's algorithm that finds k shortest paths. To speed up the routing, they use the A* algorithm for which the lower bounds of energy to destination are calculated using the backward Dijkstra's algorithm [74]. In another significant work similar to the above work, Zeng et al. [221] determine the shortest path between two nodes in a transportation network with the least amount of CO_2 emissions while staying within a preset travel time budget. They take average speed, average acceleration, and angle of inclination as the input, making them more suitable for eco-routing than microscopic CO_2 emission models such as Comprehensive Modal Emission Model (CMEM) [29] and Vehicle-specific power (VSP) [120]. Later they extended their work in [222] where they use a support vector machine (SVM) model to estimate the CO_2 emissions. They design a routing technique that ensures the vehicle emits the least CO_2 within a given journey time budget, avoiding unexpected delays. Their algorithm sorts the k paths by ranking the weighted sum of CO_2 emissions and travel time. Although the approach is intended for ICEVs, it can be adopted for PHEVs and EVs.

Huang and Peng [116] develop a travel-time-constrained eco-routing strategy based on dynamic programming, which uses the Bellman optimality principle [182] to solve the optimization problem recursively. Conversely, Zeng et al. [223] propose solving the eco-routing problem with a probabilistic travel time budget using a Lagrangian-relaxation-based approach [24]. The Lagrangian relaxation procedure is based on relaxing the explicit linear constraints by bringing them into the objective function with associated Lagrangian multipliers. Ahn et al. [8] incorporate feedback-based algorithms, as discussed in Section 3.1.5. The model introduces a link cost function for each road network edge, calculated as the weighted sum of the driver's value of time and the cost of fuel/energy on specific links. Similar to other feedback routing options, vehicles update the link cost estimates on a link using only the results of other vehicles in the same class. Aguiar et al. [7] design the route optimization problem as a minimum cost flow problem, with objective functions selected by the decision maker. Due to its multi-objective formulation, a set of Pareto-optimal solutions exists for this problem. The decision of selecting a single Pareto-optimal solution is left to the decision maker. Wu and Dong [207] introduce a formulation of the time-constrained eco-routing problem using a mixed-integer linear programming (MILP) model. This model can be efficiently solved by off-the-shelf optimizers, such as Gurobi and Cplex.

Concentrating on designing eco-routing for plug-in hybrid electric vehicles, Li et al. [137] propose a bi-level approach implemented by [113] where at first a Charge Depleting First (CDF) pulse approach [144] followed by linear programming is used to solve the resource-constrained shortest path problem, with the time being a limited resource. Houshmand et al. [114] also adopt a similar approach in their proposed eco-routing for PHEVs. They did not consider changing traffic situations and only studied scenarios involving a single vehicle with a known source and destination. In another study for connected PHEVs, Guanetti et al. [105] propose a framework where the vehicle sets the energy constraints, and the user selects the time constraints. They formulate the eco-routing problem as static and dynamic resource-constrained shortest path problems. In static eco-routing problems, they use a static forecast of the traffic speed over the road network. In contrast, in a dynamic eco-routing problem, a dynamic model of the traffic speed (flow/density) over the road network is used. In reality, HEVs could repeatedly recharge their batteries by cycling on the same route. Travel time would be penalized by turning in circles to recharge the battery, which is discouraging and impractical to the driver. De Nunzio et al. [69] relax the resource-constrained shortest path problem (RCSPP) to a standard shortest path problem on an acyclic graph. They note that the constrained Bellman-Ford method [206] may tackle this optimization problem since it maintains track of partial routes and discards undesirable ones. However, because the time complexity of the constrained Bellman-Ford algorithm grows exponentially with the graph size, it is still an impractical approach. They applied a slightly modified version of the Bellman-Ford algorithm. The modified version comes from a previous study [70] whose authors formulate the bi-objective eco-routing (minimize energy use and journey time) as a single-objective via weighted-sum scalarization [80].

Sun and Liu [185] develop an eco-routing algorithm for vehicles in a signalized traffic network. Rather than using GPS-based vehicle trajectory data, which is employed by many previous eco-routing algorithms, they use high resolution traffic data, such as vehicle arrival and signal status information. They offer a method for incorporating environmental costs into a vehicle routing algorithm based on the Markov decision process (MDP). They introduce a linear programming formulation of MDP to handle multiple objectives. The linear programs can be solved using standard linear programming solution techniques, e.g., simplex method [149] or inter points method [147].

In a recent work, Teng et al. [191] propose a path ranking algorithm for a bi-objective eco-routing model aiming to minimize fuel consumption and travel time. In the first stage, they employ an efficient reliable shortest path algorithm to determine the optimal fuel consumption path and calculate the upper bound for travel time. In the second stage, a K reliable shortest path algorithm [50] is used to incrementally identify reliable paths based on travel time, eliminating dominated paths until a termination condition is met. Here, the authors assume that travel time and fuel consumption are independent. Several research studies have revealed a significant correlation between the travel time and fuel consumption of a given link and its neighboring links [52]. In a subsequent work [192], the authors propose a fuel consumption model considering the spatial link correlation between fuel consumption and travel time. The spatial correlation is measured using variance-covariance matrices. Subsequently, they adopt a similar path-finding algorithm as in [191]. Similar to [191], Chen et al. [56] introduced a bi-objective reliable path-finding model specifically designed for electric vehicles.

3.2.3 Vehicle-based Constraints. In the case of EVs, the vehicle's initial charge level, battery capacity, and desired charge level after the trip are vital factors to keep in mind while formulating the eco-routing problem. In one of the first works in this domain, Artmeier et al. [23] treat the eco-routing problem as a shortest path problem with constraints on the vehicle's charge level, such that it can never be negative and can never exceed the battery's maximum charge level. Negative edge weights are allowed to indicate energy captured during regenerative braking; but there are no negative cycles. They point out that the most commonly used shortest path algorithms, such as contraction hierarchies [101], highway hierarchies [175], and transit vertex routing [31], cannot be used to address their problem due to the negative weights caused by recuperation. They evaluate the shortest path problem using four strategies (Dijkstra's, expand, expand-distance, and First-In-First-Out) [60]. The algorithm's time complexity is $O(n^2)$ for positive weights but exponential in the general case. At the same time, the Bellman-Ford technique (pick the vertices in a First-In-First-Out way) is $O(n^3)$ for arbitrary weights. The authors extend their work in [22] where they introduce the concept of energy graph. The algorithm takes as input a directed graph, in which every edge's velocity and energy consumption are known. It generates a modified directed graph with a weight function providing the energy consumption for every edge independently from its predecessor.

Wang et al. [203] aim to reduce the total time vehicles take to reach their destinations, taking into account both travel and recharging duration at homogeneous charging nodes, i.e., charging rates at different nodes are identical. They look at two different approaches to the problem. In the single-vehicle routing problem, they formulate a mixed-integer nonlinear programming (MINLP) problem. They show that they can reduce it to a lower-dimensional problem by exploiting the properties of an optimal solution. They also obtain a Linear Programming (LP) formulation allowing them to decompose it into two simpler problems yielding near-optimal solutions. For a multi-vehicle problem, where traffic congestion effects are included, they use a similar approach by grouping vehicles into "subflows" and seeking optimal routing decisions for each subflow. They extend this work in [159], where they consider inhomogeneous charging nodes, i.e., charging rates at different nodes are not identical. Charging an EV battery can take anywhere from minutes to hours, depending on the voltage and current of the outlet. As a result, charging rates and timeframes significantly rely on the charging station class and substantially impact the optimization problem's solution. Besides, they do not impose full recharging constraints compared to [177]. Pourazarm et al. [160] solve the above mentioned problem from their previous work [159, 203] using dynamic programming, resulting in optimal solutions with lower computational complexity compared to [159]. Their model is identical for both homogeneous and inhomogeneous charging nodes.

Eisner et al. [81] show that the battery capacity constraints can be modeled as cost functions on the edges. To apply Dijkstra's algorithm, they generalize Johnson's potential shifting technique [121] to negative edge cost functions. Wang et al. [204] propose a framework where the algorithm can find the optimal recharge detour if the destination cannot be reached with energy on board. Yi and Bauer [216] define the routing problem as a stochastic programming problem and control the risk of exceeding the remaining battery energy. Based on the normality assumption for energy cost on each road segment, convex relaxation and transformation [42, 150] are used to solve the initial discrete optimization issue. The optimal path is built using a highly efficient primal-dual interior point algorithm [151] on the relaxed problem. Recently, De Nunzio et al. [68] compare various practical solution approaches for the eco-routing problem of Hybrid Electric Vehicles (HEVs). The comparison focuses on solution accuracy and computation time in addressing this constrained optimization problem. However, certain constraints, such as battery limits, are relaxed in the approach designed to maintain a low computational burden. Consequently, this method may not be suitable for solving the eco-routing problem for All-Electric Vehicles (AEVs), where the battery could be fully depleted, necessitating constraints to enforce a minimum bound on the battery level.

3.2.4 Hybrid Constraints. All the different types of constrained eco-routing discussed above primarily aim to mitigate one constraint at a time. Several other works (e.g. [17, 145, 152]) attempt to optimize multiple objectives simultaneously. Nie and Li [152] propose an eco-routing problem that minimizes the total travel cost (monetary value of both energy and time) while meeting a given CO_2 emission standard. They solve the constrained shortest path problem using off-the-shelf solvers [118]. The findings imply that disregarding the impacts of turning movements and acceleration may result in sub-optimal routes. They claim that the same technology is unsuitable for EVs, owing to the scarcity of charging facilities and the possibility that a proposed route would be impractical given an EV's initial charge level. They present two strategies for identifying an optimal path: backward recursion and approximate dynamic programming. Luo et al. [145] design eco-routing as a constrained combinatorial optimization problem in the Model Predictive Control (MPC) framework and use the parallel Tabu Search algorithm [27] to solve it. The objective is to reduce the total time, emissions, and fuel consumption for all vehicles moving across a network. In a similar work, Alfaseeh and Farooq [17] develop multi-objective eco-routing strategies for connected and automated vehicles based on a dynamic distributed routing framework. In this study, they compare the results when only travel time is optimized, only greenhouse emissions are optimized, or when a combination of travel time and emissions is optimized. Simliarly, Djavadian et al. [79] developed a multi-objective eco-routing system utilizing a real-time end-to-end connected and automated vehicle routing scheme [94]. The objective was to simultaneously minimize travel time, greenhouse gas (GHG), and NO_x emissions. Although NO_x is not explicitly included in the objective function, the results demonstrated that the proposed multi-objective routing could potentially reduce NO_x emissions by 18.5%. This substantial improvement was achievable due to the multi-objective eco-routing's indirect addressing of the main factors influencing NO_x, namely, long travel time and high speed.

3.3 Critical Analysis: Pros and Cons in Existing Research

In this section, we compare different approaches used by the existing studies and discuss their advantages and disadvantages. As mentioned earlier, the existing eco-routing algorithms can be categorized into unconstrained and constrained eco-routing. Next, we briefly discuss the pros and cons of various techniques in each category.

For unconstrained eco-routing, most existing studies utilize fundamental search-based algorithms like Dijkstra's algorithm and A* algorithm. The primary advantages of utilizing these algorithms lie in their simplicity of implementation and their online search methodology, making them adaptable to various energy consumption models and conducive to incorporating real-time navigation information such as traffic conditions, traffic lights, and other dynamic factors. These algorithms do not require preprocessing and can easily accommodate dynamic changes in the road network, such as updates in travel time and fuel consumption due to changed traffic conditions. In contrast, more advanced pathfinding algorithms, such as contraction hierarchies [102, 180] and hub labeling [6, 139], require significant preprocessing costs and, therefore, are not suitable for dynamic updates. Furthermore, these more advanced algorithms typically require significant memory to store the indexes. The key disadvantage of the search-based algorithms is their high query processing time. For instance, Dijkstra's algorithm exhaustively searches through the search space, resulting in a substantial computational burden [78, 164]. While the A*-based algorithm mitigates this burden to some extent by employing heuristics to limit the search effort, the efficiency of the algorithm often depends on the effectiveness of the designed heuristic, which can still lead to relatively long runtime [104].

Several existing studies use the Bellman-Ford algorithm to handle negative edge weights caused by regenerative braking of EVs, which can lead to negative energy consumption for some edges. While this algorithm offers similar advantages to the Dijkstra's algorithm such as its adaptability to dynamic updates, it tends to run much slower than Dijkstra's algorithm [66]. Introducing negative edge weights in the road network provides a more accurate representation of real-world energy consumption on routes but also significantly increases computation time. Therefore, when designing real-world systems, it is important to assess whether adding negative edge weights significantly improves energy consumption estimation. If not, graphs should be restricted to non-negative weights so that Dijkstra's or A* algorithms can be applied for better runtime.

Another line of research employs optimization-based approaches to compute the eco-route. These methods typically formulate the problem using mathematical equations and utilize third-party libraries or off-the-shelf solvers for computation. However, since optimization-based methods often involve maintaining a large number of variables on each node of the graph, they tend to scale poorly [68]. As indicated in Table 2, these approaches are generally suitable only for small to medium-scale networks.

Other miscellaneous approaches, such as the feedback-based approach used in many existing works, involves frequent communication between vehicles and the navigation system. Its primary advantage is its ability to provide more accurate eco-routing by utilizing real-time information. However, a notable drawback is that this approach requires vehicles to be equipped with sensors and the capability to communicate with the server and, in some cases, other vehicles [83, 202, 222]. Additionally, if the number of participating vehicles (e.g., vehicles with sensors) is small, the system's accuracy may be compromised. Therefore, for this approach to be effective, a large number of participating vehicles is ideally needed, covering at least the major parts of the network. Moreover, the communication between the vehicle and the navigation system often introduces additional delays. Learning-based approach has also been used for eco-routing. The primary advantage of utilizing this approach lies in its ability to adapt to dynamic traffic conditions in real time [211]. However, learning-based methods typically necessitate the collection of large data from previous trips. Consequently, the quality of the solution may be contingent upon the quality of the data gathered, potentially leading to issues such as data dependency and limited transferability.

For constrained eco-routing, the problem is typically formulated as the resource-constrained shortest path problem, known to be NP-complete [14, 37, 44]. Given the computational challenge inherent in the problem, solutions for the constrained eco-routing problems often require significant runtime to solve. To compute the optimal solution, most existing approaches rely on optimization-based techniques, which unfortunately entail significant computational overhead and suffer from scalability limitations. Alternatively, some studies delve into search-based methods, yet many rely on Dijkstra-based algorithms, leading to exhaustive searches throughout the solution space. Nonetheless, these approaches commonly suffer from long runtime. On the contrary, another category of research often trades-off the solution quality for faster computation. These algorithms typically find approximate solutions and expedite query processing by relaxing constraints or utilizing approximate energy consumption values. It is crucial to assess the path quality of these approximate techniques to determine if the benefits, such as faster processing times, are worthwhile. Table 4 in the Supplementary Material provides a summary of the advantages and disadvantages of different routing approaches used in previous research.

4 CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Eco-friendly navigation has received significant research attention in the last decade. Recently, the popularity of electric vehicles has been increasing, and many countries are moving towards net zero emissions. Eco-friendly routing has already shown promising results in real-world deployment [1], but many areas remain out of focus. Based on the review of eco-routing algorithms in Section 3, this section discusses the challenges and future works that eco-routing algorithms present, emphasizing what it will take to make eco-friendly navigation efficient, sustainable, and practical. Section 4.1 discusses challenges associated with data availability and the quality of the data. Section 4.2 highlights possible directions for improving route quality. Section 4.3 covers issues and future directions related to routing effectiveness. Section 4.4 discusses important variants of eco-routing queries. Looking at the bigger picture, we will discuss the eco-routing problem at a citywide scale with applications in urban planning in Section 4.5.

4.1 Data Availability and Quality

To compute eco-friendly routes accurately, access to real-world data such as vehicle characteristics, real-time traffic, road network structures and weather data is crucial. However, obtaining such data is often challenging, which poses a key hurdle for research in this field. While real-world maps and weather data are easily accessible from sources like OpenStreetMap and OpenWeather, datasets related to real-time or historical traffic information and vehicle/driver characteristics are not as readily available. Researchers working in this area often augment their models with additional data, such as real-time traffic information [116, 137, 145] and vehicle-to-vehicle communication details [51, 202, 221, 222], to improve predictive accuracy. Unfortunately, much of this supplementary data is not publicly available, making replication or expansion of these studies difficult for other researchers. The process of collecting such data is resource-intensive and time-consuming, presenting practical challenges. Another significant challenge is data quality; inaccurate or outdated data can lead to suboptimal route recommendations, undermining the core objective. Data can be of poor quality due to various reasons, including errors in data collection or entry, incomplete or missing data, outdated information, and inconsistencies in data format or structure [138]. Additionally, factors such as environmental conditions, sensor malfunctions, and human errors can contribute to data inaccuracies. These challenges highlight the importance of implementing robust quality control measures to ensure data reliability and usefulness for eco-routing research.

To overcome data availability and quality challenges in eco-routing research, collaborative efforts are the key. This includes promoting data sharing among organizations and researchers, establishing standardized protocols for data collection and sharing, and supporting open-data initiatives. Stringent quality control measures should be implemented to ensure data accuracy. It is essential to implement robust data validation and cleaning processes. This includes identifying and correcting errors, filling in missing data, and ensuring consistency in data format and structure. Additionally, regular updates and maintenance of datasets can help prevent data from becoming outdated, ensuring that eco-routing algorithms are based on reliable and up-to-date information. Additionally, funding for research projects focusing on data collection and maintenance, as well as the development of data aggregation platforms, can further facilitate access to high-quality datasets for eco-routing research.

4.2 Improving Route Quality

To accurately estimate energy consumption and emissions, the state-of-the-art estimation models require a detailed mobility profile of the vehicle along a route [228] including acceleration/deceleration and idling time. Such a profile is among the most critical factors affecting energy consumption and emissions [13]. However, most existing techniques that aim to find eco-routes use simplistic graph representation by assigning each road segment of the road network with an average speed or average fuel consumption along the road, ignoring detailed mobility profiles and driving behavior (e.g., aggressive or moderate) altogether. As noted in [89], this simplistic assumption returns sub-optimal route choices because such a representation fails to capture driving behaviors and detailed mobility profiles of the candidate routes, resulting in poor quality estimates (up to 42% inaccurate [89]). Besides, continuous monitoring of mobility information may be a privacy concern to many users. Additionally, many existing techniques employ a one-size-fits-all approach, ignoring different vehicles (e.g., truck vs. car) and driver's behaviors (e.g., aggressive vs. calm). Consequently, these approaches might recommend identical routes for diverse vehicles and drivers, which is suboptimal as the most environmentally friendly route can vary depending on the vehicle type and/or driver characteristics [152].

4.3 Efficient Route Computation

As discussed in Section 3.3, almost all existing works rely on basic search-based algorithms such as A*-search or Dijkstra's algorithm to compute the path with the lowest energy consumption or emissions. A major issue with these algorithms is that they are not suitable for large graphs such as road networks as it may take several seconds for these algorithms to answer a single shortest path query [209]. Therefore, these approaches are unsuitable for large-scale deployment in real-world navigation systems that need to compute tens of thousands of routes per second [209]. As discussed in Section 4.2, high-quality energy/emission estimates require detailed mobility profiles of the vehicles, which necessitate advanced graph representations because the traditional road network graphs cannot effectively capture the mobility profiles. Unfortunately, the existing efficient path planning techniques (e.g., pruned highway labeling, G-tree, contraction hierarchies, etc.) [4] cannot be applied or trivially extended for these advanced graph representations.

Besides, a large body of work has focused on developing routing algorithms that build indexes on the graph in a pre-processing phase and significantly improve the query performance, e.g., contraction hierarchies [103, 180], hub-labeling [4, 16, 139], etc. However, these more efficient algorithms are not typically suitable for eco-routing because the energy consumption is generally computed on-the-fly and, therefore, pre-processing may not be possible. An exciting direction for future work is to design new data modeling, indexing, and query processing techniques to efficiently compute eco-routes while considering detailed mobility profiles, driving behaviors, and vehicle types (challenges discussed in Section 4.2). Developing innovative indexing and query processing methods is crucial for integrating intricate mobility profiles to precisely predict fuel consumption and emissions while efficiently computing eco-friendly routes. It is imperative that these indexes are capable of efficiently handling dynamic updates in underlying data, such as real-time traffic updates.

4.4 Advanced Eco-Friendly Routing Queries

All the works discussed above mainly focus on finding the most eco-friendly route for a given source and destination. However, modern navigation systems provide many advanced routing-related services (such as trip planning, diverse route recommendation and points-of-interest search) while mainly focusing on minimizing travel time or distance. There is a need to develop techniques to provide eco-friendly alternatives to such services, i.e., minimizing energy consumption. Next, we discuss some advanced eco-friendly queries that need to be studied.

Eco-friendly Trip Planning. In a trip planning query [179, 183], a user needs to visit multiple locations, and the goal is to find a route that minimizes the total cost (e.g., travel time, energy consumption, distance, etc.). For example, a delivery truck may need to deliver multiple parcels, or a shared autonomous vehicle may need to pick up and drop several people from/at different locations [190]. Future works should address the eco-friendly trip planning query, which aims to minimize the total energy consumption or emissions.

Diverse Eco-friendly Routes. A user (or an autonomous vehicle) may want to compare multiple routes based on traveling time, energy consumption, emissions, and distance before choosing a route. Future works should design efficient techniques to report a set of meaningful routes that are eco-friendly and diverse (i.e., are significantly different from each other in terms of the path overlap).

Eco-friendly POI Selection. Searching for nearby points of interest (POIs) is needed in many real-world applications. A range query returns all POIs within a given distance from a user's location. A k-nearest neighbor (kNN) query retrieves the k closest POIs for a user [3]. Future works should develop efficient algorithms for kNN and range queries by considering energy consumption or emissions instead of distance, e.g., finding a nearby library that requires the lowest energy consumption to travel there.

Personalized Eco-routing. Most of the existing eco-routing algorithms try to optimize well-defined objective functions such as minimising energy consumption while satisfying certain constraints. However, users typically have certain preferences (e.g., avoiding certain types of routes) and such users are likely to take recommended routes that meet their preferences. With advances in machine learning algorithms and availability of large-scale historical trajectory datasets, there is an opportunity to recommend more personalized routes to the users. For example, an eco-routing algorithm may learn the driver's preferences, driving behavior, or the roads' dynamics to suggest personalized eco-routes based on the learned information. Techniques such as reinforcement learning [124] used for robots or video game agents might be interesting to be explored in eco-friendly navigation. Recently, machine learning-based approaches are changing how we build systems, e.g., learned index [130].

4.5 Citywide Eco-Friendly Navigation and Urban Planning

Most studies are based on vehicles choosing routes that minimize their energy consumption. The techniques developed for eco-friendly navigation for individual vehicles may not be suitable for selecting routes for a large population because these may lead to traffic congestion (e.g., as a result of recommending similar routes to a large number of users or autonomous vehicles), resulting in overall higher energy consumption and emissions [184]. Instead of treating each routing query individually, researchers should design techniques that consider a large number of routing queries and aim to minimize the overall energy consumption/emissions (aka system-optimal eco-routing). System-optimal eco-routing is a fascinating area for future research. Such a study will help us better understand the effects on eco-routing systems' performance. It should also address the personal preferences of different users, e.g., some users prefer fastest routes whereas others may prefer the most eco-friendly routes or the time-constrained eco-friendly routes, etc. According to [26], system optimal routing techniques reduce the trade-off between emissions and travel time.

Besides, researchers should investigate the impact of eco-friendly navigation adaptation (i.e., the percentage of the population using eco-friendly routes) on overall energy consumption, emissions, and traffic density on different road segments. It will help identify potentially problematic areas (e.g., roads with unusually high emissions). Furthermore, future studies should include how a change in the road network (e.g., adding/closing a lane or a road) affects the overall traffic, energy consumption, and emissions. U.S. National Highway Traffic Safety Administration reported [195] that 53.1% of traffic-crossing accidents occur with left turns (equivalent to right turns in countries with left-hand traffic), compared to only 5.7% involving right turns. Eco-friendly navigation could affect left turns for right-hand traffic (and vice versa) and average vehicle speed. Thus, exploring its impact on road safety is an intriguing area for future research.

5 CONCLUSION

This paper presents a systematic and comprehensive literature review on routing approaches for eco-friendly routing applications. Several different taxonomies are presented to categorize eco-friendly routing techniques. The review covers most of the significant aspects of eco-routing research, including energy consumption models, the impact of vehicle types, traffic, and road conditions. All these aspects are analyzed under two broad categories: unconstrained eco routes; and constrained eco routes. A large number of influential papers from different sub-domains of eco-routing are systematically selected and reviewed. The existing techniques are reviewed, examined, and their summaries are presented in a tabular format using the taxonomies presented in the paper. Finally, several major research challenges are highlighted, and possible future directions for eco-routing research are outlined.

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A SUPPLEMENTARY MATERIAL

A.1 Scope of the Review

Figure 8 depicts an overview diagram showing the principal components of an eco-routing system, guiding us to the structure of our review paper. This diagram presents three significant components of eco-routing and the interaction among these components. Eco-routing requires *vehicle parameters* (e.g., engine specifications), *traffic information*, and the details of the *underlying road network*. An energy consumption model is also needed which estimates the energy consumption based on vehicle parameters, traffic, and road network information. While we briefly discuss the above mentioned important aspects, the key focus of this survey is on eco-routing algorithms that find an eco-friendly route for a given origin-destination pair by taking input from the energy consumption models, road network, and traffic.

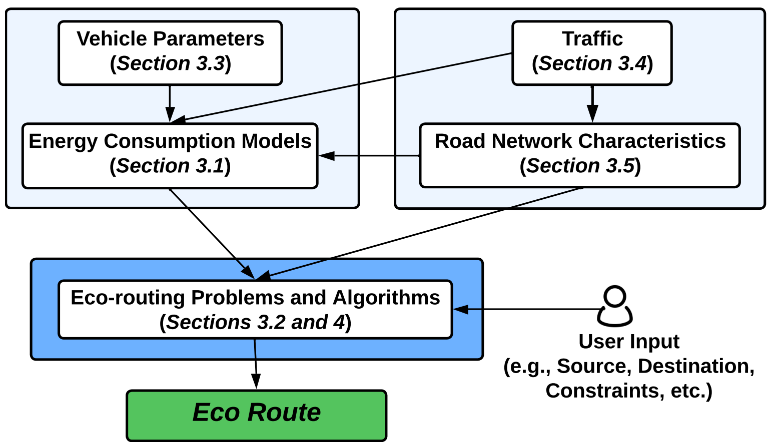

Fig. 8. Overview of eco-friendly navigation system and scope of this survey.

A.2 Review Methodology

We used the systematic literature review (SLR) approach [240, 244] to select the relevant state-of-the-art research reviewed in this survey. The digital libraries used for searching the relevant papers were: ACM Digital Library (http://portal.acm.org), IEEE Digital Library (http://ieeexplore.ieee.org), ISI Web of Science (http://www.isiknowledge.com), Science@Direct (http://www.sciencedirect.com), Scopus (http://www.scopus.com), Springer Link (http://link.springer.com) and TRID database (https://trid.trb.org/). We used the following search string where * indicates a wildcard (e.g., "rout*" matches "routing", "route", "routes", etc.):

`"eco rout*" OR "eco paths" OR "eco-friendly rout*" OR "eco-friendly paths" OR "fuel efficient rout*" OR "fuel efficient paths" OR "fuel optimal rout*" OR "fuel optimal paths".`

We also manually added 67 papers from Google Scholar (https://scholar.google.com) using a similar search method. In total, we obtained 2494 articles (see Fig. 9). After removing the duplicates, we were left with 1675 papers. We excluded the papers that were published before 2010. We screened the titles and abstracts of the remaining 511 papers and excluded the papers using the following two criteria: 1) if a paper does not study eco-routing in a road network, we excluded the paper (e.g., some papers studied Internet routing); 2) we only consider the studies that discuss routing techniques (not just focusing on the energy consumption models) and demonstrate the efficacy using an experimental

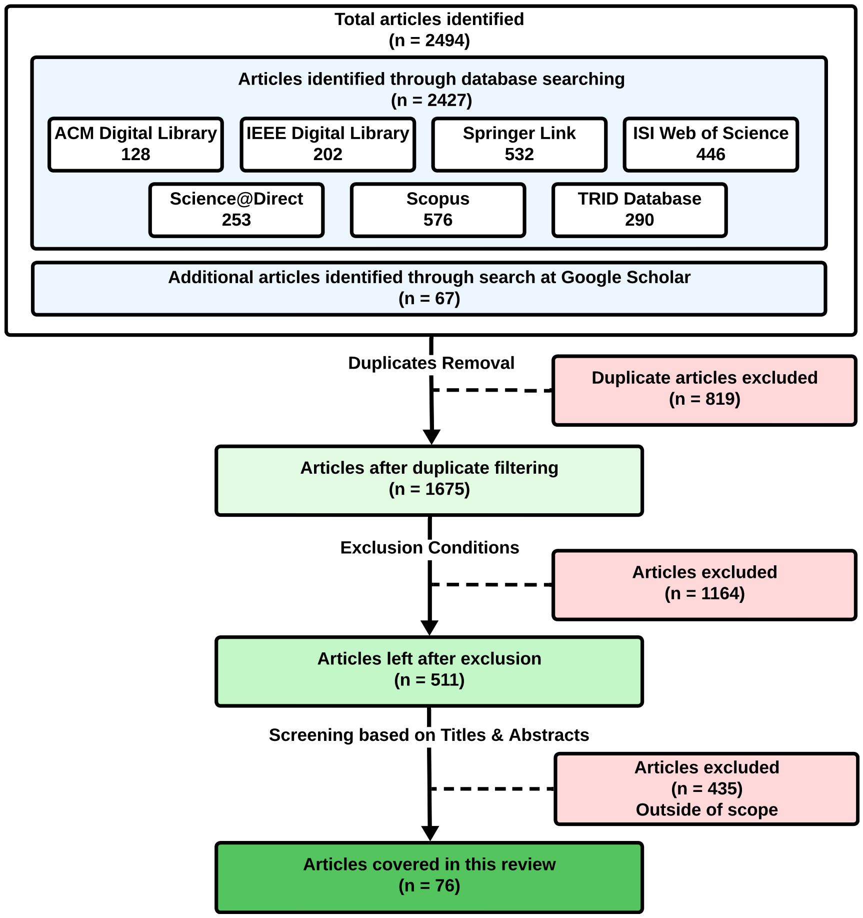

Fig. 9. System Literature Review (SLR) flow diagram.

study. This left us with 76 papers which we review in this survey. Fig. 10 shows the distribution of these papers for different years.

A.3 Additional Figures and Tables

SUPPLEMENTARY REFERENCES

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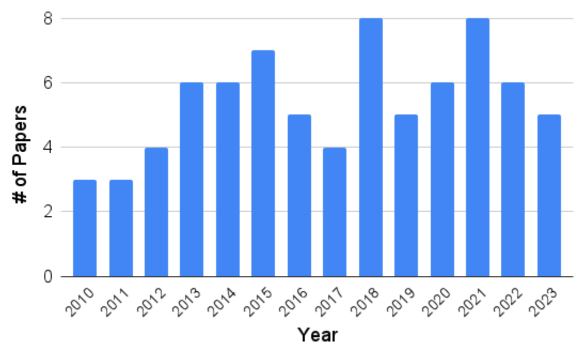

Fig. 10. Distribution of papers reviewed in this systematic literature review.

Factors affecting energy consumption	**Examples**	**Percentage (%) of effects**	**References**
Travel Related	Travel distance, travel time etc.	18% to 23%	[10]
		14% to 41%	[236]
		8.73% to 42.15%	[30]
Weather Related	Temperature, humidity, wind etc.	up to 1%	[228]
Vehicle Related	Engine, loading, vehicle speed and acceleration, transmission etc.	Most important factor (percentage not available)	[35]
Traffic Related	Vehicle-to vehicle interaction, traffic signal, traffic incidents etc.	22%	[242]
		25%	[241]
		47%	[230]
Roadway Related	Grade, curvature, type & roughness etc.	3.5%	[237]
		5% to 7.04%	[239]
		5.5%	[238]
		15% to 20%	[233]
		7% to 26%	[234]
Driver Related	Driver behavior, gear selection, idle time etc.	4.35%	[245]
		6%	[232]
		20%	[235]
		up to 25%	[243]
		27%	[234]
		30% to 40%	[231]
		up to 35%	[89]

Table 3. Summary of key factors affecting energy consumption. Here "Percentage of effects" shows how significant a factor's influence is on energy consumption. The table is an enriched version of information presented in [228].

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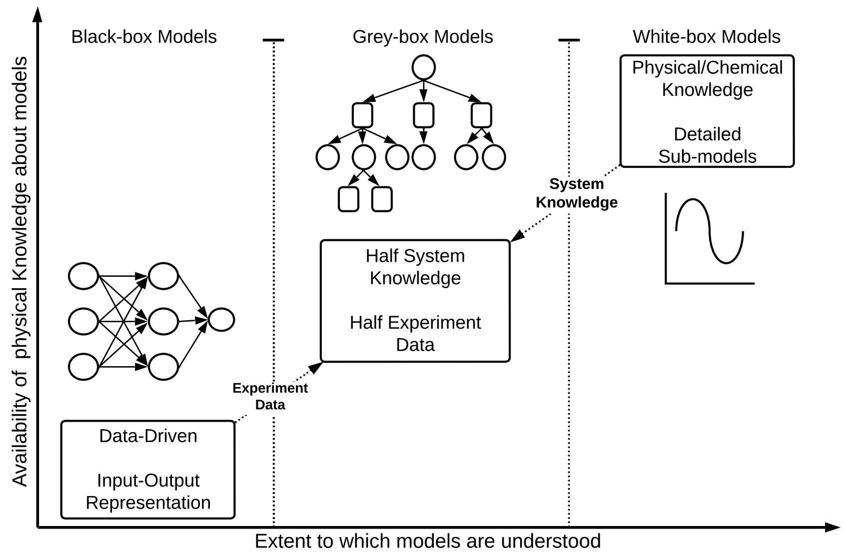

Fig. 11. Different types of energy consumption models and their levels of transparency. The figure is adapted from Zhou et al. [228].

Routing Algorithm	Advantages	Disadvantages
Dijkstra-based approaches	• Easy to implement. • Easy to adapt to other applications. • Online algorithm, supports real-time update.	• Slow runtime. • Large search space.
A*-based approaches	• Faster runtime than Dijkstra's algorithm. • Easy to adapt to other applications. • Online algorithm, supports real-time update.	• Slower than advanced index-based algorithms • Application specific heuristics needs to be designed. • Poorly designed heuristic may worsen performance.
Bellman Ford-based approaches	• Can handle negative edge weights edge-weight. • Easy to adapt to other applications. • Online algorithm, supports real-time update.	• Slower than both Dijkstra's and A* algorithms. • Real-world benefits of handling negative weights at the cost of higher computation cost not clear
Optimization-based approaches	• Typically high accuracy. • Can utilize off-the-shelf solvers to solve the problem.	• Poor scalability in terms of network size. • Require additional knowledge for mathematical modelling.
Feedback-based approaches	• High accuracy. • Involve real-time communication.	• Vehicles need to be equipped with sensors. • Require a large number of participating vehicles.
Learning-based approaches	• Adapt well to real-time traffic conditions.	• Require the collection of large data from previous trips. • Data dependency and limited transferability.
Approximate-based approaches	• Typically fast runtime. • Easy to implement. • Allow trade-offs between quality and runtime.	• Potentially low accuracy.

Table 4. Advantages and Disadvantages of the key routing algorithms used in the previous works

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