Review Article

Multi-Factor Taxonomy of Eco-Routing Models and Future Outlook

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Traditionally, routing decisions have been based on minimizing travel time as the associated cost. Eco-routing considers the environmental aspects (e.g., emissions and fuel) as part of the travel cost to mitigate the undesirable impact of transportation systems on the environment. Unlike the existing eco-routing review papers, this research work is aimed at providing a three-factor taxonomy at a more disaggregated level from the optimization perspective and map eco-routing studies to the proposed taxonomy. Furthermore, the strengths and weaknesses of the presented models are summarized. Our main findings include (a) a majority of studies optimized one objective at a time; (b) the microscopic level of aggregation of the flow and emission/fuel models was rarely employed for large case studies, due to the associated complexity; and (c) all of the reviewed studies were applied in a centralized routing system environment. In the near future, when intelligent vehicles will be on the roads, a multi-objective distributed routing framework can be employed with a microscopic level of aggregation for both traffic and emission models, which is capable of operating on largescale networks in real time. Additionally, short-term spatiotemporal prediction of GHG cost is a crucial aspect to be tackled.

1. Introduction

To alleviate the negative impact of transportation systems on the environment, several approaches have been suggested: (1) substituting the fossil fuel with cleaner energy sources, (2) improving the technology of vehicles, and finally, (3) employing intelligent transportation system (ITS), which is a form of improvement in information and communication technology (ICT). The ITS solution is the most promising one as it can control several indicators, such as speed, traffic signals, and route guidance to minimize the negative impact on the environment [1]. GHG emission is one of the worst environmental impacts, and vehicle routing can be employed to minimize it while directing vehicles to their destinations. This type of routing is known as eco-routing [2]. Initially, in the context of route guidance as well as traffic assignment, routing considered a single objective—in particular, the objective involved minimizing travel time [2]. Nevertheless, researchers have started incorporating

more than one objective while assigning or guiding traffic. Dealing with multiple objectives is associated with higher complexity due to the heterogeneous interactions between different objectives. For instance, enhancing network throughput may conflict with emission reduction, if the resulting optimal speed for traffic flow is higher than the operating speed required for fewer emissions. On the other hand, less idling would contribute to fewer emissions as well as high throughput. It is profound to note that CO_2 emissions as a routing objective are aligned with fuel consumption [3], but other pollutants, such as CO, HC, and NOx, are not necessarily aligned [4]. While determining the optimal route with multiple objectives, the fastest or the shortest route may not be optimal from the environmental perspective [5, 6]. Also, a routing strategy that aims to minimize individuals' emissions may give worse results in terms of the total network emissions, similar to the case of a standard travel time-based user equilibrium (UE) assignment [7]. In this study, databases available at Ryerson

University's digital library (a complete list of scientific databases available at Ryerson library can be found at https://library.ryerson.ca/articles/) and Google scholar are used to explore the relevant journals. A range of search strings have been utilized, including (note that this is not an exhaustive list of search strings that we used) multi-objective routing, eco-routing models, eco-routing AND distributed routing systems, environmental routing, classification AND eco-routing models, taxonomy AND eco-routing studies, Information and Communication Technology (ICT) advancements AND eco-routing, and eco-routing literature review. In terms of the temporal window, our search involved all the work since 1988 to date.

To develop a better understanding and to use eco-routing models more effectively, there is a strong need to investigate these models further and systematically classify the existing body of work. It is essential to note that the previous eco-routing review papers mainly focused on three categories, which are models with environmental objective, models with environmental constraints, and models for environmental assessment. However, in this project, eco-routing models have been classified at a more disaggregated level. Critical factors have been chosen that distinguish a model from another in the context of optimization. Developing a multi-factor taxonomy would guide researchers and practitioners to choose the most appropriate approach that matches their problem scope and specifications. Furthermore, a clear illustration of strengths and weaknesses based on state-of-the-art would provide a clear direction for the potential future work, which could fill the gaps identified. It is worth mentioning that we only considered the eco-routing models that were applied to personal transportation. Toll pricing, eco-routing in the context of traveling salesman problem, and issues around the use of electric vehicles were not taken into consideration. Table 1 illustrates the acronyms and abbreviations in this research work.

The main contributions of this work are as per the following:

(1) Develop a three-factor taxonomy that captures the essential characteristics of eco-routing models and map the literature accordingly

(2) Define the strengths and drawbacks of the most up-to-date eco-routing models

(3) Suggest new ideas and possible opportunities for future work by utilizing the recent developments of the ICT

This work is organized as follows: section 2 includes a brief overview of routing, eco-routing, and traffic assignment concepts. The main types of traffic assignment and traffic assignment relationship with routing are illustrated. The optimization formulation of vehicle routing and eco-routing as an extension of the initial routing concept is demonstrated. Section 3 presents the approaches available for estimating emissions. Section 4 maps the reviewed eco-routing studies to the proposed taxonomy. Section 5 includes a discussion and concludes the major findings. Finally, section 6 incorporates suggestions and discussions on the future direction of eco-routing models.

2. Vehicle Routing, Eco-Routing, and Traffic Assignment

Routing is guiding vehicles to their destinations based on a single criterion, such as travel time, distance, emissions, and fuel, or any combination of them. The concept of vehicle routing has been used by public road agencies for decades. The main tool used by the agencies is the roadside variable message signs (VMSs). Nevertheless, with the ICT advancements, route guidance services by the private parties have ballooned due to the commercial introduction and affordability of the standalone personal navigation devices and smartphones [8]. More recently, environmental variables, like CO_2 emissions and fuel consumption/type, were taken into account, and eco-routing was introduced to replace the conventional routing concept that only aimed to minimize travel time. Other synonym terms of eco-routing can be pollution routing [9] or green routing [10].

Traffic assignment plays a profound role in forecasting travel time in long-term transportation planning. Additionally, it has a substantial role in short-term traffic operation management and control [11]. Traffic assignment is the last step of the transportation demand forecasting process that focuses mainly on the choice of the path from an origin to a destination. The route choice is based on the objectives set by drivers or by governments [12]. Figure 1 illustrates the possible sources of data, the classification of traffic assignment, components of traffic assignment, and the relationship between traffic assignment and routing. Traffic assignment models are classified into two major categories: the static (STA) and the dynamic traffic assignment (DTA). The STA models do not represent the congestion phenomenon and consider equal in- and outflow from a link which is unrealistic. The main outputs of STA models are average speed, traffic volume, traffic composition, and the level of service [13] that are used to estimate the weights of traffic characteristics to define the routes [14]. On the other hand, DTA models are based on a direct relationship between congestion and traffic flow [13]. DTA represents the real situation more efficiently in which it considers the changes in the traffic flow with time. As a result of the high spatial and temporal resolution associated with DTA, a more reliable estimation of weights reflecting on traffic characteristics is achieved [11]. DTA is an iterative process that examines the progress of achieving either user equilibrium (UE) or system optimal (SO) assignment [15]. Achieving UE or SO is associated with weights of the different traffic characteristics taken into account (travel time, distance, emissions, and fuel) for every link. As presented in Figure 1, both STA and DTA consist of two components which are traffic flow model and travel choice principle.

Traffic flow models can take three forms: microscopic, mesoscopic, and macroscopic [3]. The *microscopic* model considers the detailed temporal characteristics of every vehicular agent in the network. It requires models that account for the behavioural aspect of the drivers. The outputs can include the position, speed, and acceleration of every vehicle at each

TABLE 1: Acronyms and abbreviations.

| Acronyms and abbreviations	Full name
STA	Static traffic assignment
DTA	Dynamic traffic assignment
UE	User equilibrium
SO	System optimal
W_t, W_d, W_e, and W_f	Weights of travel time, distance, emissions, and fuel, respectively
T_i, D_i, E_i, and F_i	Travel time, distance, emissions, and fuel of link i, respectively
IS1	Model adopting microscopic traffic and emission models, small case study, and optimizing one routing objective
IL1	Model adopting microscopic traffic and emission models, large case study, and optimizing one routing objective
AS2	Model adopting macroscopic traffic and emission models, small case study, and optimizing more than one routing objective
AL1	Model adopting macroscopic traffic and emission models, large case study, and optimizing one routing objective
AL2	Model adopting macroscopic traffic and emission models, large case study, and optimizing more than one routing objective
MS2	Model adopting different levels of aggregation of traffic and emission models, small case study, and optimizing more than one routing objective
ML1	Model adopting different levels of aggregation of traffic and emission models, large case study, and optimizing one routing objective
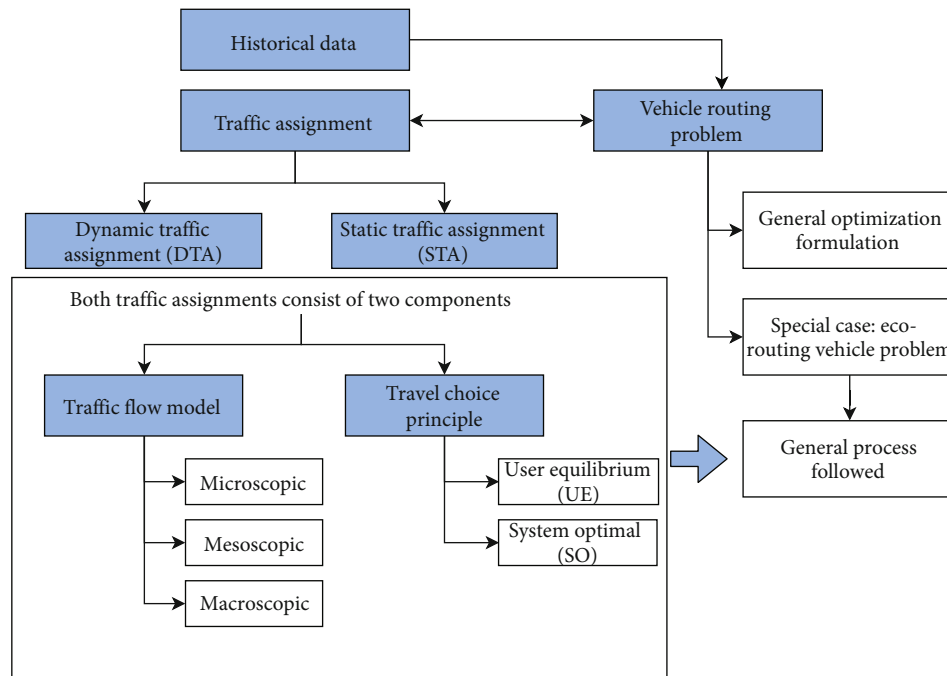
FIGURE 1: Traffic assignment classification, components, and traffic assignment relationship with routing.

time step. The *mesoscopic* model goes between the microscopic and macroscopic flow models. It represents the vehicle flow in aggregate terms, and the behaviour rules are captured in detail. Finally, the *macroscopic* requires aggregated information about the vehicular dynamics. The main drawback here is that it cannot capture reality and certain traffic incidents, such as queues or spillbacks [14].

Wardrop formulated two basic travel choice principles for traffic assignment [16]. The first principle is the *user equilibrium (UE)*: *"The journey cost on all the routes actually used are equal, and less than those which would be experienced by a single vehicle on any unused route"*, while the other being the *system optimal (SO)*: *"The average journey cost is a minimum for all routes in a network"*. Compared to an assignment based on this principle, a lower average travel cost cannot be achieved by any other assignment. SO assignment is what authorities seek to achieve as the total travel cost in a network is minimized. This type of traffic assignment means that

some users may experience a higher travel cost to achieve SO assignment. In other words, it may be unfair to certain users when the global benefit is achieved.

With regard to the relationship between traffic assignment and routing, a brief illustration is as follows. Routing vehicles involves guiding them based on one objective (travel time, distance, emissions, or fuel) or more than one objective (both travel time and emissions). To route vehicles, the cost of the objectives considered is required. For instance, if vehicles are routed to the fastest route, travel time could be the objective and the cost of every link in the traffic network is needed. The cost of an objective can be obtained from different sources: sensors distributed in the network, probe vehicles collecting information about the objectives taken into account from the network, statistical and historical data sets, and traffic assignment. Traffic assignment, and more specifically, the DTA, routes vehicles to their destinations by an iterative process for defined traffic flow and specific time period. When applying traffic assignment for the first iteration, the costs of links are estimated/assumed, and routes are calculated accordingly. Then, every future iteration calculates the costs of links based on the previous iteration's routes. This process continues until equilibrium is reached (UE or SO) as discussed above. The equilibrium-state cost of a link is the cost employed while routing vehicles, and this summarizes the relationship between routing and traffic assignment. Thus, the performance of vehicle routing is explicitly dependent on the traffic assignment due to the fact that the outcome of the traffic assignment process is the input for a routing process [17].

From the optimization perspective, Equation (1) illustrates the general formulation of the objective function for a routing problem:

$$\min\left\{\sum_{i=1}^{n} W_t.T_i + \sum_{i=1}^{n} W_d.D_i + \sum_{i=1}^{n} W_e.E_i + \sum_{i=1}^{n} W_f.F_i\right\},$$
(1)

where T_i is the travel time on link i; D_i is the distance traversed on link i; E_i is emissions on link i which can be CO_2, CO, NOx, or any other pollutant; F_i is fuel consumed on link i; n is the number of links of a path k; and W_t, W_d, W_e, and W_f are weights associated with travel time, distance, emissions, and fuel, respectively. It is worth mentioning that variables in Equation (1) (T, D, E, and F) have different units and weights transform them into a consistent unit (e.g., monetary value).

Figure 2 illustrates the general logic followed while applying eco-routing. Traffic variables (speed, distance, acceleration, deceleration, etc.) are the typical outcomes of either traffic flow models as described in section 2 or real data collected. Traffic variables are fed into an emission/fuel model, as it is described in section 3. The estimated variables of traffic and emissions/fuel are used for the optimization process to define the optimal route. When the route is chosen, traffic characteristics are modified accordingly. It is important to note that this is an iterative process, for possibly every t seconds.

3. Vehicle Emission Modelling

Since the 1960s, the negative impact of emissions has been considered while managing transportation systems. A wide variety of gaseous pollutants and fine particulate matter from fuel consumption are emitted from vehicles on roads. Carbon monoxide (CO), nitrogen oxides (NOx), and particulate matter (PM) have been listed as critical air pollutants by most environmental protection agencies and departments (e.g., U.S., EU, Australia, and Hong Kong) [11] due to their severe undesired effects on humans and the ecosystem. Different factors affect emissions, including distance travelled, speed, time spent in a specific driving condition, and fuel consumed. Hence, in terms of estimating emissions, there are several models employed based on the scale and details available. Aligned with the two main categories of traffic assignments as in section 2, emission models are set to be either static or dynamic. Below in subsections 3.1 and 3.2, further classification is applied on static and dynamic emission models as illustrated in Figure 3.

3.1. Static Emission Models. This type is based on macroscopic information of the traffic network. Although several studies have shown that the static emission models cannot estimate emissions precisely, such models are used widely for transportation application purposes (e.g., [2, 18]). It is mainly because of their simplicity and ease of use. The static emission models are further classified based on the level of complexity as per the following: (1) *aggregated models* that are associated with a very low resolution in terms of the data used. These models employ emission factors to estimate emissions based on vehicle kilometres travelled (VKT), vehicle miles travelled (VMT), or fuel consumed. The UK National Atmospheric Emission Inventory and the Energy Book for transport are two examples of the aforementioned models [14]. (2) *Average-speed models* are based on the average speed during a trip and emission factors. The emission factors of these models are in (*g/VKT*) or (*g/VMT*). An example includes the Computer Program to Calculate Emissions from Road Transport (COPERT) [19]. Other examples are a computer program that estimates different emission factors (MOBILE) [20] and the EMFAC2014 [21]. Since this type of model depends on the average speed of vehicles, congestion is taken into account implicitly. Nevertheless, this approach will not be a good fit for congested areas when vehicles are idling. Lastly, (3) *traffic situation models* require qualitative variables (e.g., road type, congestion level, and area type) and quantitative variables (e.g., average speed, traffic volume, VKT or VMT, and link length). Emission factors employed for these models are referenced to a specific traffic condition. Hence, a high level of subjectivity is associated with these type of models. Examples of this type include the Handbook Emission Factors for Road Transport (HBEFA) [22] and the Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) [23]. Among the three static emission models, this one is the most detailed that takes into account different variables to provide better estimation and accountability for congestion [11].
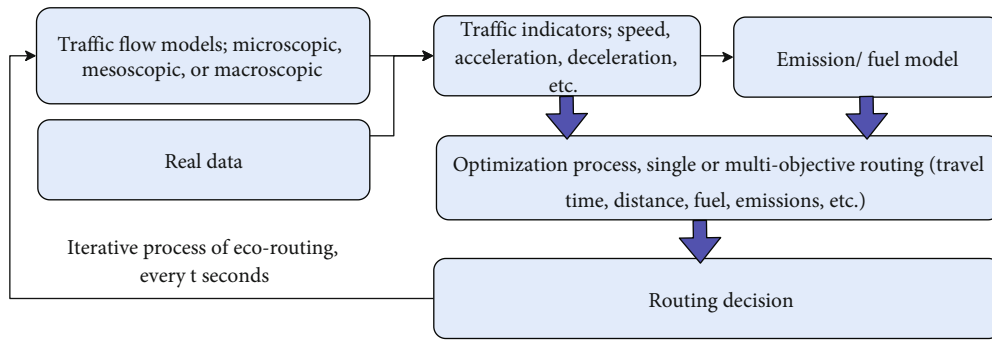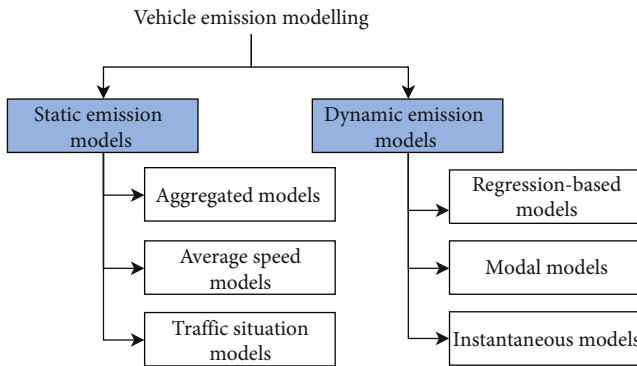
Figure 2: Eco-routing logic.

Figure 3: Vehicle emission modelling classification.

3.2. Dynamic Emission Models. This type is based on second-by-second time increment vehicular variables, further classified into three categories: (1) *Regression-based models* employ regression approaches to estimate emissions based on detailed variables that represent driving cycles. Speed, acceleration levels, or speed time profile data are required to define average emission factors (*g/s*) or (*g/VMT*) or (*g/VKT*).

This model can be used aside with microscopic data obtained from the GPS equipment and is suitable for use with the DTA models. Nevertheless, this type of model is very sensitive to overfitting of the calibrated data because of the large number of variables. Examples of this type include VERSIT+ [24] and the Virginia Tech Microscopic Energy and Emission Model (VT-Micro) [25]. (2) *Modal models* are a function of different modes of vehicular operating conditions (e.g., starts, idle, acceleration, deceleration, and cruise). Emission factors (*g/s*) or (*g/VMT*) or (*g/VKT*) are defined based on the operation mode. Both vehicle characteristics and cycle characteristics are required as inputs for this type of model. An example of this type is the Mobile Emission Assessment System for Urban and Regional Evaluation (MEASURE) [26]. And finally, (3) *instantaneous models* are the most detailed and most accurate to estimate emissions. Both dynamic operating variables (e.g., second-by-second speed, road grade, and vehicle accessory use) and static parameters (to characterize the vehicle tailpipe emissions for the appropriate vehicle/technology category) modes are required as inputs. Nevertheless, this type of model is difficult to calibrate and needs intensive vehicular characteristics, operations, and locations.

This raises the difficulty of using such a type of model with DTA. Examples include Passenger car and Heavy-duty Emission Model (PHEM) [27], Comprehensive Modal Emission Model (CMEM 2) [28], and Motor Vehicle Emission Simulator (MOVES 3) [29]. MOVES Lite is an extension of MOVES that was introduced to overcome two main shortcomings of the latter, i.e., high computational power required and complexity [30].

4. Taxonomy of the Eco-Routing Studies

A three-factor taxonomy is adopted as shown in Figure 4. The first factor of taxonomy, which reflects on the quality of the outcomes, is based on the level of aggregation of both traffic flow and emission/fuel models. Traffic models are mainly used to define average or instantaneous speed to estimate average or instantaneous emissions on links at following levels:

(i) *Microscopic* (*I*): the main characteristic of this type of models is the highly granular spatial and temporal resolution employed to estimate the traffic and emission indicators. Nevertheless, this comes at the cost of computational time, resources, and input data requirements

(ii) *Macroscopic* (*A*): the main characteristic of this category is the course level of spatial and temporal resolution. Thus, this category is associated with less accuracy compared to *I Models*. However, this type of model is used when high-resolution data points are not available and because of the simplicity associated with the problem

(iii) *Mesoscopic* (*E*): such models are in between the microscopic and macroscopic flow models in terms of the aggregation level. From an extensive literature review, it is concluded that none of the studies applied the mesoscopic level of aggregation for traffic flow as well as for emission in the context of eco-routing

(iv) *Mixed aggregation* (*M*): this category includes the models that employed different levels of aggregation for traffic and emission models
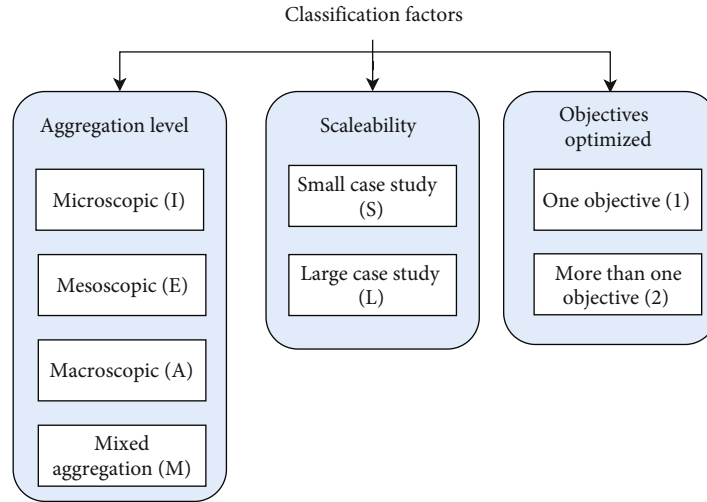
Classification factors

FIGURE 4: Abbreviations of the three-factor taxonomy.

The second factor of taxonomy is dependent on the scalability of the model. The larger the scale, the more reliable the outcomes. However, this comes at the cost of computational time and complexity. The categories are as follows:

(i) *Large case study* (*L*): entire metropolitan area or central zones of a region

(ii) *Small case study* (*S*): it can be a segment of a road, a well-defined part of a highway, or a zone with limited number of intersections

Finally, the third factor of taxonomy is related to the number of objectives optimized at a time. Generally and in most of the routing studies, single objective was taken due to the contradiction between routing objectives. Nevertheless, over time, environmental objectives have been taken into account in addition to other objectives for more sustainable transportation systems and due to their significant negative impact on the environment. In this research work, the two main categories considered are as follows:

(i) *Single objective* (1): the routing objective can be travel time, distance, GHG, or NOx

(ii) *More than one objective* (2): different combinations can be chosen while routing vehicles to their destinations. Travel time is generally prioritized and combined with one or more of other objectives, such as GHG, NOx, distance, and fuel in the case of multiobjective routing

For example, *AL2* is for eco-routing models that employed macroscopic flow and emission/fuel models and large case study and optimized more than one objective at a time.

5. Discussion and Concluding Remarks

Table 2 maps each of the reviewed eco-routing studies to a specific category based on the taxonomy factors defined.

The taxonomy is based on the profound characteristics, level of aggregation of traffic flow and emission models, scalability, and the number of objectives optimized simultaneously. The aforementioned characteristics are chosen due to their importance and ability to reflect on the applicability of each model. Classifying studies in the literature would help practitioners choose suitable models that match the characteristics of their case studies and available inputs. In addition, illustrating the detailed categorization of eco-routing studies guides researchers towards further investigations for more sustainable transport systems.

Most of the reviewed studies optimized one objective at a time, such as travel time, distance, or emissions/fuel. Examples can be found in [5, 10, 18, 33]. While optimizing environmental indicators, a reduction was achieved, and the trade-off between environmental variables and travel time was demonstrated as in [3, 38, 40]. In the literature, there was not a clear differentiation between two concepts: dynamic routing and dynamic traffic assignment. At times, the dynamic traffic assignment has been used to refer to dynamic routing. Both terms are defined in detail in section 2.

Speed is a major contributor to emissions (CO_2 and NOx) [39]. The relationship between speed and CO_2 and NOx is nonmonotonic and nonlinear. Improving speed may not always be favourable from the environmental aspect, that is, studies did not elaborate on the impact of the nature of the relationship between speed and emission, while ecorouting. Furthermore, it was not always stated if CO_2 and/or NOx emission rates were based on distance or time and link GHG/NOx cost was rarely demonstrated in detail. It is worth mentioning that when the emission factors are based on time spent on a link, the impact of distance travelled is neglected. Similarly, when emission factors are based on distance, the effect of time spent is excluded. In both cases, the traffic condition is not represented effectively.

With regard to the trade-off between emission and time, studies that compared between different routing strategies found that minimizing emissions/fuel was at the cost of a

Table 2: Eco-routing models and their specifications related to the three-factor taxonomy proposed.

Study/year Classification	Traffic model	Factor 1 Emission model	Factor 2 Scale	Factor 3 # of obj. optimized
Rakha et al. (2012) [31] (IS1)	INTEGRATION microscopic traffic assignment and simulation software	INTEGRATION	Two small case studies	One objective at a time, T or F
Ahn and Rakha (2013) [32] (IL1)	INTEGRATION	VT-micro microscopic emission model	Large case study of the Cleveland and Columbus network	One objective at a time, T or F
Sun and Liu (2015) [33] (IS1)	Microscopic real-time traffic data	Microscopic emission model	Small case study of 20 signalized intersections	One objective at a time, T or E
Elbery et al. (2015) [34] (IS1)	INTEGRATION	VT-micro model	Small case study of one highway and two arterial roads	One objective F
Elbery et al. (2016) [35] (IS1)	INTEGRATION	VT-micro model	10 zones of one highway and two arterial roads	One objective F
Bandeira et al. (2018) [7] (IL1)	Microscopic flow model VISSIM	Microscopic emission model based on vehicle-specific power (VSP)	Aveiro in Portugal that consists of 77,700 inhabitants	T for a scenario and NOx, CO, HC, and CO_2 for another scenario
Elbery and Rakha (2019) [36] (IL1)	INTEGRATION	VT-micro model	The downtown area in the city of Los Angeles (LA)	One objective F
Tzeng and Chen (1993) [2] (AL2)	Macroscopic Bureau of Public Roads (BPR) function	Macroscopic BPR function	Urban area of Taipei of 38 traffic zones, 268 nodes, and 688 links	D, TT, and CO emissions one at a time
Benedek and Rilett (1998) [18] (AL1)	Macroscopic BPR function	Macroscopic TRANSYT-7F average-speed model	A network in Edmonton, Alberta, that consists of 54 zones and 809 nodes and 1,282 links	TT and CO emissions one at a time
Luo et al. (2016) [3] (AS2)	Macroscopic flow models	VT-macro model	Hypothetical traffic network of 8 links	T, E, and F together
Patil (2016) [37] (AS2)	Macroscopic BPR function	Macroscopic Comprehensive Modal Emission Model (CMEM)	Two small networks	T & E/F for one scenario and T for another one
Aziz and Ukkusuri (2012) [38] (MS2)	Mesoscopic cell transmission model (CTM)	Macroscopic based on average speed regression emission model	Two small case studies	T and CO one at a time and together
Guo et al. (2013) [10] (ML1)	TRANSIMS microscopic and macroscopic model	Multiscale Motor Vehicle Emissions Simulator model (MOVES) and macroscopic model based on average speed	Greater Buffalo-Niagara Region	CO, NOx, and F one at a time
Andersen et al. (2013) [5] (ML1)	CAN bus data	CAN bus data	The whole road network of Denmark consisting of around 630,000 segments	D, T, E, & F one at a time
Zeng et al. (2016) [39] (ML1)	Probe vehicles	Probe vehicles	A real-world network with 4072 nodes and 12,877 links in Toyota city, Japan	D, T, E, & F one at a time
Long et al. (2016) [40] (MS2)	Mesoscopic model link transmission model (LTM)	Macroscopic based on a regression model	Largest case study contains 24 links	T and CO solely and together
Huang and Peng (2018) [41] (ML1)	Real data points	Autonomie	Ann Arbor traffic network that consists of 21,56 one-way links	T, D, and E one at a time

slight increase in travel time [3, 5, 7, 10, 38, 41]. With respect to the scalability factor, employed case studies were limited, and restrictions were made on OD pairs in [3, 33, 40]. When it comes to the level of aggregation of traffic flow and emission models, the use of macroscopic or mesoscopic models to represent traffic flow or emission is a drawback—especially with the advancements in the ICT. For instance, when average speed was utilized in [10, 37, 38, 40], emissions were underestimated. Models that utilized regression models, such as in [18, 37, 38], were dependent on vehicular speed to estimate emissions produced and/or fuel consumed. This means that they are not capable of representing congestion reliably in urban areas. For specific studies, the use of probe vehicles as in [5, 36, 39] is associated with a limitation as low MPRs would lead to unrealistic and unreliable representation. Only one model by Luo et al. [3] considered the prediction concept when evaluating objectives. In terms of NOx, which is the pollutant reflecting the impact of transportation systems on public health, there was a limited number of studies that considered it while routing vehicles.

Finally, the most up-to-date models in [34, 36] incorporated one of the ICT advancements, i.e., vehicle to infrastructure (V2I) communication. However, they were still applied in a centralized routing framework like previous studies. A centralized routing framework is associated with drawbacks related to the large investment required, high sensitivity to system failure, lack of relevancy of the information to a specific trip, and high complexity when updating a system compared to distributed routing systems [42]. Also, the main goal of the most recent studies [34, 36] was to demonstrate the effect of communication characteristics on proposed models as they utilized V2I communication. Thus, more attention should be devoted in utilizing the distributed routing systems. For instance, Farooq and Djavadian [43] proposed an end-to-end distributed dynamic routing system for connected autonomous vehicles (E2ECAV). The E2ECAV was examined with different conditions experienced in Downtown Toronto, which is an urban area that can become highly congested. The effectiveness of the proposed E2ECAV in terms of throughput, travel time, flow, density, and flow was examined in [44, 45]. The results were encouraging in which around 18% reduction of mean travel time was observed when employing 100% CAVs in the case of highly congested traffic conditions. Moreover, the study showed that the higher the MPR of CAVs, the better the throughput and the less time required to achieve 100% throughput. Furthermore, enhancements to speed, density, and flow have been noticed with higher MPRs of CAVs [44]. The general trend was that the higher the MPRs of CAVs, the better the traffic network characteristics, especially for congested and highly congested traffic conditions due to the up-to-date information about the traffic condition [44]. From the environmental perspective, Tu et al. [46] assessed the impact of applying the E2ECAV distributed dynamic routing system on the environment. Different MPRs and demand levels were investigated. When the demand level was low, the impact of employing high MPRs of CAVs was negligible. However, when the network was extremely congested, 100% CAV decreased the total GHG and NOx by 40% and 12%, respec-

tively. Generally speaking, higher MPRs led to lower total GHG emissions in the network, while the optimal MPR differed for different demand levels. The optimal MPR was 70% CAV for uncongested and highly congested traffic conditions that contributed to 5% and 41% decrease in GHG and NOx, respectively. Nevertheless, the optimal MPR of CAVs was 100% for congested traffic conditions [46].

6. Potential Directions

As most of the studies are aimed at optimizing one objective at a time while routing vehicles, more research efforts should be devoted towards the multi-objective routing. Furthermore, it is paramount to consider public health while routing vehicles that was rarely captured in the studies reviewed. Hence, more attention should be dedicated towards the quantification of indicators, such as exposure and dispersion. Exposure is being in the presence of some substance in an environment. Dispersion is also an indicator that has been used to measure the impact of transportation on public health. Dispersion represents one cause of the pollutant movement [47].

Researchers should consider incorporating eco-routing option or multi-objective routing in routing software like WAZE [48] and Google Maps [49] especially that citizens are more aware of the undesired impact of their trips on the environment. Nevertheless, incentives should be investigated.

As evident from [42], the efficiency of a routing system plays an important role in mitigating congestion that has an explicit negative impact on the environment. Since the most up-to-date studies are still dependent on centralized routing systems that have limitations [42], distributed routing systems (e.g., [42, 43, 50, 51]) that have proven their capabilities in outperforming the centralized routing systems should be considered for future models. More emphasis on dynamic routing should be given due to the advancements in the ICT, which would facilitate the process of representing traffic conditions more realistically. Crowdsourcing is a proposed tool to make efficient decisions in transportation based on crowd experience [52]. It is suggested to share information about emissions produced by crowds with other users via cellphones to avert the negative impact on the environment. A study by Wu et al. [53] utilized cellular and traffic sensor data to estimate route flow. This can be extended to incorporate the environmental dimension while routing. The employment of microscopic models for both flow and emission/fuel is profound as the higher the spatial and temporal resolution of the data points, the better the reflection on the real condition and the higher the accountability for the congestion phenomenon. Investigating the impact of eco-routing for different congestion levels and different MPRs of intelligent vehicles would be an added value to the literature. Predicting traffic characteristics, such as speed, flow, and density, is an essential tool for managing traffic flow efficiently. Prediction can be implemented for the short-term and long-term. The traffic variables that can be predicted are the average speed, density, flow, and travel time [54]. By linking the concept of prediction to eco-routing, emissions can be predicated similarly to other traffic indicators and vehicles

would be routed accordingly [3]. An example of prediction can be a study by Jiang et al. [55]. Traffic and emissions were predicted on an expressway by using data from probe vehicles and detectors. The authors predicted speed by using the virtual trajectory method that was used to estimate emissions on links [55]. In terms of the case studies, larger networks as in [10, 18, 32, 36] would be preferable to illustrate the effectiveness and scalability of proposed approaches.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

References

[1] S. K. Zegeye, B. De Schutter, H. Hellendoorn, and E. Breunesse, "Model-based traffic control for balanced reduction of fuel consumption, emissions, and travel time," in *Proceedings of the 12th IFAC Symposium on Transportation Systems*, pp. 149–154, Redondo Beach, California, September 2009.

[2] G. H. Tzeng and C.-H. Chen, "Multiobjective decision making for traffic assignment," *IEEE Transactions on Engineering Management*, vol. 40, no. 2, pp. 180–187, 1993.

[3] L. Luo, Y. E. Ge, F. Zhang, and X. (. J.). Ban, "Real-time route diversion control in a model predictive control framework with multiple objectives: traffic efficiency, emission reduction and fuel economy," *Transportation Research Part D: Transport and Environment*, vol. 48, pp. 332–356, 2016.

[4] J. M. Bandeira, D. O. Carvalho, A. J. Khattak et al., "Empirical assessment of route choice impact on emissions over different road types, traffic demands, and driving scenarios," *International Journal of Sustainable Transportation*, vol. 10, no. 3, pp. 271–283, 2016.

[5] O. Andersen, C. S. Jensen, K. Torp, and B. Yang, "Ecotour: Reducing the environmental footprint of vehicles using eco-routes," in *2013 IEEE 14th International Conference on Mobile Data Management*, pp. 338–340, Milan, Italy, June 2013.

[6] M. Kubička, J. Klusáček, A. Sciarretta et al., "Performance of current eco-routing methods," in *2016 IEEE Intelligent Vehicles Symposium (IV)*, pp. 472–477, Gothenburg, Sweden, June 2016.

[7] J. M. Bandeira, P. Fernandes, T. Fontes, S. R. Pereira, A. J. Khattak, and M. C. Coelho, "Exploring multiple eco-routing guidance strategies in a commuting corridor," *International Journal of Sustainable Transportation*, vol. 12, no. 1, pp. 53–65, 2018.

[8] Y.-C. Chiu, J. Bottom, M. Mahut et al., *A primer for dynamic traffic assignment*, Transportation Network Modeling Committee, Transportation Research Board, 2010.

[9] T. Bektas and G. Laporte, "The pollution-routing problem," *Transportation Research Part B: Methodological*, vol. 45, no. 8, pp. 1232–1250, 2011.

[10] L. Guo, S. Huang, and A. W. Sadek, "An evaluation of environmental benefits of time-dependent green routing in the greater Buffalo–Niagara region," *Journal of Intelligent Transportation Systems*, vol. 17, no. 1, pp. 18–30, 2013.

[11] Y. Wang, W. Y. Szeto, K. Han, and T. L. Friesz, "Dynamic traffic assignment: a review of the methodological advances for environmentally sustainable road transportation applications," *Transportation Research Part B: Methodological*, vol. 111, pp. 370–394, 2018.

[12] C. S. Papacostas and P. D. Prevedouros, *Transportation engineering and planning*, Englewood Cliffs, NJ : Prentice Hall, 1993.

[13] Y.-C. Chiu, J. Bottom, M. Mahut et al., "Dynamic traffic assignment: a primer," *Transportation Research E-Circular*, no. E-C153, 2011.

[14] W. Y. Szeto, X. Jaber, and S. C. Wong, "Road network equilibrium approaches to environmental sustainability," *Transport Reviews*, vol. 32, no. 4, pp. 491–518, 2012.

[15] D. Watling and M. L. Hazelton, "The dynamics and equilibria of day-to-day assignment models," *Networks and Spatial Economics*, vol. 3, no. 3, pp. 349–370, 2003.

[16] F. S. Zuurbier, *Intelligent route guidance*, TRAIL, 2010.

[17] R. Jayakrishnan, W. K. Tsai, J.-S. Oh, and J. Adler, *Event-based atis: practical implementation and evaluation of optimized strategies tech. rep.*, California Partners for Advanced Transit and Highways (PATH), Institute ofTransportation Studies, UC Berkeley, 2001.

[18] C. M. Benedek and L. R. Rilett, "Equitable traffic assignment with environmental cost functions," *Journal of Transportation Engineering*, vol. 124, no. 1, pp. 16–22, 1998.

[19] L. Ntziachristos, Z. Samaras, S. Eggleston et al., "Copert iii," in *Computer Programme to calculate emissions from road transport, methodology and emission factors (version 2.1)*, European Energy Agency (EEA), Copenhagen, 2000.

[20] US Environmental Protection Agency, *User's guide to mobile 6. 1 and mobile 6. 2 mobile source emission factor model*, 2003.

[21] California Air Quality Research Board, *User's guide*, California Environmental Protection Agency, 2014.

[22] A. INFRAS, "Handbook emission factors for road transport 3.2," *Quick reference. Version,*, vol. 3, 2004.

[23] P. G. Boulter and I. S. McCrae, "Assessment and reliability of transport emission models and inventory systems (artemis)," *final report*, Transportation Research Board, 2007.

[24] R. Smit, R. Smokers, and E. Rabe, "A new modelling approach for road traffic emissions: Versit+," *Transportation Research Part D: Transport and Environment*, vol. 12, no. 6, pp. 414–422, 2007.

[25] H. Rakha, K. Ahn, and A. Trani, "Comparison of MOBILE5a, MOBILE6, vt-micro, and cmem models for estimating hot-stabilized light-duty gasoline vehicle emissions," *Canadian Journal of Civil Engineering*, vol. 30, no. 6, pp. 1010–1021, 2003.

[26] I. Fomunung, S. Washington, and R. Guensler, "A statistical model for estimating oxides of nitrogen emissions from light duty motor vehicles," *Transportation Research Part D: Transport and Environment*, vol. 4, no. 5, pp. 333–352, 1999.

[27] S. Hausberger, J. Rodler, P. Sturm, and M. Rexeis, "Emission factors for heavy-duty vehicles and validation by tunnel measurements," *Atmospheric Environment*, vol. 37, no. 37, pp. 5237–5245, 2003.

[28] G. Scora and M. Barth, *Comprehensive modal emission model (cmem) version 3.01 user's guide*, vol. 23, University of

California Riverside Center for Environmental Research and Technology, 2006.

[29] United States Environmental Protection Agency, *Motor vehicle emission simulator (moves): User's guide for moves 2014a*, The United States Evironmental Protection Agency, 2014.

[30] X. Zhou, S. Tanvir, H. Lei et al., "Integrating a simplified emission estimation model and mesoscopic dynamic traffic simulator to efficiently evaluate emission impacts of traffic management strategies," *Transportation Research Part D: Transport and Environment*, vol. 37, pp. 123–136, 2015.

[31] H. A. Rakha, K. Ahn, and K. Moran, "INTEGRATION Framework for Modeling Eco-routing Strategies: Logic and Preliminary Results," *International Journal of Transportation Science and Technology*, vol. 1, no. 3, pp. 259–274, 2012.

[32] K. Ahn and H. A. Rakha, "Network-wide impacts of eco-routing strategies: a large-scale case study," *Transportation Research Part D: Transport and Environment*, vol. 25, pp. 119–130, 2013.

[33] J. Sun and H. X. Liu, "Stochastic eco-routing in a signalized traffic network," *Transportation Research Procedia*, vol. 7, pp. 110–128, 2015.

[34] A. Elbery, H. Rakha, M. Elnainay, W. Drira, and F. Filali, "Eco-routing using v2i communication: system evaluation," in *2015 IEEE 18th International Conference on Intelligent Transportation Systems*, pp. 71–76, Las Palmas, Spain, September 2015.

[35] A. Elbery, H. Rakha, M. Y. ElNainay, W. Drira, and F. Filali, "Eco-routing: an ant colony based approach," in *Proceedings of the International Conference on Vehicle Technology and Intelligent Transport Systems*, pp. 31–38, Rome, Italy, 2016.

[36] A. Elbery and H. Rakha, "City-wide eco-routing navigation considering vehicular communication impacts," *Sensors*, vol. 19, no. 2, p. 290, 2019.

[37] G. R. Patil, "Emission-based static traffic assignment models," *Environmental Modeling & Assessment*, vol. 21, no. 5, pp. 629–642, 2016.

[38] H. M. A. Aziz and S. V. Ukkusuri, "Integration of environmental objectives in a system optimal dynamic traffic assignment model," *Computer-Aided Civil and Infrastructure Engineering*, vol. 27, no. 7, pp. 494–511, 2012.

[39] W. Zeng, T. Miwa, and T. Morikawa, "Prediction of vehicle CO_2 emission and its application to eco-routing navigation," *Transportation Research Part C: Emerging Technologies*, vol. 68, pp. 194–214, 2016.

[40] J. Long, J. Chen, W. Y. Szeto, and Q. Shi, "Link-based system optimum dynamic traffic assignment problems with environmental objectives," *Transportation Research Part D: Transport and Environment*, vol. 60, pp. 56–75, 2018.

[41] X. Huang and H. Peng, "Eco-routing based on a data driven fuel consumption model," 2018, https://arxiv.org/abs/1801.08602.

[42] X. Yang and W. W. Recker, "Modeling dynamic vehicle navigation in a self-organizing, peer-to-peer, distributed traffic information system," *Journal of Intelligent Transportation Systems*, vol. 10, no. 4, pp. 185–204, 2007.

[43] B. Farooq and S. Djavadian, *Distributed traffic management system with dynamic end-to-end routing, u.s. provisional patent service no. 62/865,725*, The United States Patent and Trademark Office (USPTO), 2019.

[44] L. Alfaseeh, S. Djavadian, and B. Farooq, "Impact of distributed routing of intelligent vehicles on urban traffic," in *2018 IEEE International Smart Cities Conference (ISC2)*, pp. 1–7, Kansas City, MO, USA, September 2018.

[45] S. Djavadian and B. Farooq, "Distributed dynamic routing using network of intelligent intersections," *ITS Canada ACGM (2018)*, Canada Annual General Meeting Conference, 2018.

[46] R. Tu, L. Alfaseeh, S. Djavadian, M. Saleh, B. Farooq, and M. Hatzopoulou, "Quantifying the impacts of dynamic control in connected and automated vehicles on greenhouse gas emissions and urban NO2 concentrations," *Transportation Research Part D: Transport and Environment*, vol. 73, pp. 142–151, 2019.

[47] A. Y. Watson, R. R. Bates, and D. Kennedy, *Atmospheric transport and dispersion of air pollutants associated with vehicular emissions*, University of Michigan, 1988.

[48] J. E. Dickinson, T. Cherrett, J. F. Hibbert et al., "Fundamental challenges in designing a collaborative travel app," *Transport Policy*, vol. 44, pp. 28–36, 2015.

[49] J. Campbell, *Map use and analysis. Wm. C*, Brown Dubuque, 1993.

[50] Y. E. Hawas and H. S. Mahmassani, "Comparative analysis of robustness of centralized and distributed network route control systems in incident situations," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1537, no. 1, pp. 83–90, 1996.

[51] J. Lee and B. (. B.). Park, "Evaluation of route guidance strategies based on vehicle-infrastructure integration under incident conditions," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2086, no. 1, pp. 107–114, 2008.

[52] A. Misra, A. Gooze, K. Watkins, M. Asad, and C. A. le Dantec, "Crowdsourcing and its application to transportation data collection and management," *Transportation Research Record*, vol. 2414, no. 1, pp. 1–8, 2014.

[53] C. Wu, J. Thai, S. Yadlowsky, A. Pozdnoukhov, and A. Bayen, "Cellpath: fusion of cellular and traffic sensor data for route flow estimation via convex optimization," *Transportation Research Procedia*, vol. 7, pp. 212–232, 2015.

[54] M. Shahgholian and D. Gharavian, "Advanced traffic management systems: an overview and a development strategy," 2018, https://arxiv.org/abs/1810.02530.

[55] Z. Jiang, X. (. M.). Chen, and Y. Ouyang, "Traffic state and emission estimation for urban expressways based on heterogeneous data," *Transportation Research Part D: Transport and Environment*, vol. 53, pp. 440–453, 2017.