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Review

Dynamic traffic assignment: A review of the methodological advances for environmentally sustainable road transportation applications

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A R T I C L E I N F O

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A B S T R A C T

The fact that road transportation negatively affects the quality of the environment and deteriorates its bearing capacity has drawn a wide range of concerns among researchers. In order to provide more realistic traffic data for estimations of environmental impacts, dynamic traffic assignment (DTA) models have been adopted in transportation planning and traffic management models concerning environmental sustainability. This review summarizes and examines the recent methodological advances of DTA models in environmentally sustainable road transportation applications including traffic signal control concerning vehicular emissions and emission pricing. A classification of emission estimation models and their integration with DTA models are accordingly reviewed as supplementary to the existing reviews. Finally, a variety of future research prospects of DTA for environmentally sustainable road transportation research are discussed. In particular, this review also points out that at present the research about DTA models in conjunction with noise predictive models is relatively deficient.

1. Introduction

Faced with the economic and social advances of civilization, transportation planners and traffic engineers no longer solely focus on congestion when solving transportation problems or optimizing transportation systems. In recent years, the fact that road transportation negatively affects the well-being of the environment and deteriorates its bearing capacity has drawn an enormous amount of concern. According to the United States Environmental Protection Agency (USEPA), road transportation (automobiles, trucks, and buses) is recognized as the greatest source of carbon monoxide (CO), nitrogen dioxide (NO_x), and sulfur dioxide (SO_x) from the burning of fuel, as well as the main contributor of reactants for producing particulate matter (PM) through chemical reactions in the atmosphere. Numerous studies have confirmed that these

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vehicular emissions explicitly contribute to various health problems including cancer, cardiovascular and respiratory diseases, and perinatal mortality (Pearson et al., 2000; HEI, 2010). Transportation is also a significant source of greenhouse gas emissions (GHG in short, e.g., carbon dioxide (CO_2)), which leads to irreversible anthropogenic global warming. Scientists believe that the climate changes and damage costs could be catastrophic concerning the ecological degradation in a long run (Hansen, 2008). These cautions underscore the need for greater efforts at enhancing environmental awareness from the transportation sector and make it imperative to monitor the relationship between transportation and the environment, as well as to develop transportation systems that ensure economic growth, but at the same time are sustainable and preserve the ecosystem.

In the last decade, remarkable advances in road traffic emission models have been achieved with the rapid growth of comprehensiveness, complexity, and accuracy (see Smit et al., 2008, 2009, 2010; Fontes et al., 2015). These advances provide transportation planners and traffic engineers a variety of estimation tools for assessing the effects of vehicular emissions and allow for from second-by-second emission descriptions to yearly emission inventories. Meanwhile, an increasing number of studies combining road transportation modeling with emission modeling emerge in the field of environmentally sustainable road transportation research. Traffic assignment models are always a key component of the integrated modeling.

The fundamental aim of a traffic assignment process is to reproduce the pattern of vehicular movements based on certain behavioral rules, and then the outputs of the process are used as the inputs to emission models. Based on the consideration of the temporal dimension, traffic assignment models are classified into three categories: dynamic traffic assignment (DTA), semi-dynamic traffic assignment, and static traffic assignment (STA) models (Bliemer et al., 2017). A semi-dynamic traffic assignment model can be considered a series of connected STA models (e.g., Nakayama and Conors, 2014). Unlike STA, a semi-dynamic traffic assignment model has multiple time periods for route choice and allows the residual traffic of one period to transfer to the following time periods. A semi-dynamic traffic assignment model often considers only a single time step for network loading (i.e., flow propagation through the network) within each route choice period. This contrasts to a DTA model in which within each time period for route choice, there exist (smaller) time steps for network loading (Bliemer et al., 2017). Note that there are quasi-dynamic models, but they are in fact static capacity constrained STA models (e.g., Bifulco and Crisalli, 1998; Smith, 2013; Bliemer et al., 2014) that are more realistic, mainly regarding adopting hard capacity constrained and having queues (albeit point queues) to model congestion, compared with classical capacity restrained type STA models with the use of Bureau of Public Roads functions for their costs.

With the merit of computational efficiency and mathematical simplicity for encapsulation in an analytical framework, STA models have been favored by policymakers for strategic transportation planning among the three classes of models. STA models are also commonly adopted for the design and management of environmentally sustainable road networks. In the review by Szeto et al. (2012), the applications of STA models to the design and management of environmentally sustainable road networks are well summarized. However, the limitations of STA models are widely recognized, which is the incapability to model traffic dynamics (e.g., queue spillback, and speed variations). It has been scientifically proven that traffic dynamics are closely related to vehicular emissions. For example, faster accelerations and stop-and-go conditions tend to increase emission rates (Rakha and Ahn, 2004; Barth and Boriboonsomsin, 2008; Litman, 2015). DTA models are acknowledged to be able to capture more realistic traffic flow characteristics such as shock waves, expansion waves, and queue spillback (Szeto and Lo, 2006), which shows high potential for improving the accuracy of emission estimations. Hence, the implementations of DTA models in solving transportation problems or optimizing transportation systems with environmental considerations are beginning to receive greater attention. However, at the time of this writing, no review on the methodological advancements for solving these problems or optimizing the systems can be found.

In this paper, a review is given on the methodological advancements of the incorporation of environmental sustainability concerns into various road transportation problems, focusing on the use of DTA models. We aim to discuss and summarize the significance of the implementation, the suitability, and the feasibility of the DTA models integrated with emission models, as well as the trade-off between the computational complexity and accuracy of integrated models, by surveying and categorizing a variety of successful applications in the literature. Great attention is also given to the identification of the potential research directions in this rapidly developing research field.

The main contributions of this paper are as follows.

- This paper provides a critical and comprehensive literature review of the methodological advances for environmentally sustainable road transportation applications, focusing on the use of DTA models.
- This review presents a systematic classification of emission estimation models and their integration with DTA models, providing guidance for the future model development of dynamic and emerging environmentally sustainable transportation applications.
- This review identifies some research gaps in current studies and highlights several highly inspiring research directions with practical relevance for the future studies of dynamic and environmentally sustainable transportation research.

The remainder of this paper is organized as follows. The second section provides a brief review of the commonly used road traffic emission models, with a focus on their applications integrated with traffic assignment models. Section 3 reviews the fundamentals of DTA models from the two major components, namely the network loading model and the travel choice principle, and discusses the recent advances in incorporating environmental concerns into these components. Section 4 discusses the integrated studies of DTA and emission models from two main categories: traffic signal timing optimization and emission road pricing. Finally, some potential future research directions are suggested in the last section.

2. Vehicle emission modeling

Szeto et al. (2012) pointed out that environmental impacts from road transportation primarily comprise emissions and noise emitted. To mitigate the impacts, various measures have been implemented, including actions on transportation infrastructure and traffic management measures. To quantify the impacts and benefits of these measures, the integration studies of noise and DTA models have not been prevailingly carried out compared to those of emissions. Hence, this review mainly focuses on the limited integrated studies of emissions and DTA models.

The effort to specify the issues of automobile emissions can be traced back to 1960s (Soltau and Campbell, 1968; Jackson et al., 1969). A vast variety of gaseous pollutants and fine particulate matter from fuel combustion are emitted from vehicles on roads, among which carbon monoxide (CO), nitrogen oxides (NO_x), and particulate matter (PM) have been listed as *criteria air pollutants* by most environmental protection agencies/departments (e.g., U.S., EU, Australia, and Hong Kong) because of their severe adverse effects on humans and the ecosystem. As indicated by Cappiello (2002) and Boulter et al. (2007), the levels of emissions are influenced by many variables and parameters, including vehicle technical specifications, vehicle status, vehicle operating conditions, and external environment conditions (such as air conditions and road characteristics). It is therefore helpful to present a summary of the emission models in this section for the discussion of their integration with DTA models in the studies to be reviewed in the later sections.

Emission models provide an emission estimate by multiplying a determinative emission factor expressing the mass of pollutants emitted per unit distance, time, or mass fuel burnt by the corresponding vehicle activity data (i.e., vehicle kilometers or miles travelled (VKT or VMT), total time spent in particular driving conditions, or fuel consumption) (Smit et al., 2010). Emission models are becoming more sophisticated, reflected in the level of resolution, the level of details for input data, the extent of incorporating driving behaviors, etc. (Smit et al., 2009). Researchers have actively contributed to the literature regarding the effects of the increased model complexity on accuracy, as well as recommendations on different applications/scales through meta-analysis and classification (e.g., Rakha et al., 2004; Mellios et al., 2006; Smit et al., 2010). Although the classification framework varies among studies (e.g., Cappiello, 2002; Smit, 2006; Boulter et al., 2007; Smit et al., 2008; 2009; 2010; Wismans et al., 2011b; Szeto et al., 2012; Demir et al., 2014; Fontes et al., 2015), two key factors are spotted. One is the level of aggregation over space and time and another is the driver behavior aggregation in the modeling process. To connect emissions to congestion more directly and provide appropriate suggestions on integrated implementations, in this review, the taxonomy used for traffic assignment models, namely static and dynamic modeling (Cappiello, 2002), is adopted for categorizing the commonly applied emission models. Table 1 summarizes the main characteristics of these models.

2.1. Static emission models

According to Cappiello (2002), for the development of this type of emission model, the exhaust emissions are measured as the total generated during the driving cycle in a dynamometer test. As discussed before, to assess the environmental impacts of road traffic using these static emission models, vehicle activity data on the aggregate level, such as national statistics (e.g., public road and street mileage), field measurements (e.g., traffic flow data gathered using video cameras), or traffic volume predicted from STA models, are mostly adequate when a high resolution is not required. Although these models cannot give accurate emission estimates, they are commonly used for transportation planning purposes due to their relative simplicity. Following the classification framework from Smit et al. (2008), these static models are further categorized into the following types with increasing complexity:

2.1.1. Aggregated models

Examples of this type of model are the UK National Atmospheric Emissions Inventory (NAEI, 2012) and the energy workbook for transport (AGO, 2006). The resolution of this type of model in both spatial and temporal dimensions is the lowest. The emission factors are calibrated by a number of measurements over given driving cycles and are usually in terms of mass of pollutant per vehicle per unit distance (g/VKT or g/VMT) or mass of pollutant per unit of fuel consumed (g/L). A constant emission factor is used to estimate the emissions from a particular type of vehicle and a general type of driving without an explicit definition. Hence, the estimation requires inputs only on network-wide fleet composition and VKT (or VMT or fuel consumption).

Little information on vehicle operation is taken into account by these models, let alone traffic dynamics. Owing to the simplicity of the emission factors, these models are easy to apply and most suitable for estimating large-scale emissions inventories, such as national or regional emission inventories, on a strategic level (Cappiello, 2002; Wismans et al., 2011b). Indeed, a number of integrated studies on a strategic level (e.g., network design problem) have implemented this type of model in combination with STA models in the early stage (e.g., Tzeng and Chen, 1993; Nagurney, 2000a,b; Qiu and Chen, 2007; Jia et al., 2009; and Chen and Xu, 2012).

2.1.2. Average-speed models

Examples of this type of model include COPERT (EEA, 2000), MOBILE (USEPA, 2002), and EMFAC (The California Air Resources Board, CARB, 2014). This type of model is based on the principle that the average emission factor varies according to the average speed during a trip (Boulter et al., 2007). In this type of emission model, the emission factor (in g/VKT or

Table 1
An overview of existing emission models.

Model type		Examples	Emission factor unit	Common inputs				
				Emission factor type	Traffic-related	Environment-related	Vehicle-related	Driving pattern-related
Static	Aggregated	UK National Atmospheric Emissions Inventory (NAEI, 2012), The energy workbook for transport (AGO, 2006)	g/VKT, g/VMT, g/L	Discrete	Network VKT/VMT, network-wide fleet composition	NA	Fuel scales	NA
	Average-speed	COPERT (EEA, 2000), MOBILE (USEPA, 2002), and EMFAC (CARB, 2014)	g/VKT, g/VMT	Continuous	Congestion level, trip/link VKT/VMT, detailed (link-wide) fleet composition	NA	Vehicle type	Average speed
	Traffic situation	HBEFA (INFRAS, 2010), ARTEMIS (Boulter and McCrae, 2007)	g/VKT, g/VMT	Discrete	Congestion level, VKT/VMT per driving situation, detailed fleet composition, level of service	Road type, area type, speed limit	Vehicle type	Average speed
Dynamic	Regression	VERSIT+ (Smit et al., 2007), VT-Micro (Ahn et al., 2002)	g/s or g/VKT, g/VMT	Continuous/ discrete	Trip/link VKT/VMT, detailed fleet composition	NA	Vehicle type	Instantaneous vehicle speed and acceleration
	Modal	MEASURE (Fomunung et al., 1999)	g/s or g/VKT, g/VMT	Discrete	Link VKT/VMT, detailed fleet composition	Road grade	Vehicle characteristics	Modal variables from instantaneous vehicle speed and acceleration
	Instantaneous	PHEM (Hausberger et al., 2003), CMEM (Scora and Barth, 2006), MOVES (USEPA, 2014)	g/s	Discrete	Link VKT/VMT, detailed fleet composition	Road grade	Vehicle characteristics	Speed-time profiles

g/VMT) for each category of vehicle is a continuous function of average speed, sometimes corrected with different factors taking account of different conditions. In essence, the inputs are trip-based or road section-based average speed and VKT (or VMT), which are relatively easy to obtain from static traffic assignment models or field measurements.

Since these models are developed based on actual driving pattern data with vehicle average speed being the sole descriptor of driving patterns, congestion is implicitly accounted for in these models on different levels (Smit et al., 2008). However, the average speed is not an adequate congestion indicator (e.g., both a free-flow condition of an arterial and a stop-and-go situation on a freeway give the same average speed), which leads to significant errors in estimations of emission factors. Nevertheless, most of them, such as the estimation model as part of the TRANSYT-7F programme developed by Penic and Upchurch (1992) and Wallace et al. (1998), are usually algorithmically tractable and can be solved efficiently. With appropriate interfacing with STA models, their estimations can be obtained down to the link level, which enables wider applications in planning, such as tolling design (e.g., Yin and Lawphongpanich, 2006; Li et al., 2012). However, the emissions are modeled to occur uniformly along the length of the link without further differentiation under various traffic conditions, which is deemed insufficiently realistic.

2.1.3. Traffic situation models

Examples of this type of model include Handbook Emission Factors for Road Transport (HBEFA) (INFRAS, 2010) and Assessment and Reliability of Transport Emission Models and Inventory Systems (ARTEMIS) (Boulter and McCrae, 2007). This type of model advances in terms of capturing cycle dynamics by correlating the average emission rates with various driving cycle parameters, which in turn are referenced to specific traffic situations. These models define traffic situations as a combination of several dimensions, including area type, road type, speed limit, and level of service. For different vehicle categories, the computation of the emission factor (in g/VKT or g/VMT) for each traffic situation relies on representative speed-time curves. Hence, this type of model requires qualitative variables (e.g., congestion level, road type, and area type) or quantitative traffic situation variables (e.g., average speed, traffic volume, and link length) that represent traffic situations, as well as the VKT (or VMT) data per driving situation as inputs.

Either through qualitative (textual) or quantitative descriptions, the definitions of traffic situations may result in inconsistencies in interpretation as Boulter et al. (2007) pointed out. Despite this shortcoming, traffic situation models tend to be best suited to local applications (e.g., emission estimations for individual links, street atmospheric dispersion modeling, etc.) among all types of static emission models, thanks to their capability of providing emission estimations with more detailed traffic characteristic considerations on the link level.

2.2. Dynamic emission models

In contrast to the static modeling approach, the dynamic modeling approach measures emissions from driving cycles in a dynamometer test continuously (typically second-by-second). Hence, other than the standard traffic related inputs on links such as VKT/VMT and fleet composition, the operational conditions of a vehicle are taken into account to a high resolution when emissions are recorded simultaneously. As pointed out by Cappiello (2002), with continuous measurements, both modal and instantaneous analysis and modeling are adopted for developing dynamic emission models, based respectively on more aggregated modal variables or on instantaneous vehicle kinematic variables (Boulter et al., 2007). Hence, most classification frameworks (e.g., Boulter et al., 2007; Wismans et al., 2011b) have further divided them into three groups: regression-based models, modal models, and instantaneous models.

2.2.1. Regression-based models

Examples include VERSIT+ (Smit et al., 2007) and the Virginia Tech Microscopic Energy and Emission Model (VT-Micro[1]) (Ahn et al., 2002). This type of model employs regression approaches to modeling emissions with a substantial set of descriptive variables characterizing driving cycles. Detailed driving pattern data at high temporal resolution (e.g., instantaneous speed, acceleration levels, or speed-time profile data) are required for obtaining average emission factors (g/s, g/VMT or g/VKT) based on the regression equations, in which the emission factors can be considered either discrete or continuous, depending on whether categorical variables are used as inputs. This type of model can estimate emissions on a highly detailed level in conjunction with microscopic data from GPS equipment. This type of model offers a great amount of freedom to implement in conjunction with DTA models. However, due to the use of a large number of explanatory variables, this type of model is susceptible to over-fitting calibration data (Cappiello et al., 2002).

2.2.2. Modal models

An example of this type of model is the Mobile Emissions Assessment System for Urban and Regional Evaluation (MEASURE) (Fomunung et al., 1999). In this type of model, an emission factor (g/s, g/VKT, g/VMT) for a certain vehicle type is expressed as a discrete function of different modes of vehicle operating conditions (e.g., starts, idle, acceleration, deceleration, cruise, etc.). In principle, both vehicle characteristics (e.g., odometer readings, catalytic converter type, fuel injection

[1] VT-Micro is developed as a regression model from experimentation with numerous polynomial combinations of speed and acceleration and can be applied on an instantaneous basis.

type, etc.) and cycle characteristics (e.g., the percentage of the cycle exceeding various thresholds, acceleration, deceleration, cruise speed, etc.) are required for the data sets of emissions tests for model development. These models typically required detailed information on vehicle movements (e.g., instantaneous data on speed, acceleration, and road gradient) as inputs to determine the emission factor (Smit et al., 2010). The total emission during a trip or a road section is computed by weighting each modal emission factor by the time spent or distance traveled in the corresponding mode. Similar to regression-based models, this type of model is also capable of modeling the effects of congestion on emissions, provided that congestion is reflected in the input driving patterns. Traffic dynamics are incorporated indirectly by distinguishing various operating modes. Compared with situation-based models, this type of model requires more detailed vehicle characteristics and operations in order to produce more accurate emission estimates.

2.2.3. Instantaneous models

Examples include PHEM (Passenger car and Heavy duty Emission Model) (Hausberger et al., 2003), Comprehensive Modal Emission Model (CMEM[2]) (Scora and Barth, 2006), and Motor Vehicle Emission Simulator (MOVES[3]) (The United States Environmental Protection Agency, 2014). This type of model is indeed a more detailed type of modal model (Boulter et al., 2007). Emission factors (g/s) are estimated from the measurements of a driving cycle or an engine test at the highest resolution (typically one second) using speed and acceleration, or by using the description of the engine power requirement. Since these models inherently and directly take the dynamics of driving cycles into account, the estimation of emissions is the finest in theory. Usually in these models, various components model the different processes in the vehicle related to emissions, requiring 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) as inputs (Scora and Barth, 2006). However, this type of model is relatively difficult to calibrate and more data-intensive compared with regression-based and modal models. The merits of instantaneous models can only be exploited with the detailed and precise measurements of vehicle characteristics, operations, and locations as inputs, which leads to the difficulty in the combined use with DTA models because of data availability.

3. DTA for integration with emission models

Traffic assignment models are crucial for traffic flow and travel time forecasting in long-term transportation planning and project appraisal, as well as in short-term traffic operation management and control. These models determine the flow on each link and capture the interaction between demand and supply. If a (departure) time dimension is introduced to the assignment module (and traffic flow module), the formulation can be generalized from an STA to a DTA context.

In the literature, the outputs of STA models, including traffic volume, traffic composition, and the level of service (i.e., volume-to-capacity ratios, average travel speeds), etc., are widely used to estimate traffic emissions (see Szeto et al., 2012). However, the limitations associated with STA models are widely recognized as its ignorance of realistic traffic dynamics (i.e., dynamic queuing and spillback phenomena), as well as the spatial and temporal vehicular interactions. For example, simplified congestion functions (i.e., Bureau of Public Roads travel time function) are mostly used in classical capacity restrained type STA models to relate average travel times to traffic flows on a link level but do not consider speed variations and stop-and-go traffic conditions, particularly in congested networks. Given the time-varying nature of traffic flow, to truly assess traffic emissions, a DTA model should be considered. Using the outputs from DTA models not only deliver greater compatibility with emission estimation models but also have high potential in improving emission estimates with higher temporal and spatial resolutions. As indicated in Section 2, noise estimation models are not that widely combined with DTA models compared to emission models. Hence, this review mainly focuses on the limited integration of emission models and DTA models.

Both static and dynamic traffic assignment models consist of two main components, namely the *travel choice principle* and the *network loading model*. In the past decade, extensive comprehensive reviews on DTA models or their components have been conducted (e.g., Hoogendoorn and Bovy, 2001; Peeta and Ziliaskopoulos, 2001; Szeto and Lo, 2005; 2006; Jeihani, 2010; Mun, 2007; Rakha and Tawfik, 2009; Szeto and Wong, 2012; Bliemer et al., 2017). For the detailed mathematical formulations, formulation and solution approaches, classifications, and implementations of DTA models or components, readers are welcome to consult the wealth of literature listed above. This section mainly focuses on the compatibility of DTA models with emission models, through discussion on the two major components, i.e., the *network loading model* and the *travel choice principle.*

3.1. Network loading model

The network loading model depicts how traffic propagates inside a road network and hence governs the network performance in terms of travel time. It is sometimes called a traffic flow model or component and can be further divided into two sub-models: link and node models. The outputs of the network loading model in DTA heavily affected by the types of link

[2] This model can be categorized as a power-based model, a subcategory of instantaneous models according to Boulter et al. (2007) because the model was developed based on vehicle power.

[3] This model is one of the examples of vehicle specific power-based models.

Table 2
Network loading or traffic flow models.

Classification based on the level of detail	Example	
Macroscopic	Link model	Vickrey's model (Vickrey, 1969), Exit function (M-N model) (Merchant and Nemhauser, 1978), Link performance function (Janson, 1991; Ran and Boyce, 1996), Whole link model (Friesz et al., 1993), METANET (Messner and Papageorgiou, 1990), Lighthill–Whitham–Richards (LWR) model (Lighthill and Whitham, 1955 and Richards, 1956), Payne–Whitham model (Payne, 1971; 1979; Whitham, 1974), Phase Transition Model (PTM) (Colombo, 2002, 2003; Blandin et al., 2011), etc.
	Node model	Directed capacity proportional model (Tampère et al., 2011; Flötteröd and Rohde, 2011; Corthout et al., 2012), Capacity consumption equivalence model (Gibb, 2011), etc.
Mesoscopic	DynaSMART (Jayakrishnan et al., 1994), DynaMIT (Ben-Akiva et al., 1998), CONTRAM (Taylor, 2003), MATSIM (Cetin, 2005), Mezzo (Burghout et al., 2006), Dynus T (Chiu et al., 2011), DTALite (Zhou and Taylor, 2014), etc.	
Microscopic	Cellular automaton model (Nagel and Schreckenberg, 1992), PARAMICS (Smith et al., 1995), CORSIM (US-DoT, 1995), VISSIM (Fellendorf, 1996 and PTV, 2003), MITSIMLab (Ben-Akiva et al., 1997), SUMO (Krajzewicz et al., 2002), INTEGRATION (Van Aerde and Rakha, 2012), etc.	

model and node model chosen. Based on the level-of-detail with the representation of traffic, network loading models are typically classified into macroscopic, mesoscopic, and microscopic (Hoogendoorn and Bovy, 2001; Rakha and Tawfik, 2009). A summary of commonly utilized network loading models in the literature is provided in Table 2. Note that the traffic flow simulation software can be regarded as a network loading model of DTA (Szeto and Wong, 2012).

Macroscopic traffic flow models describe traffic from the viewpoint of the collective vehicular flow, using macroscopic variables (e.g., link flows). Starting from single link loading, the Vickrey model (Vickrey, 1969), exit-function-based traffic flow model (M–N model) (Merchant and Nemhauser, 1978), and performance function based network loading model (Janson, 1991; Ran and Boyce, 1996; Chen and Hsueh, 1998) have been used to capture congestion on a link in DTA models in the early stage, but yet they fail to describe some fundamental traffic dynamics such as queue spillbacks. To address this issue, a first-order kinematic wave traffic flow model, the LWR model, was captured in DTA models (e.g., Kuwahara and Akamatsu, 2001; Lo and Szeto, 2002; Friesz et al., 2013b; Long et al., 2015) and solved by Daganzo's (1994, 1995) solution scheme (i.e., Cell Transmission Model (CTM)), Newell's (1993) solution scheme, or the Link Transmission Model (LTM) solution procedure (Yperman, 2007). More advanced solution schemes have been developed based on LTM, including the General Link Transmission Model (GLTM) solution procedure (Gentile, 2010) and the event-based solution procedures for continuous time LTM for triangular fundamental diagrams (Raadsen et al., 2016) and nonlinear fundamental diagrams (Bliemer et al., 2018), respectively. Recently, the analytical reformulations of the LTM and the Vickrey model are also emerging to allow the development of novel solution approaches to solve DTA models with macroscopic network loading models (e.g., Long et al., 2015; Han et al., 2013a, 2013b, and 2013c).

Although the first-order kinematic wave models have been used extensively in DTA models compared to second- or higher order kinematic wave models owing to the merits of the analytical tractability of the first-order models, they are not capable of explicitly capturing complex waves of vehicular traffic (e.g., start-stop waves, oscillatory congested traffic, and capacity drop or traffic hysteresis patterns), and hence lead to the inaccuracy in the estimates of higher-order traffic variables (e.g., acceleration/deceleration and perturbation). To overcome these limitations, higher-order traffic flow models have been proposed, including the Payne–Whitham model (Payne, 1971; 1979; Whitham, 1974) and its further development by Aw and Rascle (2000) and Zhang (2002). In contrast to the one-to-one relationship between traffic flow and density in first-order kinematic wave models, they explicitly describe the scattered density-flow pairs using a set-valued fundamental diagram. More recently, the PTM has gained increasing popularity for their capability of representing complex waves while keeping the LWR structure for light traffic (Piccoli et al., 2015). One of the significant advantages of the second-order traffic flow models is their capability of capturing higher-order variations in velocity and acceleration and hence producing more accurate emission rate estimates (Piccoli et al., 2015).

While link models compute dynamic traffic flow propagation along road segments, node models determine flows over the intersections and affect the congestion dynamics in the adjacent links. Recent advances on macroscopic node models have been made to pose formulation requirements, including Tampère et al. (2011), Flötteröd and Rohde (2011), Gibb (2011), and Corthout et al. (2012). For an overview of the state-of-the-art macroscopic node models, interested readers are referred to the study of Smits et al. (2015).

In contrast to macroscopic traffic flow models which deal with the collective traffic flow dynamics, microscopic traffic flow models track each vehicle at a high temporal resolution. A microscopic traffic flow model usually consists of sub-models that describe assorted human driver behavior, including gap-acceptance, speed adaptation, lane-changing, overtakes, and car-following (Olstam and Tapani, 2004). Most previous research on microscopic traffic flow theory has been focused on the car-following logic, among which the introduction of Gazis–Herman–Rothery models (Gazis et al., 1961), safety-distance models (Kometani and Sasaki, 1959), and psycho-physical car-following models (Wiedemann, 1974) have laid the theoretical foundation for the continuing development of micro-simulation models or software packages. Several commonly used micro-simulation models are provided in Table 2, such as AIMSUN (Barcelo et al., 1997) embedding a safety-distance type model, MITSIMLab with a Gazis–Herman–Rothery-type car-following model, and VISSIM incorporating a psycho-physical model.

Microscopic traffic flow models can provide outputs in terms of the position, instantaneous speed, and acceleration of each vehicle at each time step. For a comprehensive review of the existing micro-simulation models, please refer to Algers et al. (1997) and Olstam and Tapani (2004).

Mesoscopic traffic flow models are hybrids of macroscopic and microscopic traffic flow models, which describe the traffic entities at a high level of detail, while their behavior and interactions are traced at a lower level of detail. The modeling approaches can vary from model to model. For example, in the cluster models under this scope (e.g., CONTRAM), traffic flow propagation is based on the macroscopic traffic flow theory wherein the traffic is represented by small packets or groups of vehicles rather than individual vehicles. Alternatively, individual traffic movements are modeled in some other mesoscopic traffic flow models (e.g., DYNASMART, MATSIM) and the behavior of vehicles traversing roadways is determined using a macroscopic speed/density function. Mesoscopic traffic flow models achieve a balance between the computational cost and the simulation accuracy.

To conclude, non-microscopic traffic flow models always require less computational effort and are relatively easier to calibrate. Though they do not allow for a detailed representation of traffic behavior as microscopic traffic flow models do, such as lane changing, they can capture many traffic flow phenomena which are important for emission estimations. Therefore, macroscopic or mesoscopic traffic flow models are better suited for modeling larger networks (e.g., regional modeling) than microscopic traffic flow models (Wismans et al., 2011b). On the other hand, microscopic traffic flow models are usually appropriate for a local area only, as an extensive amount of computation and memory are required for calibrating and simulating a large transportation network at a level of detail down to individual vehicles. Nevertheless, a multi-resolution modeling approach has been exploited by many practitioners in recent years (Zhou et al., 2015), where different types of traffic flow models can be used to provide multiple levels of modeling details regarding network dynamics and traveler/driver choices in order to produce satisfactory results in an integrated fashion. For instance, macroscopic or mesoscopic traffic flow models can be used to model the whole large network, together with microscopic traffic flow models generating more detailed traffic flow information on a single intersection therein.

Cappiello (2002) indicates that the integration between network loading and emission models can be achieved on various levels in term of temporal scale, spatial aggregation, and vehicle aggregation. In general, the output of the macroscopic network loading models can be easily fed to macroscopic emission models, so is the integration of microscopic network loading models and microscopic emission models (Zegeye et al., 2013). This indicates that the choice of network loading models directly influences the selection of the interfacing emission models. Moreover, the purpose of integration, the requirements of accuracy, the constraints of data availability, as well as the computational time requirement are crucial factors for both model selections. While featuring a good compatibility between emission and network loading models, the integration always aims to achieve a balanced trade-off between accuracy and computational complexity.

3.2. Travel choice principle

A travel choice principle models traveler's propensity to travel, and if so, how they select their routes, departure times, modes or destinations (Szeto and Lo, 2006). Typically, the travel choice principle of DTA is the dynamic extension of the route choice principle of STA, including the Dynamic User Optimal (DUO) principle (Friesz et al., 1989) extended from Wardrop's (1952) first principle, the Dynamic System Optimal (DSO) principle (Merchant and Nemhauser, 1978) extended from Wardrop's second principle or the Dynamic Stochastic User Optimal (DSUO) principle (Ran and Boyce, 1996) extended from the stochastic extension of Wardrop's (1952) first principle, etc. These principles assume that travelers select their routes and/or departure times to minimize their individual actual/marginal/perceived travel time/cost respectively, while the environmental impacts are typically not considered in these principles.

Although a list of choices can be included in a travel choice principle of DTA, the travel choice principles used in DTA with environmental objectives in the literature only consider route choice, as listed in Table 3. From this table, we can see that the routing principles adopted are not restricted to Wardrop's principles. It is because under Wardrop's routing principles, the emissions produced may not be the most favorable to the surrounding environment, which has been demonstrated in a variety of studies using static approaches (e.g., Rilett and Benedek, 1994; Benedek and Rilett, 1998; Sugawara and Niemeier, 2002; Chen and Yang, 2012). Although the theoretical finding can be derived from STA models, it can often be dangerous to generalize the conclusions from STA models to actual traffic systems due to the ignorance of traffic dynamics. As Rilett and Benedek (1994) suggested, it is of vital importance that traffic assignment models produce comprehensive and accurate outputs for evaluating the environmental impacts of traffic assignment. To remedy the limitations of STA models, recent efforts have been contributed to identifying and analyzing the environmental impacts of route choice behavior using DTA models with a higher spatial and temporal resolution, as listed in Table 3.

Ahn and Rakha (2008) examined the environmental impacts of route choice behavior using second-by-second GPS commute data and a micro-simulation study limited to a highway corridor and an arterial route. The simulation results illustrate that the faster highway route choice is not always the best from an environmental and energy consumption perspective. It is suggested that an emission- and energy-optimized traffic assignment can significantly improve emissions over the standard user equilibrium and system optimum assignment, which urges environmental concerns to be incorporated in traffic routing. Moreover, according to the comparison of the estimates from a static emission model (MOBILE6) and dynamic emission models (VT-micro (ORNL) model and CMEM model), it is demonstrated that macroscopic emission estimation tools can produce erroneous conclusions due to their ignorance of transient vehicle behavior along a route. It is also worth noting that

Table 3
DTA with environmental objectives.

Reference	Route choice principle	Network loading model	Emission estimation		The largest network used
			Estimation model	Pollutants	
Ahn and Rakha (2008)	Minimizing the total system emissions of a specific pollutant, minimizing total energy (fuel) consumption, DUO, and DSO	Microscopic simulation (INTEGRATION)	MOBILE6, VT-Micro (ORNL), and CMEM	CO, hydrocarbon (HC), NO_x, and CO_2	Highway and arterial corridors in DC and Fairfax, VA, USA
Aziz and Ukkusuri (2012)	Minimizing total system CO emissions, minimizing the weighted sum of total system travel time cost and total system CO emission cost, and DSO	Macroscopic simulation (CTM)	An average speed based nonlinear regression model (Lin and Ge, 2006; Zhang et al., 2010) estimated from emission data provided by MOBILE 6.2	CO	Nguyen and Dupuis (1984) network (14 nodes, 3 origin-destination (O-D) pairs)
Ahn and Rakha (2013)	Minimizing traveler’s fuel consumption and DUO	Microscopic simulation (INTEGRATION)	VT-Micro model (integrated within INTEGRATION)	HC, CO, NO_x, CO_2	The downtown Cleveland and Columbus networks
Guo et al. (2013)	Minimizing traveler’s emissions of a specific pollutant, minimizing traveler’s fuel consumption, and DUO	Microscopic simulation (TRANSIMS)	MOVES	CO, NO_x	The greater Buffalo–Niagara metropolitan region’s transportation network
Long et al. (2016)	Minimizing total system CO emissions, minimizing both total system travel time and total system CO emissions (i.e., Pareto optimization), and DSO	Macroscopic simulation (LTM)	The same as Aziz and Ukkusuri (2012)	CO	Modified Nguyen and Dupuis (1984) network (17 nodes, 2 O-D pairs)

emissions are sensitive to changes in a vehicle's speed and acceleration profiles. Given the fact that significant increases in emissions occur under high engine load conditions (e.g., during acceleration), minimizing high-emitting driving behavior has potential in improving air quality. Recently, Ahn and Rakha (2013) further investigated the trade-off between emissions and travel time in daily route choices by more comprehensive microsimulations. The transient vehicle behavior is taken into account in this study. The results demonstrate the significant impacts of emission-minimized routing in reducing network-wide fuel consumption and emission levels. The analysis results further indicate that the reduction is more significant in grid networks compared to freeway corridor networks, and rises with an increase in the level of network congestion and market penetration of such routing vehicles. Guo et al. (2013) also simulated and approximated a "green user equilibrium" (i.e., emission- or fuel consumption-minimized routing) and conducted a realistic assessment of its impacts. They further proposed a "targeted market penetration" strategy wherein travelers with the greatest potential for emission reductions are chosen to follow the green route assignment. Such a strategy is demonstrated to bring more environmental benefits than the random market penetration strategy, which assumes that the travelers who choose to follow the green route assignment are randomly distributed throughout the study area. Moreover, the heterogeneity in emission reduction is spotted among different types of vehicles for each pollutant. All these studies concluded that the flow pattern based on minimizing route travel time does not necessarily correspond to the flow pattern based on the least total emissions or the least fuel consumption in the traffic assignment, based on field data or simulation results. They also demonstrated that there are tangible environmental benefits associated with emission-minimized routing.

On the other hand, the consideration of emissions in route choice decisions has been analytically modeled as well. Aziz and Ukkusuri (2012) integrated an emission-based component into a DTA framework, leading to a model for system optimal assignment with regard to minimization of a weighted sum of total system travel time cost and CO emission cost, and a model for minimizing the total system CO emissions only. Based on the CTM, the resultant models with the incorporation of an emission model are formulated as two nonlinear and nonconvex mathematical programs and further approximated for their solvability with the CPLEX solver. The study demonstrated the significant effect of integrating an emission-based objective into route choice on reducing emissions. Nevertheless, there are certain model limitations such as vehicle holding leading to possible misestimation of travel time and the ignorance of fleet heterogeneity of the CTM. Long et al. (2016) indicated that the approximated quadratic programming models in Aziz and Ukkusuri (2012) can be very inaccurate for emission estimations except for a very congested traffic state. Adopting the LTM as the network loading model, Long et al. (2016) also solved the system optimal traffic assignment problems that minimize total system travel time, total system CO emissions, and both. Coupling with the same average speed based emission function, the two system optimal problems with emission considerations are both formulated as mixed integer linear programming problems (MILPs). Although both modeling accuracy and computational efficiency are improved in this study, their DTA models with environmental objectives are still for single destination network applications only. Moreover, the existing analytical models can be extended where emissions other than CO (e.g., NO_x, HC, etc.) are considered, since different pollutants possess varied emission characteristics, leading to different emission functions.

As reflected in Table 3, the studies on DTA models with environmental considerations are rather limited. It may be because it is hard to solve the resultant models, including nonlinear and nonconvex programs, MILPs, and those involved complicated microsimulations, for exact solutions quickly for large network applications. This may also explain why the networks used in some literature are not large.

As discussed before, the environmental impacts can be greatly reduced by incorporating emission-based objectives into route choice behavior in the traffic assignment process. However, it is not practically easy to achieve the environmentally system optimal or emission-minimized assignment in the real world without the implementation of traffic or demand management strategies, since drivers do not consider environmental impacts to be minimized at their own initiatives during the route selection process. Nevertheless, system optimal assignments always provide benchmarks for the design of road pricing strategies. The environmentally system optimal models in Aziz and Ukkusuri (2012) and Long et al. (2016) lay the theoretical foundation for developing emission-based pricing strategies.

In addition to the route choice principle embedded in traffic assignment models for travelers, environment-related issues in freight routing have also attracted much attention from the operations research field. The *Pollution Routing Problem* or *Eco-routing* involving the minimization of pollutant emissions, which is a variant of the traditional vehicle routing problem, has been investigated with different aspects of operational constraints (e.g., Bektaş and Laporte, 2011; Franceschetti et al., 2013; Nie and Li, 2013). Interested readers are welcome to consult the recent comprehensive reviews by Lin et al. (2014), Alam and McNabola (2014), and Demir et al. (2014) for more information of this research field.

4. Specific dynamic transportation problems with environmental considerations

Not surprisingly, numerous studies focus on the evaluation of emission impacts. Wismans et al. (2011b) provided a brief review of the application of microscopic DTA models for the assessment of emission impacts among a series of externalities to road transportation networks. Fontes et al. (2015) summarized the most recent integrated microsimulation studies combining road traffic and emission modeling for the evaluation of emission impacts and provided best practices on the link representation in the traffic flow model for minimizing emission estimation errors in future applications. Indeed, the evaluation of emission impacts is only the first step to mitigate these impacts.

In the literature, the mitigation of environmental impacts from road traffic is mostly addressed with combating traffic congestion through two broad methods, namely supply and demand management. The supply management strategies include increasing the transportation network capacity through improving current transportation infrastructure or adding new transportation infrastructure (e.g., building new roads, expanding existing roads) and increasing the utilization of existing infrastructure through the introduction of traffic management measures (e.g., traffic signal controls, ramp metering, and variable message sign controls). On the other hand, the demand management strategies emphasize to reduce travel demand or to redistribute this demand in space or in time, one of which is the use of road pricing. Szeto et al. (2012) firstly reviewed the transportation planning and traffic management problems that explicitly consider environmental issues, mainly within the scope of static traffic modeling. In view of higher fidelity and accuracy of modeling results, DTA models are playing increasingly important roles in these transportation planning and traffic management problems. Given that no studies are on dynamic transportation planning problems with environmental and DTA considerations at the time of this writing, this section reviews the most current studies on various dynamic traffic management problems, including traffic signal control and emission pricing.

4.1. Traffic signal control

It is important to note that the magnitudes of vehicle emissions are heavily affected by the various modal activities of vehicles (Pandian et al., 2009), such as starts, stops, acceleration, deceleration, etc. Excessive alteration of modal activities is witnessed especially near intersections since they generally serve as the most restrictive bottlenecks in urban networks. On the other hand, the optimization of traffic signal settings can be a positive means of controlling vehicular emissions, owing to its inherent ability to define vehicle movements throughout a signalized intersection.

Building upon the solid literature foundation of traditional traffic signal optimization problems (e.g., Improta and Cantarella, 1984; Meneguzzer, 1995; Lo, 1999, 2001; Wey, 2000; Lin and Wang, 2004; Cascetta et al., 2006), the incorporation of vehicular emission considerations into the optimization of traffic signal timings has been achieved progressively. Robertson et al. (1980) made the debut of minimizing fuel consumption in the optimization of traffic signals. An integrated TRANSYT computer program incorporating a macroscopic traffic flow model, a macroscopic fuel consumption model, and a signal optimizer is utilized in this study. Vehicle dynamics at intersections are poorly taken into account. As pointed out by Rakha et al. (2000), such macroscopic models do not account for time variations in speed, let alone in acceleration, which significantly impacts the accuracy of emission evaluation. More recently, Li et al. (2004) proposed a signal timing optimization model to reduce emissions, in which emissions are calculated using the emission factors from the MOBILE model. Though the emission measurements are based on dynamometer testing, the data is too aggregate for the analysis of intersection emissions. To comprehensively evaluate the emission impacts by traffic signal timing, studies integrating modal models or instantaneous emissions with dynamic traffic models gradually come to the fore (see Hallmark et al., 2000; Rakha et al., 2000; Rouphail et al., 2001; Williams and Yu, 2001; Chen and Yu, 2007; Zhang et al., 2009; Li and Shimamoto, 2011; Guo and Zhang, 2014; Kölbl et al., 2015). The simulation results from these studies have demonstrated the effectiveness of improved signal timing or coordination in reducing fuel consumption and vehicular emissions.

The simulation approach has also been widely applied for optimizing mobility and minimizing environmental impacts of traffic signal timing at intersections as summarized in Table 4. Two types of integrations are observed. The first type is the utilization of microscopic traffic flow simulation models, from which the outputs are accurate and consistently interfacing with modal or instantaneous emissions models (e.g., Park et al., 2009; Stevanovic et al., 2009; Kwak et al., 2012; Ma et al., 2014; Zhou and Cai, 2014; Stevanovic et al., 2015; Mascia et al., 2017). Such an integrated study can serve as an effective tool for the comprehensive optimization of the traffic signals for vehicular emission mitigation from corridors, major arterials, and large-scale networks while it relies on computationally intensive simulations. Since dynamic emission models demand the temporal and spatial resolution of data inputs, these integrated optimization problems are mostly tackled by simulation-based heuristics, e.g., simulation-based genetic algorithm, which incorporates traffic simulations during the functional evaluation of heuristics.

To achieve a trade-off between computational complexity and accuracy, the second type aims at cross-resolution integration (e.g., analytical dynamic traffic flow models coupling microscopic emission models). However, the interfacing process is not straightforward, which involves the construction of speed profiles and vehicle trajectories (e.g., Lv et al., 2013), or the aggregation of individual vehicle behavior (e.g., Lin et al., 2013). Such aggregation or approximation is carried out on limited datasets with simplified assumptions, whose fidelity has yet to validate. Recently, Osorio and Nanduri (2015a,b) developed a metamodel (surrogate model), which combines simulated travel time and emissions with their analytical approximations. Their model has been successfully applied to a real network problem and solved within a tight computational budget.

In spite of the greater acceptability among real-life deployment, simulations are time-consuming and the results cannot be easily extended to other cases. In contrast, an analytical-based approach presents more value in a prescriptive view, since theoretical insights can be derived and solution properties can be determined. One related study was by Khalighi and Christofa (2015), who investigated the fundamental problem of green time optimization towards emission minimization through a combination of previously introduced analytical models based on traffic flow theory. The emissions are estimated by modal emission rates with regard to the estimated time spent in each operating mode, which is analytically derived from the time-space/queuing diagram and is a function of demand, vehicle arrival times, saturation flow, and signal control pa-

Table 4
Dynamic traffic signal optimization studies considering emissions.

	Network loading model/procedure	Route choice principle	Emission model	Objective function(s)/side constraint(s)	Solution approach	Signal setting decisions	The largest network used
Park et al. (2009)	Microscopic CORSIM	Not available (NA)	Regression-based model VT-micro model	Total queue time or fuel consumption as the main measure to be optimized individually; Vehicular emissions (HC, CO, CO_2, NO_X) are secondary measures to be calculated	Simulation-based single-objective genetic algorithm (GA)	Common cycle length, offsets, green times	4 intersections in Charlottesville, Virginia, USA
Stevanovic et al. (2009)	Microscopic VISSIM	NA	Instantaneous model CMEM	Fuel consumption and CO_2 emissions	GA embedded in "VISSIM-based genetic algorithm optimization of signal timings" (VISGAOST) (Stevanovic et al., 2007)	Common cycle length, offsets, green times, and phase sequences	A 14-intersection network in Park City, Utah, USA
Wismans et al. (2011a)	Macroscopic DTA Model Streamline by Raadsen et al. (2010)	DUO	Traffic situation model ARTEMIS	Multiple objective functions: total travel time, CO_2 emissions, and noise	Simulation-based NSGA-II, SPEA2, and SPEA2+	Settings of one variable-message sign and two traffic lights (e.g., green time)	A hypothetical network with single origin-destination (O-D) pair and three routes
Kwak et al. (2012)	Microscopic TRANSIMS	NA	Regression-based model VT-micro model	Total fuel consumption as the main measure to be optimized; Vehicular emissions (HC, CO_2, CO, NO_x) are secondary measures to be calculated	Simulation-based single-objective GA	Common cycle length, offsets, phase sequences, and green times	4 intersections on an urban corridor in Charlottesville, VA, USA
Lin et al. (2013)	Macroscopic S model by Lin et al. (2012)	NA	Regression-based model VT-micro model	Weighted sum of total travel delay and emissions (CO, NO_x, HC)	A multi-start sequential quadratic programming algorithm	Cycle lengths, offsets, and green times	A 17-intersection urban road subnetwork

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Table 4 (*continued*)

	Network loading model/procedure	Route choice principle	Emission model	Objective function(s)/side constraint(s)	Solution approach	Signal setting decisions	The largest network used
Zhang et al. (2013)	Macroscopic CTM	NA	Modal model Modal emission factors from Frey et al. (2001) and a static Gaussian plume air dispersion model (Turner, 1994)	Total travel delay and mean excess emission (CO) exposure	Simulation-based single-objective GA	Common cycle length, offsets, green times, and phase sequences	A 5-intersection arterial network in the San Francisco Bay Area, USA
Ma et al. (2014)	Microscopic VISSIM and SUMO	NA	Instantaneous model CMEM	Average travel delay, total fuel consumption, total emissions (CO, HC, NO_x) individually and integrated (the same as Li et al., 2004)	Simulation-based single-objective GA	Green times for a fixed time control scheme and minimum and maximum green time extensions for each stage in the vehicle actuated signal control scheme	An isolated intersection with 6 signal phases in Wuhan, China
Zhou and Cai (2014)	Microscopic PARAMICS	NA	Instantaneous model CMEM	Total economic cost of delay cost, fuel consumption cost, and emission costs (for CO, NO_2, non-methane volatile organic compound (NMVOC), $PM_{2.5}$).	Simulation-based single-objective GA	Green times	An intersection with 4 signal phases in Guangzhou, China
Khalighi and Christofa (2015)	Macroscopic An analytical model based on deterministic queuing theory and a triangular fundamental diagram	NA	Modal model Modal emission rates based on vehicle specific power (VSP) (Shabihkhani and Gonzales, 2013)	Total HC emissions or total NO_x emissions	Matlab routine for constrained nonlinear problems, *fmincon*	Green times	An intersection with 6 signal phases in Athens, Greece
Osorio and Nanduri (2015a)	Macroscopic and microscopic An analytical urban traffic model based on the finite capacity queueing theory (Osorio, 2010) and AIMSUN	DSUO	Modal model A modal fuel consumption model based on both Ferreira's (1982) and Akçelik's (1983) models, and a macroscopic analytical model approximated from Akçelik's (1983) model.	The weighted sum of expected trip travel time and expected total fuel consumption	Simulation-based optimization framework of Osorio and Bierlaire (2013); The trust region (TR) sub-problem solved by a derivative-free algorithm (Conn et al., 2009)	Green times	A 15-intersection network with 9 signalized intersections (51 signal phases) in Lausanne, Switzerland

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Table 4 (*continued*)

	Network loading model/procedure	Route choice principle	Emission model	Objective function(s)/side constraint(s)	Solution approach	Signal setting decisions	The largest network used
Osorio and Nanduri (2015b)	Macroscopic and microscopic The same as Osorio and Nanduri (2015a)	DSUO	Instantaneous model An instantaneous model based on the model of Panis et al. (2006) and its approximated macroscopic version	The weighted sum of travel time cost and expected total emission cost (CO_2, NO_x, volatile organic compound (VOC), and PM)	The same as Osorio and Nanduri (2015a)	Green times	The same as Osorio and Nanduri (2015a)
Stevanovic et al. (2015)	Microscopic VISSIM	NA	Instantaneous model CMEM	Multiple objective functions: network vehicular throughput, total fuel consumption, and total number of vehicular conflicts	NSGA-II embedded in VISGAOST (Stevanovic et al., 2007)	Common cycle length, offsets, green times, and phase sequences	5 signalized intersections on a corridor in West Valley City, Utah,
Han et al. (2016)	Macroscopic LWR model	NA	Modal model A modal emission model for aggregate link emission rates based on Post et al. (1984) using the vehicle dynamics estimated from the LWR model	Expected vehicle delays as an objective function with emission side constraints or emission alone as the main objective function	Transformation into a mixed integer linear program (MILP), which was solved by ILOG CPLEX	Dynamic cycle lengths and dynamic green splits	A 4-intersection hypothetical network

rameters. Though computation times for emission estimations is significantly lowered and sufficient for real-time operations, such an application is limited to every single cycle of an isolated intersection.

Another analytical-based dynamic signal control study was undertaken by Han et al. (2016). They developed a mixed integer mathematical programming approach to tackle the significant difficulty and burdens in solution computation caused by nonlinear and nonconvex nature of emission-related objectives/constraint. Their approach relies on the development of the macroscopic relationship between the aggregate emission rate and the vehicle occupancy on the same link. This relationship is obtained based on both regression analysis and extensive numerical simulations. The relationship is then approximated by piecewise affine functions and the associated uncertainties are handled explicitly using robust optimization techniques so that the resultant problem can be formulated as a mixed integer linear program and solved to global optimality efficiently. Compared to the traditional mixed integer nonlinear program, this robust optimization formulation for signal control admits abundant theories for analysis as well as effective and well-developed solution schemes. Nevertheless, such macroscopic relationship may be not adequate for an accurate emission estimation. Moreover, extensive numerical simulations or empirical data are required to calibrate such a reduced model, which can be time-consuming or expensive to do so.

4.2. Emission pricing

In dynamic route choice modeling within the context of emission considerations, a significant reduction in vehicular emissions is demonstrated by the studies reviewed in Section 3.2. However, it is practically not easy to achieve this reduction in reality without the implementation of traffic or demand management strategies, because drivers do not consider environmental impact minimization at their own initiatives during route selection. One way to deal with this is to internalize the environmental impacts or the corresponding costs by emission pricing.

Emission pricing can be analyzed through static and dynamic modeling approaches. According to Ma et al. (2017), albeit the dynamic modeling approach is more complex and computationally demanding than the static counterpart, it is not deniable that time-varying tolls can be implemented to achieve a better network performance and more realistic travel behavior is captured by considering traffic dynamics in the modeling framework. Moreover, in order to provide more accurate data inputs for the estimation of vehicular emissions, the dynamic modeling approach tends to be a better choice.

Compared with dynamic congestion tolling studies (see Yao et al., 2012 and Ma et al., 2017 for a detailed survey), there were limited dynamic emission pricing studies or dynamic road pricing incorporating emissions in the past two decades. Table 5 lists the literature on the dynamic road pricing incorporating emissions.

Among the studies in Table 5, only two studies adopted the simulation approach. Kickhöfer and Kern (2016) adopted the simulation-based approach for evaluating the policy of emission cost internalization for a real-world scenario. An agent-based microsimulation framework, i.e., MATSim, with a heterogeneous population consideration is combined with a traffic situation model, HBEFA. The simulated average emission costs per vehicle kilometer under the first-best emission toll policy are consistent with the estimated average emission costs per vehicle kilometer in the literature. However, neither the emission tolls nor the estimates adequately reflect marginal costs with respect to the damage to human health, since the differentiation of pollution concentration among exposed populations is not accounted for. Hence, Kickhöfer and Nagel (2015) further incorporated activity location density in their toll calculations in order to monetize the effects on human health and investigated the impacts of such emission toll on emission levels, exposure cost reductions, and system welfare. A potential trade-off was observed between the minimization of emission exposure and the traditional minimization of vehicle kilometers traveled. Overall, this proposed emission exposure toll provides a more comprehensive evaluation of policies that aim at reducing environmental externalities in urban settings.

Other studies in Table 5 adopted the analytical approach. Indeed, being different from traffic management measures (e.g., traffic signal control) in nature, road pricing studies generally aim at providing theoretically derived insights in order to carry out a long-term strategic decision. Hence, the analytical approach is more commonly adopted in the emission pricing research area, as shown in Table 5. However, the studies have different pricing focuses and choice considerations, and also use different pricing schemes, traffic flow and emission models, and networks for illustration as summarized in this table. The studies also give different important findings. Zhong et al. (2012) incorporated the emission impacts through an aggregate emission factor together with a dispersion model into a pollution charge implementation problem as a side constraint. The necessary optimality condition for operating the transportation system with environmental constraints is discussed for both the whole link model and the deterministic queueing model. It is found that different externality structures of the two models result in different tolling structures to achieve dynamic system optimal assignment. Friesz et al. (2013a) formulated their multiple objective dynamic congestion pricing problem into a mathematical program with equilibrium constraints. The vehicular emissions are estimated based on a macroscopic function of speed only. The result demonstrates the ability of the optimal tolling scheme design in reducing both total travel time and emissions. Wen and Eglese (2016); Whitham (1974) investigated the effects of different road toll strategies on minimizing total time and CO_2 emissions on two alternative routes through a bi-level pricing model. A macroscopic fuel consumption function depending on speed is incorporated into the model, in combination with a simplified simple queueing model for delay estimations together with a free-flow traffic assumption. Their finding reveals that the multiple step toll pricing strategy and the time-varying toll pricing strategy outperform the constant toll pricing strategy in terms of CO_2 emission mitigation. With the technology advances in intelligent transportation systems, the easier implementation of multiple step and time-varying tolling strategies make their finding more of practical significance. However, such results cannot be generalized unless a more accurate traffic flow model is

Table 5
Dynamic road pricing studies considering emissions.

	Pricing focus	Travel choice(s) considered (and the travel choice principle)	Pricing scheme	Network loading model	Emission model	The largest network used
Zhong et al. (2012)	Congestion with link emission constraints	Route and departure time (DUO under pricing based on internalizing the external cost)	First best	Macroscopic The whole link model (FIFO) and deterministic queuing model (two vertical queue models)	Average-speed model An emission rate function dependent on average vehicle speed, traffic flow, aggregate emission factor, and link length, and a dynamic dispersion model (i.e., the operational street pollution model)	Two parallel links (single O-D pair)
Friesz et al. (2013a)	Congestion and emissions (CO, NO_x, HC)	Route and departure time (simultaneous route-and-departure choice DUO proposed by Friesz et al. (1993))	Second best	Macroscopic The LWR-Lax model	Average-speed model Speed-related emission function in the emission factor model by CARB (2000)	6 links and 5 nodes (2 O-D pairs)
Kickhöfer and Nagel (2016, published online 2013)	Congestion and emissions (SO_2, $PM_{2.5}$, NO_x, non-methane hydrocarbons (NMHC), and CO_2)	Route and mode (DUO, minimizing traveler's route utility; logit model for mode choice)	First best	Microscopic MATSim	Traffic situation model The MATSim-HBEFA tool developed by Hülsmann et al. (2011)	Munich metropolitan area (17,888 nodes and 41,942 links)
Kickhöfer and Kern (2015)	Congestion and emission exposure cost (SO_2, $PM_{2.5}$, NO_x, NMHC, and CO_2)	Route and mode (the principle is the same as above)	First best	Microscopic MATSim	Traffic situation model The same as Kickhöfer and Nagel (2016, published online 2013)	Munich metropolitan area (17,888 nodes and 41,942 links)
Wen and Eglese (2016)	Congestion or emissions (CO_2) to be optimized individually	Route and departure time (DUO)	Second best	Macroscopic A standard (M/M/c) queuing model (i.e., random arrival, random service, and c service channels)	Average-speed model Fuel consumption model (Department of Transport, 2009) and conversion factors from fuel consumption to the CO_2 emissions and fuel cost	Two parallel links
Ma et al. (2017)	Congestion and emissions (CO and fuel consumption as a proxy for overall emissions)	Route and departure time (DUO)	First best	Macroscopic Double queue model	Average-speed model Dynamic extensions of the model by Wallace et al. (1998) and the model by Boriboonsomsin et al. (2012)	2 hypothetic networks and Sioux Falls network (single destination)

adopted and used on a larger network. By extending the static emission model by Wallace et al. (1998) under a monotonicity assumption, Ma et al. (2017) sought for and examined the first-best emission pricing through the existence of a free flow dynamic system optimal solution where the generalized system cost including total travel times and emissions were minimized. Their results also show the importance of the free-flow (uncongested) traffic state in developing network pricing schemes and managing traffic congestion, emissions/fuel consumption, and other related issues. One may focus on the free-flow traffic state in a network and devise pricing schemes and other management strategies to sustain such free-flow state. This not only is beneficial to the network as a whole from the perspective of congestion and emission control but also leads to simplified dynamic network models (since traffic dynamics are much simpler under the free-flow traffic state) so that the optimal pricing scheme or other strategies can be much easily calculated.

It can be concluded from Table 5 that static emission models (e.g., aggregate emission models, average speed models) are still widely adopted to access the effect of emissions due to their nice mathematical properties (continuity, monotonicity, etc.) in this research area. Most of the emission pricing strategies have compromised the accuracy of emission estimates for mathematical tractability to a large extent. However, whether such emission estimates without capturing traffic dynamics are adequately accurate for emission pricing design remains doubtful. Though a balance has to be stricken between mathematical complexity and the realism of the emission function (Ma et al., 2017), more detailed emission models for the better representation of traffic dynamics (e.g., mesoscopic emission models) can still be considered within such an analytical modeling framework. Moreover, the analytical models or the methodologies in general reviewed are all tested on either hypothetic or small networks. A road toll pricing model for a larger network has not been undertaken yet and is of vital significance for generality and applicability.

Emission tolls can be charged by toll facilities. Therefore, a number of studies have contributed to the analysis and modeling of emission impacts on toll facilities, especially electronic toll collection (ETC) plazas (e.g., Sisson, 1995; Klodzinski et al., 1998; Saka et al., 2001; Bartin et al., 2007). Field measurements and simulation results have revealed that ETC technology is an effective tool in reducing emissions in areas where toll facilities are deployed, by decreasing the number of stop-and-go situations (Coelho et al., 2005). Hence, ETC can be viewed as an effective tool for minimizing the deleterious effect of the stops on pollutant emissions.

5. Future research directions

After reviewing the recent integration studies of DTA and emission models, some gaps in the literature are discovered. This section proposes a few future research directions from the aspects of modeling approaches, solution methods, and applications.

5.1. Modeling approaches

5.1.1. DTA modeling

For DTA modeling, three future directions can be identified. First, recent studies (Geroliminis and Daganzo, 2008; Yildirimoglu and Geroliminis, 2014; Leclercq et al., 2014) have demonstrated that the low-scattered Macroscopic Fundamental Diagram (MFD) shows promising results in modeling the complex dynamics of urban congestion. MFDs have also been incorporated into DUO assignment (Yildirimoglu and Geroliminis, 2014). Yet its extensions to DSO with respect to system travel time or the combination of system travel time and emissions has not been found (see Table 3). These extensions provide useful benchmarks for developing more environmentally friendly real-time traffic control and demand management strategies. Fruitful future analytical studies can be performed in this direction.

Second, as reflected in Table 3, existing DTA models with environmental objectives are developed based on the deterministic setting using classical deterministic traffic flow models. However, in reality, demand and supply stochasticity are often observed but have not considered in DTA with environmental objectives yet. Therefore, one direction can be to encapsulate existing traffic flow models/network loading procedures (e.g., SCTM) or improve existing traffic flow models/network loading procedures (e.g., LTM) to deal with supply uncertainty and use existing stochastic programming or chance constraint techniques to deal with demand stochasticity. Another direction is to develop modeling approaches to deal with uncertainties associated with MFDs.

Third, though the integration between traffic simulation models and emissions models have become a fast-evolving research area as can be seen in Table 4, a study by Song et al. (2012) has identified the deficiency of microscopic traffic simulation models integrating instantaneous emission models for emission estimations. The observed systemic errors are primarily due to the fact that the VSP distribution, which is the best explanation of vehicle emissions, is not sensitive to the common parameters used for calibrating or validating traffic simulation models (Song et al., 2012). Therefore, future studies are needed for improving the accuracy of characterizing traffic dynamics by further investigating the internal mechanism of simulation models such as car-following, deceleration, and acceleration models, so that the VSP distribution can be more accurately predicted by integration studies.

5.1.2. Cross-resolution integrated modeling

To get a balanced trade-off between computational complexity and accuracy, the cross-resolution integration of macroscopic traffic flow models and microscopic emission models is worth investigating. The interfacing process requires transform of macroscopic traffic variables (e.g., average density, average flow, and average speed) into mesoscopic/microscopic ones, or the approximation of a macroscopic relationship between aggregate emissions rates and macroscopic traffic quantities (e.g., link occupancy). Recent advances in the development of macroscopic statistical emission models, speed profile generation models, and trajectories reconstruction models have been successfully achieved (e.g., Zegeye et al., 2013; Skabardonis et al., 2013; Shabihkhani and Gonzales, 2013; Sun et al., 2015; Zhou et al., 2015; Chen et al., 2016; Chen et al ., 1998). The computational efficiency makes it particularly appealing in the evaluation or design of various traffic management strategies concerning emissions. Nevertheless, there are non-negligible errors associated with such a simplification or approximation. Future research should also be carried out to further calibrate and validate the proposed models with more real-world congestion and emission data.

5.1.3. Integration with pollutant concentration models

Currently, the common measure for quantifying the impacts of vehicular emissions is the weight of pollutants emitted. The measures of the impacts of vehicular emissions can also be spatial distribution, air quality index, personal exposure, and individual vulnerability. The social and economic dimensions of such measures are of vital importance when it comes to meeting air quality goals, the assessment of health risks, and addressing health equity issues. Few reviewed studies (e.g., Zhong et al., 2012; Zhang et al., 2013) have incorporated an air dispersion model into their work. Most studies focus on tailpipe emissions, and either do not calculate or fail to do so at a sufficient temporospatial granularity the impacts of the emissions on air quality and public exposure. Local pollutant concentrations are dependent on a number of factors such as the weather, chemical processes, non-transport sources, and canyon effects. Fontes et al. (2015) confirm the inadequate modeling efforts found in transportation studies that focus on the pollutant concentration and health impacts of traffic. Existing methods based on Gaussian plume dispersion models (e.g., Zhang et al., 2013) rely on the stationarity assumption, and can only work with annual averages of weather conditions and pollutant concentrations. Hybrid approaches combining road link dispersion modeling with city-scale chemical transport modeling (e.g., Stein et al., 2007) have been used to predict air quality index (e.g., Beevers et al., 2012; Yim et al., 2013). However, emissions from non-transport sectors are not accounted for in these studies. A potentially viable yet data-intensive approach concerns with fusing multiple data sources and performs high-dimensional regression. This approach has been used by Zheng et al. (2013) and should be further explored in the future.

5.1.4. Heterogeneity in modeling

In emission modeling (except the aggregate modeling approach), heterogeneity in vehicle categories (e.g., diesel- or gasoline-driven vehicles, light-duty or heavy-duty vehicles) and the emission patterns of pollutants are generally taken into account. However, in most integrated studies reviewed in Section 4, the driver and vehicle populations are aggregated to a coarse level of detail (e.g., homogeneous) for simplicity. Since the emission rates of different types of vehicles differ significantly under the same driving condition, such negligence of vehicle heterogeneity might result in the non-optimal design of transportation strategies. The network loading model/procedure in these studies should be modified to, for example, a multiclass CTM, to capture different vehicle types while taking into account the effects of spatial queues such as queue spillback. Moreover, a multiclass LTM can be developed to replace the multiclass CTM to speed up the computation time. For those integrated studies with the consideration of different vehicle types, they do not take the cleaner fuel (e.g., natural gas) vehicles into emission modeling, which is gaining higher penetrations as a sustainable solution to reduce emissions. Such cleaner fuel vehicles produce significantly fewer PM, CO_2, and NO_x emissions and their specific populations and emission rates should be considered for more realistic modeling.

Besides different vehicle types, emissions from different road transportation modes are worth further investigation. Intuitively, road public transit (i.e., buses) is often considered as an environmentally friendly alternative to cars in light of its positive impact on the reduction of emissions with a higher passenger car unit. However, recent microsimulation studies have indicated that though bus trips are more fuel efficient than car trips on average, buses could be as polluting as private cars on a per passenger basis under low ridership situations (Lau et al., 2011). Similar to cars, buses generate higher emissions in congested networks as well, due to lower speeds, higher frequency of acceleration and deceleration events, and higher dwell times at stops (Alam and Hatzopoulou, 2014). It is also pointed by Waraich et al. (2016) that there is a paucity of literature that quantifies and understands the emissions generated by public transit on the disaggregate level. Hence, it is important to develop a multi-modal DTA model to take into account the vehicle dynamics of different public transit modes for more accurate emission estimations and analysis. However, the integrated study of multi-modal DTA and emission models are hardly found. Moreover, the realistic mode choice of travelers and passenger flow dynamics should be considered in that model for improving emission estimation accuracy. The conceptual modeling approach proposed by Chiabaut (2015) can be a basis for this future research direction.

Besides heterogeneity in road transportation modes, heterogeneity in route choices in traffic modeling is worth addressing. Urban transportation systems consist of different vehicle types, each of which has different routing behaviors for various purposes. For example, vacant taxis tend to cruise slowly to search for taxi customers whereas occupied taxis tend to go to their customer destinations as quick as possible. Moreover, car drivers on freeways travel at their highest speed whenever possible whereas they cruise slowly for searching parking spaces. Their travel behavior determines travel speed which in turn determines emissions. In fact, it has been indicated that a great part of taxi emissions are emitted from non-service cruising for passengers and vary significantly depending on the time of day (Yu and Peng, 2013). It is therefore important to capture their behavior into a dynamic integrated model for an accurate prediction of emissions. Yet this line of research has not been found. Meanwhile, different vehicles interact in the same road space and their traffic dynamics and interactions must be duly considered. Hence, one future direction is to develop a dynamic integrated model with the consideration of various routing behaviors (e.g., taxis cruising for passengers, cars cruising for parking, etc.) and the traffic dynamics of different vehicles in a network for enhancing environmental sustainability. Using MFDs to model taxi traffic movements can be a good starting point as taxi traffic is often scattered over a large area.

5.1.5. Developing traffic control measures towards traffic noise reduction

According to World Health Organization (2011), the noise pollution damages, mostly from road traffic, make it second only to air pollution in terms of environmental hazards. The dynamic approach for calculating noise levels and population exposures is of vital importance due to the within-day dynamics of varying population densities. Moreover, Chevallier et al. (2009) demonstrated that traffic dynamics have a substantial impact on noise levels at signalized intersections and roundabouts. Kaddoura et al. (2017) indicated that implementing traffic control measures, such as reduced speed levels, turn restrictions or pricing schemes, possibly allow for a reduction in noise exposures. However, besides the dynamic pricing approach internalizing road traffic noise damages proposed by Kaddoura et al. (2016, 2017), noise predictive models are not yet widely integrated with DTA models for designing traffic control measures. Further work is expected in developing traffic control measures towards traffic noise reduction, along with other measures of effectiveness simultaneously, such as congestion and emissions. Such integration studies can be assisted with the critical reviews on principal noise models by Steele (2001), Quartieri et al. (2009), and Garg and Maji (2014).

5.2. Solution methods

Because modeling environmental considerations typically result in highly nonlinear and nonconvex objective or constraint functions (see Section 3.2 and Table 4), heuristic methods have been applied to solve these types of problems (as seen in Table 4). Besides genetic algorithm, various meta-heuristics, such as chemical reaction optimization (Lam and Li, 2010), have been proposed and proved to be efficient in tackling nonlinear, nonconvex problems. The application of hybrid or multi-objective variants of such meta-heuristics to solve nonlinear, nonconvex problems with environmental considerations may be another future research direction. Moreover, effective parallel and distributed algorithms or computing platforms possess the potential of cutting down the runtime and are worth to be implemented in the future. Furthermore, running time can be shortened by developing effective surrogate models for time-consuming DTA or simulation models. This solution approach has only been recently considered in the field of dynamic environmental sustainability by Osorio and Nanduri (2015a,b). There is a great potential for this line of research.

5.3. Applications

5.3.1. Dynamic traffic management strategies

Besides dynamic traffic signal control considered in Section 4.1, there are various dynamic traffic management strategies such as variable message sign (VMS) or dynamic route information panel (DRIP), variable speed limits, dynamic road marking, and ramp metering, whose effects on vehicular emissions are also significant. Currently, only limited research has evaluated the impacts of the emissions imposed by ramp metering (e.g., Csikós and Varga, 2012; Zegeye et al., 2013; Pasquale et al., 2015), variable speed limits (e.g., Zegeye et al., 2010), and traffic-calming measures (e.g., Ghafghazi and Hatzopoulou, 2014, 2015). However, the design of these dynamic traffic management strategies has rarely found. Moreover, the average speed emission model is mostly adopted in all these evaluation studies for simplicity. It was advocated by Panis et al. (2006) that the analysis of the environmental impacts of any traffic management and control policies requires not only their impact on average speeds but also on other aspects of vehicle operation such as acceleration and deceleration. Hence, it is anticipated that further improvements in both the performance evaluation and design of dynamic traffic management strategies can be made by incorporating more realistic and accurate emission models in the aforementioned applications.

5.3.2. Transport demand management

In terms of transport demand management, dynamic emission pricing has been mainly researched and the studies have been reviewed in this paper. According to these studies, three future research directions on emission pricing can be identified. First, as stated in Section 4.2, the analytical models or the methodologies are all tested on either hypothetic or small networks. More effort should be put to develop a road emission toll pricing model for a larger, more realistic network so as to apply the model to more general situations.

Second, the reviewed models and methodologies are based on traditional traffic flow models. MFDs have not been used in this application. In fact, MFDs have been successfully applied to examine congestion pricing (Zheng et al., 2012; Simoni et al., 2015), parking (Geroliminis, 2015; Zheng and Geroliminis, 2016), and signal control (Gayah et al., 2014). MFDs should be a great potential to be used in emission pricing studies.

Third, emissions are just one of the environmental externalities but dynamic environmental other than emission pricing studies have not been found. To internalize the environmental externalities more accurately, other environmental externalities, such as traffic noise, must be duly considered in the pricing strategies. Therefore, one research direction is to extend the analysis of the current dynamic emission pricing studies to consider other environmental externalities.

Apart from the dynamic emission pricing studies reviewed, there are a number of transport demand management strategies playing a prominent role in achieving vehicular emission reduction targets. By reducing travel demand or the number of vehicles on roads, emissions from excessive acceleration and deceleration induced by congestion can significantly decrease. With the development of communication technology, more platforms for ride matching are provided to facilitate dynamic and on-demand ridesharing (including carpooling) systems, leading to a reduction of the number of vehicles on roads. These problems involve not only the complex optimization of dynamic matching (Agatz et al., 2012) but also travelers' behaviors (e.g., route choice, scheduling) in traffic assignment (Furuhata et al., 2013). It is believed that great research opportunities are provided by this emerging area of environmentally sustainable transportation. For example, a comprehensive evaluation of the environmental impacts of such dynamic ridesharing involving routing and scheduling using a DTA framework has not yet been performed.

5.3.3. Autonomous vehicles

As autonomous driving capabilities (e.g., adaptive cruise control, lane keeping, and self-parking) become increasingly widespread, the future of fully autonomous vehicles seems more certain. This technology has the potential to reduce traffic congestion and emissions and improve safety. Autonomous vehicle technology makes driving patterns more efficient without the need for frequent brakes or acceleration and averts traffic accidents that cause severe traffic jams. The revolutionary changes brought by this technology are undeniable, especially its impacts on the travel behaviors, which will reshape the traffic flow modeling for future transportation problems. Future study is required to calibrate the associated roadway parameters (e.g., capacity, free-flow speed, and jam density) and modify the traffic propagation mechanism (or the network loading model in general) for autonomous vehicles. To further provide a framework for studying the environmental impacts of autonomous vehicles on road networks, more development on DTA models for autonomous vehicles (e.g., Levin and Boyles, 2016) is eagerly anticipated.

5.3.4. Electric/hybrid electric vehicles

Since electric vehicles do not generate pollutants on a local level (e.g., roadside emissions) and can potentially rely on energy from a selection of renewable sources (Millo et al., 2014), they are regarded as a valuable solution to environmental sustainability. The hybrid electric vehicles can also lead to a certain level of the environmental benefits of electric vehicles for a short distance. Despite continuous development in battery technology, the charging time and driving range are still considered as barriers to its popularization. The traffic assignment for electric vehicles will be further constrained by driving range and availability of charging infrastructures. To our best knowledge, a DTA model with path distance constraints for electric vehicles remains undeveloped; so do the corresponding solution algorithms.

5.3.5. Transportation planning

Transportation planning is long recognized as an important issue and involved with the design and siting of transport facilities (generally streets, highways, bike lanes, and public transport lines) as well as highway expansion or construction. Such transportation network design problems have been extensively studied using STA models in the literature (see Farahani et al., 2013). These problems have also been researched using DTA models (e.g., Janson, 1995; Waller and Ziliaskopoulos, 2001; Heydecker, 2002) but with less attention. DTA models can account for traffic dynamics and time-variant demand. The traffic flow modeled by DTA can be consistent with the kinematic wave theory, taking traffic interaction among adjacent links into account. Hence, DTA models can provide more realistic traffic flow data as inputs for a more accurate emission estimation. Moreover, the time-variant demand consideration is crucial for proposing different emission mitigation measures realistically. Conducting a comprehensive road network design that combines DTA models with the consideration of environmental issues will be a natural evolution in the transportation research field. Extensions to multimodal network design including green transport and public transit modes is also another future research direction.

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