Chapter 15
Green Vehicle Routing

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15.1 ▪ Environmentally Sustainable Routing

Transport services enable economic growth but at the same time have negative environmental impacts including land use, *Greenhouse Gas* (GHG) emissions, pollution, noise, summer fog, and toxic effects on the ecosystem such as acid rain. According to the TERM 2011 Report published by the European Environment Agency, transport (including international maritime) contributed 24% of the overall GHG emissions in the EU-27 countries in 2009, with road transport accounting for 17% of the total GHG emissions (see Vicente [58]).

The focus of this chapter is to review and explore a new and a growing line of research, namely "green" logistics, and in particular "green" vehicle routing, which aims to minimize the harmful effects of transportation on the environment. The main concern of this chapter is to look at vehicle routing models where environmental issues are taken into account on top of the normal economic issues, primarily at an operational level of decision making. Emphasis will be placed on modeling rather than solution methods, which are often modifications of existing methods covered elsewhere in this book. Two related areas of research which fall under the broad area of green logistics, namely routing of hazardous materials and waste collection, will be excluded from this chapter (see, e.g., Ghiani et al. [29]). Although problems arising in such contexts are related to the environment, the hazards or recycling issues are associated with the commodities being transported rather than the environmental effects of transportation per se. We refer interested readers to the general surveys by Sbihi and Eglese [50] and Dekker, Bloemhof, and Mallidis [12] for other types of problems not covered here. Similarly, we do not cover the broad field of green supply chain management, which encompasses a wide variety of activities from product design and material sourcing to manufacturing and remanufacturing but is clearly beyond the scope of this chapter. Interested readers can refer to Srivastava [52] for a review of the literature on green supply chain management.

15.1.1 ▪ External Costs of Transportation

The environmental damage caused by transportation activities has long been recognized since the 1950s (see McKinnon [40]), although no significant work addressing this issue was done until the early 2000s. The most prominent environmental impacts of freight transportation are as follows:

- *Atmospheric emissions.* This is due to combustion engines used in goods vehicles which, while converting fuel into energy, emit pollutants such as CO, CO_2, NO_X, and particulate matter. These pollutants have harmful effects on humans (e.g., respiratory problems and asthma) and the environment (e.g., acid rain and summer fog) (see Cullinane and Edwards [11]).
- *Noise pollution.* The three sources generating noise are propulsion, tyre/road contact, and acceleration (see Cullinane and Edwards [11]). Noise from a vehicle's power unit comprising the engine, air intake, and exhaust becomes dominant at low speeds of 15–20 mph and at high acceleration rates of 2 m/sec^2 (see Knight, ed.) [37]). Annoyance, communication difficulties, and loss of sleep are some of the negative consequences on human life, although road vibrations caused by very heavy vehicles might also damage the neighboring buildings over time.
- *Accidents.* Road traffic accidents are responsible for personal injuries and death.

McKinnon [40] identifies nine factors as being critical for reducing the externalities of logistics activities. These are modal split, average handling factor, average length of haul, vehicle utilization (average payload and empty running), energy efficiency, emissions, other externalities which cannot be measured through energy use (e.g., noise and accidents), and monetary valuation of externalities. Although it is, in general, difficult to calculate the exact external costs of transportation, estimations exist. For intercity truck freight transportation, Forkenbrock [26] proposes four general types of costs: accidents, emissions, noise, and those associated with the provision, operation, and maintenance of public facilities. Forkenbrock [27] presents a similar analysis for freight trains and compares this to external costs of trucking. The general conclusion is that the external costs of trucking are over three times that of freight trains.

Of the different types of externalities mentioned above, a review of the emerging literature on "green" vehicle routing shows an increasing trend in looking at emissions and fuel consumption and their minimization in operational route planning (see Eglese and Black [18]). This is not surprising given the detrimental consequences of GHG emissions, a by-product of fuel usage, not to mention the implications of fuel on the economy. We now turn our attention to this body of research and first show how fuel consumption and emissions can be estimated, and then discuss how they can be accounted for within the traditional approaches for the VRP.

15.2 ▪ Fuel Consumption and Emission Models for Road Transportation

The amount of CO_2 emitted by a vehicle is directly proportional to fuel consumption. In the literature, two ways to estimate fuel consumption for vehicles have been suggested: *on-road measurements*, which are based on real-time collection of emissions data on a running vehicle, and *analytical fuel consumption* (or *emission*) models, which estimate fuel consumption based on a variety of vehicle, environment, and traffic-related parameters, such as vehicle speed, load, and acceleration. In this section, we briefly review some of the analytical models described in the literature. The reader is referred to Ardekani, Hauer, and Jamei [1], Esteves-Booth et al. [21], and Boulter, McCrae, and Barlow [6] for general reviews of vehicle emission models.

Analytical models for fuel consumption can be broadly classified into three classes, namely (i) emission factor models, (ii) average speed models, and (iii) modal (including instantaneous) models (see Esteves-Booth et al. [21]). Emission factor models are the simplest in form and are used at a macroscale level (regional or national emission estimations), particularly when data related to a vehicle's journey are limited. These models use an emission factor often expressed per unit of distance. Average speed models are speed-related functions to estimate emissions at a road network scale and do not include detailed enough parameters for an analysis at a microscale level. Finally, modal models operate at a higher level of complexity, specific enough for use at a microscale level and use detailed inputs, such as acceleration and road gradient, which are drawn from a running vehicle engine even on a second-by-second basis. As emission factor models are rather simplistic with major disadvantages such as their inability to represent driving cycles with good accuracy, we will restrict our review below only to the last two classes of models but refer the interested readers to Esteves-Booth et al. [21] for a detailed exposition of emission factor models.

15.2.1 ▪ Average Speed Models

In this section, we will present two models for estimating emissions which are primarily based on speed and are obtained using regression techniques. The first of these is due to the MEET report published by the European Commission (see Hickman et al. [31]), where the authors present the following general expression to calculate the rate of emissions $E(v)$ (g/km) for an unloaded goods vehicle on a road with a zero gradient as a function of the average speed v of the vehicle (km/h):

$$E(v) = \zeta_0 + \zeta_1 v + \zeta_2 v^2 + \zeta_3 v^3 + \zeta_4/v + \zeta_5/v^2 + \zeta_6/v^3, \tag{15.1}$$

where ζ_0–ζ_6 are predefined coefficients for different types of vehicles classified according to their weight. The MEET report describes similar functions for correction factors for additional aspects, such as gradient and load, to be applied to $E(v)$. As an example, the rate of emissions according to the MEET report for a vehicle of less than 3.5 tonnes weight is given by $E(v) = 0.0617v^2 - 7.8227v + 429.51$. Another average speed model, namely COPERT described by Ntziachristos and Samaras [42], is similar to the MEET report in that it also describes an emissions model based on regression with speed as the primary determinant. The COPERT model describes two models for estimating emissions, to be used for vehicles of different classes and speed ranges. In particular, if the vehicle speed $v \in [0, v^*]$ for a given v^*, then $E(v) = Kv^{-\delta}$; otherwise $E(v) = K + av + bv^2$. As an example, for a vehicle with weight between 3.5 and 7.5 tonnes, $E(v) = 1425.2v^{-0.7593}$ if $v \le v^* = 47$ km/h, and $E(v) = 60.12 - 0.0430v + 0.0082v^2$ otherwise.

15.2.2 ▪ Instantaneous Models

The models in this category only deal with "hot" emissions, i.e., exhaust emissions of a running engine, and aim to estimate emission rates of an operating vehicle for short time intervals of its driving cycle, e.g., on a second-by-second basis. As these models require detailed and precise measurements for an operating vehicle, which are often difficult and costly to collect, these models have been claimed to be of restricted use to the research community (see Boulter, McCrae, and Barlow [6]). Below, we review some of these models.

An energy-related emissions estimation model, called the *instantaneous fuel consumption model*, or *instantaneous model* in short, is described by Bowyer, Biggs, and Akçelik [7]. The model uses vehicle characteristics such as mass, energy, efficiency parameters, drag force, and fuel consumption components associated with aerodynamic drag and rolling resistance and approximates the fuel consumption per second. The model assumes that changes in acceleration and deceleration levels occur within a one second time interval. The instantaneous model is

$$f_t = \begin{cases} \alpha + \beta_1 R_t v + \beta_2 M a^2 v/1000 & \text{for } R_t > 0, \\ \alpha & \text{for } R_t \leq 0, \end{cases} \tag{15.2}$$

where f_t is the fuel consumption per unit time (mL/s), α is the constant fuel consumption rate of an idle running engine (mL/s), and R_t is the total tractive force (kN = kilonewtons) required to move the vehicle and calculated as the sum of force induced by drag, inertia, and road grade. In this function, β_1 is the fuel consumption per unit of energy (mL/kJ) and β_2 is the fuel consumption per unit of energy-acceleration mL/(kJ m/s^2). The grade force R_t is further calculated as $R_t = b_1 + b_2 v^2 + Ma/1000 + gM\theta/100000$, where b_1 is the rolling drag force (kN), b_2 is the rolling aerodynamic force kN/(m/s^2), a is instantaneous acceleration (m/s^2), M is the total vehicle weight (kg), v is the speed (m/s), θ is the percent grade, and $g = 9.91$ (m/s^2) is the acceleration due to gravity. The model operates at a microscale level and is better suited for short trip emission estimations. Although this version of the model presented above does not use macro-level (aggregated) data such as the number of stops, an aggregated version suitable for longer journeys, as well as a more detailed version for more accurate estimations also appear in Bowyer, Biggs, and Akçelik [7]. The three versions differ with respect to the number of parameters required for estimation.

A more *Comprehensive Modal Emissions Modeling* (CMEM) is described by Scora and Barth [51], and details for heavy-duty vehicles (vehicles with a maximum operating mass of 11,794kg or above) are given in Barth, Younglove, and Scora [3]. According to this model, the fuel rate (g/s) is estimated by the following expression:

$$FR = \phi(\bar{k}\bar{N}\bar{V} + P/\eta)/\varkappa, \tag{15.3}$$

where ϕ is fuel-to-air mass ratio, $\bar{k}$ is the engine friction factor, $\bar{N}$ is the engine speed, $\bar{V}$ is the engine displacement, P is the second-by-second engine power output (kW), η is an efficiency parameter for diesel engines, and $\varkappa$ is a constant. Engine speed $\bar{N}$ is approximated by the vehicle speed v (m/s) as $\bar{N} = S(R(L)/R(L_g))v$, where S is the engine-speed/vehicle-speed ratio in top gear L_g, and $R(L)$ is the gear ratio in gear $L = 1, \ldots, L_g$. The engine power output P, on the other hand, is calculated as $P = P_t/\eta_t + P_a$, where η_t is the vehicle drive train efficiency, and P_a is the engine power demand associated with running losses of the engine and the operation of vehicle accessories such as usage of air conditioning. The total tractive power requirement placed on the vehicle at the wheels is shown by P_t (kW), which is further calculated as follows:

$$P_t = (Ma + Mg\sin\theta + 0.5C_d\rho\bar{A}v^2 + MgC_r\cos\theta)v/1000. \tag{15.4}$$

As seen from (15.4), P_t depends on a variety of parameters, including air density ρ (kg/m^3), frontal surface area of the vehicle $\bar{A}$ (m^2), coefficients of aerodynamic drag C_d, and rolling resistance C_r, in addition to those already defined above.

To give the reader an idea of the way in which some of these emission models behave, we present Figure 15.1. This figure shows the total amount of fuel consumption for a 6350kg vehicle traveling on a distance of 10 km in the vertical axis estimated by MEET and CMEM, with values of speed varying from 20–110 km/h, and assuming zero acceleration and road gradient.

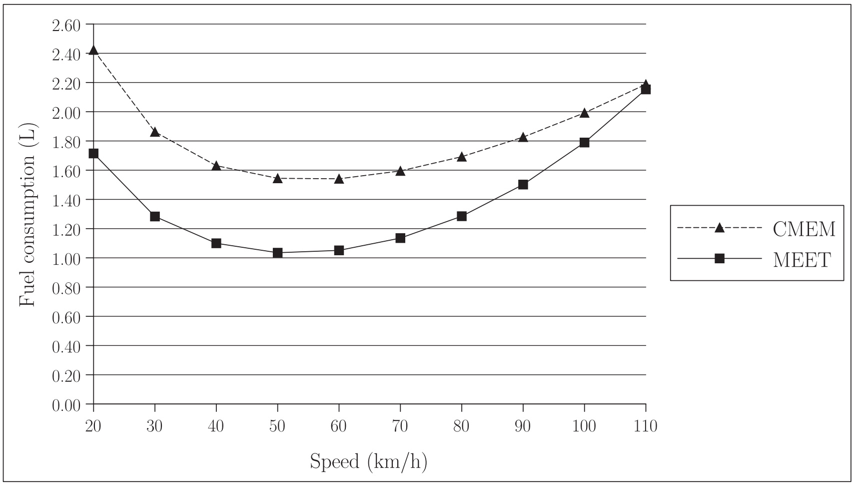

Figure 15.1. *Change of fuel consumption with speed.*

The two curves shown in Figure 15.1 are typical of the behavior of fuel consumption vs. speed and show an "optimal" speed which minimizes the total consumption. The shape of these curves changes with factors such as vehicle type, weight, acceleration, and road gradient. The reader is referred to Demir [13] and Demir, Bektaş, and Laporte [14] for a numerical comparison of a number of such models.

15.3 ▪ Minimizing Emissions in Vehicle Routing

A first line of research in accounting for emissions or fuel consumption in the VRP initially started out by looking primarily at vehicle weight as the sole determinant of emissions and the optimization thereof. Later work focused on speed optimization, mostly in combination with vehicle weight, although a number of papers have taken into account other factors as well. Some work also looked at the effect of time dependency. This section will review the work along these lines and will use the classification presented in Table 15.1 as the basis of the structure of the review.

The models presented in the remainder of the chapter will use the following notation. We are given a complete undirected graph $G = (V, A)$, where $V = \{0, \ldots, n\}$ is the set of nodes, 0 is a depot, and $A = \{(i, j) : i, j \in V \text{ and } i \neq j\}$ is the set of arcs. The distance from i to j is denoted by d_{ij}. A fixed-size fleet of vehicles denoted by the set K is available, and each vehicle has capacity Q. The set $N = V \setminus \{0\}$ is a customer set, and each customer $i \in N$ has a non-negative demand q_i as well as a time interval $[a_i, b_i]$ in which service of s_i time units long must commence.

15.3.1 ▪ Time-Independent VRP

Time independency in the context of the VRP implies an assumption that the problem data, in particular travel times between pairs of nodes, does not change with time. In this

Table 15.1. *Classification of "green" vehicle routing*

	Time-independent	*Time-dependent*
Speed fixed	Kara, Kara, and Yetiş [36] Palmer [43] Tavares et al. [54] Suzuki [53] Ubeda, Arcelus, and Faulin [56] Xiao et al. [59]	Kuo [38] Eglese, Maden, and Slater [19] Maden, Eglese, and Black [39] Conrad and Figliozzi [9] Figliozzi [24] Figliozzi [25]
Speed variable	Bektaş and Laporte [5] Demir, Bektaş, and Laporte [15]	Franceschetti et al. [28] Jabali, Van Woensel, and de Kok [34] Qian [46]

section, we review studies on green vehicle routing where this assumption is maintained. In accordance with the classification presented in Table 15.1, we first review approaches assuming constant speeds in the next section and then look at those with variable speed in the subsequent section.

15.3.1.1 ▪ Constant Speeds

Kara, Kara, and Yetiş [36] introduce the *Energy-Minimizing Vehicle Routing Problem* (EMVRP) as an extension of the *Capacitated Vehicle Routing Problem* (CVRP), where a weighted load function (load multiplied by distance), rather than just the distance, is minimized. The authors present a model for this problem that is based on a flow formulation of the VRP with a load-based objective function derived from simple physics. Xiao et al. [59] present a similar but slightly extended version of the EMVRP by factoring the fuel consumption rate of a vehicle, defined primarily with respect to the weight of the vehicle, into a standard flow-based CVRP formulation. The authors also propose a solution algorithm based on simulated annealing for this problem and report computational results on benchmark instances. Neither Kara, Kara, and Yetiş [36] nor Xiao et al. [59] consider speed as a factor in the development of their models and do not assume any time-window constraints. Palmer [43] extends this line of study by presenting an integrated routing and emissions model for freight vehicles and investigates the role of speed in reducing CO_2 emissions. The model uses a known *Vehicle Routing Problem with Time Windows* (VRPTW) heuristic as a black-box solver to produce the routing plans within the model, where speeds, as well as acceleration and deceleration, are inputs to the model rather than optimized outputs. Testing the approach on a case study of grocery stores in the UK concerning home deliveries, Palmer [43] finds that an average saving of 4.8% in

CO_2 emissions can be achieved over routes that only minimize time, but at the expense of an average increase in time by 3.8%. A smaller saving of 1.2% in CO_2 emissions can also be obtained on average compared to distance-minimizing routes, but at the expense of a 2.4% increase in distance. The work by Palmer [43] is the first to look at the effect of speeds in vehicle routing planning, although his approach does not optimize speeds but rather uses them as fixed inputs for calculating a matrix of "least cost" routes where cost might correspond to emissions. His approach does not account for vehicle loads either.

Suzuki [53] presents three formulations for a single-truck routing problem as variants of an assignment-based formulation of the TSP with time windows. The first of these formulations minimizes the total distance traveled. The other two both aim to minimize fuel consumption, but differ in the way in which this quantity is estimated. In particular, the second formulation calculates fuel consumption as a function of a vehicle's speed, whereas in the third formulation it is measured by payload and waiting time at customers. In this approach, the vehicle's fuel consumption rate (mpg) has been modeled through the regression function in the form of (15.1) with $\zeta_2, \ldots, \zeta_6 = 0$ and ζ_0, ζ_1 estimated as 2.82 and 0.07, respectively, based on data provided by US Department of Energy in 2009 on heavy-duty trucks. The vehicle speed v is provided as an exogenous parameter. The second formulation uses a similar function to estimate fuel consumption, but has payload instead of speed. Simulation results provided by Suzuki [53] indicate that the third formulation yields the highest savings in fuel consumption, suggesting that delivering heavy items earlier on in a tour is worthwhile in reducing fuel requirements.

Pradenas, Oportus, and Parada [44] extend the modeling approach put forward by Bektaş and Laporte [5] to the VRP with backhauls, in which customers are either of type linehaul or backhaul, and, in each route, the latter type should be served only after the former have been visited. A mixed integer programming formulation of the problem is presented, although the problem itself has been solved using a scatter search algorithm where speeds are treated as constant. Computational results obtained on standard benchmark instances suggest that savings of around 2% in GHG emissions can be obtained at the expense of an increase of 2–8% in operational costs. An interesting feature of this study is to incorporate cooperation among transport companies as a means to reduce emissions and use Shapley's value to calculate the value of a coalition.

Case studies using time-independent approaches for fuel and emission minimization in the context of vehicle routing have been presented by Tavares et al. [54] and Ubeda, Arcelus, and Faulin [56]. The former study is based on optimization of municipal solid waste in Cape Verde with an aim to minimize fuel consumption, the estimation of which is done through the use of the emissions function described in Ntziachristos and Samaras [42]. For short-distance waste collection, the authors report fuel savings of 9%, which implies only a small increase of 0.2% in the distance traveled. As for long-distance waste collection, savings of 52% can be achieved in fuel but at an increase of 34% in the distance traveled. The latter study looks at the use of emission factors in planning routes of a fleet of trucks for food delivery, using models for the Capacitated VRP or VRP with backhauls, and reports savings of around 25.5% in CO_2 emissions and around 30% in the distance covered using the proposed approach, but this is primarily due to cutting down the number of routes by about 43%. A similar problem concerning waste collection is described by Ramos, Gomes, and Barbosa-Póvoa [47] and is modeled as a multi-depot, multiple product VRP and solved through a multi-stage method. In a scenario where only vehicle routes are optimized, the authors report savings both in CO_2 emissions and distance traveled, reduced by 20% and 23%, respectively, over the currently employed solution.

15.3.1.2 ▪ Variable Speeds

Assuming each road segment is a server to which vehicles arrive at a certain rate, Van Woensel, Creten, and Vandaele [57] show how queueing models could be used to describe traffic flows and to calculate emissions using the MEET emissions function. Their results show that constant speed, an assumption commonly made in the VRP literature, can be misleading and leads to an underestimation of emissions, particularly under congestion when speeds are lower. These results also suggest that speed plays a fundamental role in reducing emissions and hence should be optimized, along with load, within the route planning.

This is precisely the approach taken in Bektaş and Laporte [5], who present the *Pollution-Routing Problem* (PRP) as an extension of the classical VRPTW. The PRP consists of routing a number of vehicles to serve a set of customers within preset time windows, and determining their speed on each route segment, so as to minimize a function comprising fuel, emission, and driver costs. The emission function used within the PRP is the CMEM described by Barth, Younglove, and Scora [3], and differs from previous work in that it allows one to optimize *both* load and speed as well as to account for the effect of, among other parameters, acceleration and road gradient. The modeling approach proposed in [5] assumes a vehicle of empty weight w and carrying a load f, traveling at a constant speed v on a given arc of length d (see Figure 15.2) and proposes to estimate emissions using the following formula:

$$\begin{aligned} P &\approx P_t d/v && (15.5)\\ &\approx (a + g\sin\theta + gC_r\cos\theta)(w+f)d && (15.6)\\ &\quad + (0.5C_d A\rho)v^2 d. && (15.7) \end{aligned}$$

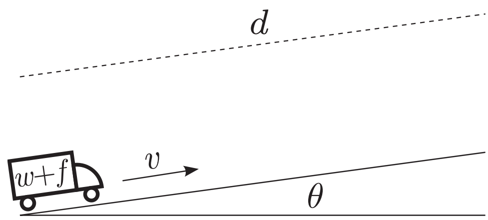

Figure 15.2. *Estimating emissions for a vehicle traveling at constant speed.*

The expression (15.5) is divided into two terms: (15.6), which shows the part of emissions induced primarily by total vehicle weight $w+f$, and (15.7), which shows the other part fundamentally induced by speed v. This divide will later be reflected in the integer linear programming formulation.

An integer programming formulation for the PRP works with a discretized speed function defined by a set R of non-decreasing speed levels $\overline{v}^r$ ($r = 1,\dots,|R|$) (Bektaş and Laporte [5] and Demir, Bektaş, and Laporte [15]). Binary variables x_{ij} are equal to 1 if and only if arc (i,j) appears in solution. Continuous variables f_{ij} represent the total amount of flow on each arc $(i,j)\in A$. Continuous variables T_j represent the time at which service starts at node $j \in N$. Moreover, σ_j represents the total time spent on a route that has a node $j \in N$ as last visited before returning to the depot. Finally, binary variables z^r_{ij} indicate whether or not arc $(i,j)\in A$ is traversed at a speed level r. Bektaş and Laporte [5] provide illustrative examples as to the difference load and speed make in reducing the emissions, with respect to time-window restrictions and customer demand distribution, propose a non-linear mixed integer mathematical model for the problem, and show how it could be linearized. An integer linear programming formulation of the PRP is shown below:

$$\text{minimize} \quad \sum_{(i,j)\in A} c_f \bar{k}\bar{N}\bar{V}\lambda d_{ij} \sum_{r=1}^{|R|} z_{ij}^r / \bar{v}^r \tag{15.8}$$

$$+ \quad \sum_{(i,j)\in A} c_f w\gamma\lambda\alpha_{ij} d_{ij} x_{ij} \tag{15.9}$$

$$+ \quad \sum_{(i,j)\in A} c_f \gamma\lambda\alpha_{ij} d_{ij} f_{ij} \tag{15.10}$$

$$+ \quad \sum_{(i,j)\in A} c_f \beta\gamma\lambda d_{ij} \sum_{r=1}^{|R|} z_{ij}^r (\bar{v}^r)^2 \tag{15.11}$$

$$+ \quad \sum_{j\in N} c_w \sigma_j \tag{15.12}$$

$$\text{s.t.} \quad \sum_{j\in V} x_{0j} = |K|, \tag{15.13}$$

$$\sum_{j\in V} x_{ij} = 1 \qquad \forall\, i \in N, \tag{15.14}$$

$$\sum_{i\in V} x_{ij} = 1 \qquad \forall\, j \in N, \tag{15.15}$$

$$\sum_{j\in V} f_{ji} - \sum_{j\in V} f_{ij} = q_i \qquad \forall\, i \in N, \tag{15.16}$$

$$q_j x_{ij} \le f_{ij} \le (Q - q_i) x_{ij} \qquad \forall\, (i,j) \in A, \tag{15.17}$$

$$T_i - T_j + s_i + \sum_{r\in R} d_{ij} z_{ij}^r / \bar{v}^r \le K_{ij}(1 - x_{ij}) \qquad \forall\, i \in V,\ j \in N,\ i \ne j, \tag{15.18}$$

$$a_i \le T_i \le b_i \qquad \forall\, i \in N, \tag{15.19}$$

$$T_j + s_j - \sigma_j + \sum_{r\in R} d_{j0} z_{j0}^r / \bar{v}^r \le L(1 - x_{j0}) \qquad \forall\, j \in N, \tag{15.20}$$

$$\sum_{r=1}^{|R|} z_{ij}^r = x_{ij} \qquad \forall\, (i,j) \in A, \tag{15.21}$$

$$x_{ij} \in \{0,1\} \qquad \forall\, (i,j) \in A, \tag{15.22}$$

$$f_{ij} \ge 0 \qquad \forall\, (i,j) \in A, \tag{15.23}$$

$$T_i \ge 0 \qquad \forall\, i \in N, \tag{15.24}$$

$$z_{ij}^r \in \{0,1\} \qquad \forall\, (i,j) \in A,\ r = 1, \ldots, |R|. \tag{15.25}$$

This mathematical formulation of the PRP presented here is an extension of the one presented in Bektaş and Laporte [5] to account for speeds 40 km/h or lower through the term (15.8) of the objective function. The objective function (15.8)–(15.11) is derived from (15.3), where $\lambda = \phi/\varkappa\psi$ and $\gamma = 1/1000\eta_t\eta$ are constants and ψ is the conversion factor of fuel from gram/second to liter/second. Furthermore, $\alpha = a + g\sin\theta + gC_r\cos\theta$ is a vehicle-arc-specific constant and $\beta = 0.5C_d\rho\bar{A}$ is a vehicle-specific constant. The parameters c_f and c_w are used to denote the per liter cost of fuel and hourly driver wage, respectively. The terms (15.9) and (15.10) calculate the cost incurred by the vehicle curb weight and payload and correspond to expression (15.6). The term (15.9) captures the effect of the vehicle speed on total cost, as indicated earlier by the expression (15.7). Finally, the term (15.12) measures the total driver costs. Constraints (15.13) state that each vehicle must leave the depot. Constraints (15.14) and (15.15) are the degree constraints which ensure that each customer is visited exactly once. Constraints (15.16) and (15.17) define the arc flows. Constraints (15.18)–(15.20), where $K_{ij} = \max\{0, b_i + \sigma_i + d_{ij}/l_{ij} - a_j\}$, and L is a large number, enforce the time-window restrictions. Constraints (15.21) ensure that only one speed level is selected for each arc and $z_{ij}^r = 1$ if $x_{ij} = 1$. This formulation can only solve small-sized PRP instances. To tackle larger instances, an adaptive large neighborhood search algorithm is described by Demir, Bektaş, and Laporte [15], where the authors present computational results for PRP instances of up to 200 nodes.

15.3.2 ▪ Time-Dependent VRP and Congestion

In contrast to the time-independent VRP, allowing for problem data to change with time gives rise to the time-dependent VRP. The changes in the time to travel along a road section can be attributed to foreseen events, such as peak-hour congestion, or unexpected changes in the traffic conditions such as those caused by accidents or changes in weather conditions. Time dependency is particularly suited to model traffic congestion, a phenomenon which occurs when the capacity of a particular transportation link is insufficient to accommodate an incoming flow at a particular point in time. Congestion has a number of adverse consequences: it increases average times of trips and increases variability in trip time which results in decreased transport reliability. Heavy congestion results in low speeds with fluctuations, e.g., 16 km/h ($\approx$ 10 mph), often accompanied by frequent acceleration and deceleration, and greatly contributes to CO_2 emissions (Barth and Boriboonsomsin [2]). According to the *International Road Transport Union* (IRU), around 100 billion liters of wasted fuel or 250 billion tonnes of CO_2 were attributed to traffic congestion in the United States in 2004 (International Road Transport Union [33]). In this section, we review the existing work on green vehicle routing where time dependency is explicitly taken into account to allow for introducing congestion into the problem setting. The next two sections look at studies with constant and variable speeds, respectively.

15.3.2.1 ▪ Constant Speeds

Kuo [38] considers a time-dependent VRP with an aim to minimize fuel consumption. The time-dependent VRP breaks away from the assumption that travel speeds or times are constant and models travel time as a function of the time of departure from a given node. The approach described by Kuo [38] assumes that time is divided into a number of intervals and v_{ij}^k represents the (known) speed between nodes i and j in each interval k. Using fuel consumption rates (e.g., miles per gallon), the total fuel consumption on a given route can be calculated. The approach uses simulated annealing to solve the underlying VRP initially using shortest distances, for which total fuel consumption is calculated. Computational results presented on randomly generated instances of 100 customers indicate that routing plans that are fuel-optimized increase both total transportation time and the total distance traveled.

Eglese, Maden, and Slater [19] show how traffic speed data collected at different times on individual road sections of a network can be used to create a Road Timetable that provides the quickest times and paths between nodes starting at different times of the day. This information takes into account the effect of regular traffic congestion that has been observed in the past. It is assumed that the vehicles being scheduled will travel at a preferred speed unless congestion on a road section makes that impossible. In that case the vehicles travel according to the average speed of the traffic on that road section. Maden, Eglese, and Black [39] present a tabu-search algorithm, called LANTIME, which uses the Road Timetable information and aims to minimize the total travel time. The approach allows more reliable routes and schedules to be planned. In addition, by minimizing the total travel time, LANTIME tends to produce routes where congestion is avoided and so provides environmental benefits. Results from a case study based on the distribution plans for an electrical goods wholesaler show that CO_2 emissions, total distance, and time can be reduced by around 7%, 7%, and 6%, respectively. This is due to avoiding routes where congestion is high, speeds are low, and emissions are high.

Figliozzi [24] presents an *Emission Minimizing VRP* (EVRP), a variant of the *Time-Dependent VRP* (TDVRP) with time windows, which takes into account congestion so as to minimize a speed-dependent CO_2 emissions function described in Hickman et al. [31]. The EVRP is modeled on a partition $T^1, T^2, \ldots, T^M$ of the total working time where in each interval a constant travel speed s^m is assumed. A set of speeds $\{v_{ij}^m(\Delta_i), v_{ij}^{m+1}(\Delta_i), \ldots, v_{ij}^{m+p}(\Delta_i)\}$ for each arc (i,j) of the network is defined as a function of the departure time Δ_i from node i, where $v_{ij}^m(\Delta_i)$ is the speed at the time of departure and $v_{ij}^{m+p}(\Delta_i)$ is the speed at the time of arrival and $p+1$ is the number of time intervals required to traverse arc (i,j). The amount of emissions on a particular link (i,j) of length d_{ij} is then calculated based on the departure time, using a function suggested in Hickman et al. [31], as follows:

$$F_{ij}(\Delta_i) = f_e \sum_{l=0}^{p} \Big(\xi_0 + \xi_1 v_{ij}^{m+l}(\Delta_i) + \xi_3 (v_{ij}^{m+l}(\Delta_i))^3 + \xi_5/(v_{ij}^{m+l}(\Delta_i))^2\Big) d_{ij}^l, \tag{15.26}$$

where d_{ij}^l is the distance traveled in each period $l = m, \ldots, m+p$ and f_c is the cost of emissions. The travel time on arc (i,j) is also modeled as a function of the departure time Δ_i from node i and is shown as $\tau_{ij}(\Delta_i)$. An integer programming formulation for the EVRP given by Figliozzi [24] is modeled on an extended network with $V' = V \cup \{n+1\}$, where node $n+1$ is a copy of the depot, $A' = \{(i,j) : i, j \in V'$, and $N' = V' \setminus \{0, n+1\}$. The model uses a binary variable x_{ijk} to denote whether vehicle k travels on arc (i,j) and T_{ik} to indicate the start of service at customer i served by vehicle k. The model also allows for pre-service idle waits in that service might start later than time of arrival, even if the arrival time is within the time window $[a_i, b_i]$ of customer i. If c_k denotes the unit cost for vehicle $k \in K$ and c_t is the cost of travel per unit time, a model of the EVRP as described by Figliozzi [24] is given below:

$$\begin{aligned} \text{minimize} \quad & \sum_{k\in K}\sum_{j\in N'} c_k x_{0jk} \\ & + \sum_{k\in K}\sum_{(i,j)\in A} d_{ij} x_{ijk} \\ & + \sum_{k\in K}\sum_{j\in N'} c_k (T_{n+1,k} - T_{0k}) x_{ijk} \\ & + \sum_{k\in K}\sum_{(i,j)\in A'} c_e F_{ij}(T_{ik} + s_i) \end{aligned} \tag{15.27}$$

$$\text{s.t.} \quad \sum_{j \in V'} x_{0jk} = 1 \qquad \forall\, k \in K, \tag{15.28}$$

$$\sum_{j \in V'} x_{j,n+1,k} = 1 \qquad \forall\, k \in K, \tag{15.29}$$

$$\sum_{k \in K} \sum_{j \in V'} x_{ijk} = 1 \qquad \forall\, i \in N', \tag{15.30}$$

$$\sum_{i \in V'} x_{ilk} - \sum_{i \in V'} x_{lik} = 0 \qquad \forall\, l \in N',\ k \in K, \tag{15.31}$$

$$\sum_{i \in N'} q_i \sum_{j \in V'} x_{ijk} \leq Q \qquad \forall\, k \in K, \tag{15.32}$$

$$a_i \sum_{j \in V'} x_{ijk} \leq T_{i,k} \qquad \forall\, i \in V',\ k \in K, \tag{15.33}$$

$$b_i \sum_{j \in V'} x_{ijk} \geq T_{i,k} \qquad \forall\, i \in V',\ k \in K, \tag{15.34}$$

$$x_{ijk}(T_{ik} + s_i + \tau_{ij}(T_{ik} + s_i)) \leq T_{jk} \qquad \forall\, (i,j) \in A',\ k \in K, \tag{15.35}$$

$$x_{i0k} = 0 \qquad \forall\, i \in V', \forall\, k \in K, \tag{15.36}$$

$$x_{n+1,ik} = 0 \qquad \forall\, i \in V', \forall\, k \in K, \tag{15.37}$$

$$x_{ijk} \in \{0,1\} \qquad \forall\, (i,j) \in A',\ k \in K \tag{15.38}$$

$$T_{ik} \geq 0 \qquad \forall\, i \in V',\ k \in K. \tag{15.39}$$

Figliozzi [24] presents a version of the EVRP with three objective functions, one to minimize the number of vehicles, one to minimize the emissions, and the last to minimize the total distance and duration of the resulting routes. The author describes a solution algorithm to solve this version of the EVRP which initially solves a TDVRP to minimize the number of vehicles, denoted by $|K|$, and then minimizes emissions by modifying both departure times Δ_i on a given route and assignments x_{ijk} subject to an additional constraint limiting the fleet size to $|K|$. Using the algorithm, computational tests are conducted on the Solomon benchmark problems of 100 nodes under three settings of congestion, namely uncongested, somewhat congested, and congested. These results indicate that small increases in fleet size imply reductions in emissions, and that uncongested travel speeds tend to reduce emissions on average but some instances exhibit the opposite trend. These instances are when the uncongested travel speed is higher than the speed which minimizes the emissions per unit distance. The author concludes that changes in emissions are related to certain characteristics of the problem, e.g., randomly distributed customers vs. clustered, tight vs. loose time windows, and average number of customers.

A continuous approximation model for solving the EVRP is described by Saberi and Verbas [49]. The authors present results of computational experimentation on benchmark instances, to look at the spatial and temporal effects of congestion due to variations in speed. The results suggest that the optimal number of dispatches during the peak period is smaller than that of off-peak. An application of the EVRP and the algorithm just described on a case study in Portland, Oregon is presented in Figliozzi [25], where scenarios with and without congestion are considered. Of the implications of the results presented in Figliozzi [25], we mention the importance of optimizing travel times and the location of the depot on reducing emission levels.

15.3.2.2 ▪ Variable Speeds

Jabali, Van Woensel, and de Kok [34] take a similar approach to Figliozzi [25] by using the same emissions function in a formulation of the time-dependent VRP (but without time windows) with speed as an additional decision variable. Travel times are modeled by partitioning the planning horizon into two parts, where one partition corresponds to a peak period in which there is congestion and assumes the vehicle speed as fixed, whereas the other partition assumes free-flow speeds which could be optimized. The primary difference between the work of Jabali, Van Woensel, and de Kok [34] and Figliozzi [24] is that the latter explicitly models a “transient” zone in which a vehicle changes from congestion to free-flow speeds. In other words, for a vehicle traveling on a given link, part of the link would be traveled at lower levels of speed due to congestion and the rest would be free-flow for when the congestion dissipates. If v_c denotes the congestion speed and v_f denotes free-flow speed on a road segment of length d, and the vehicle is subject to congestion speed for Ψ units of time from when it starts to traverse the link, then the total travel time is described by

$$T(t) = \begin{cases} d/v_c & \text{if } t \leq \Psi - d/v_c, \\ t(v_c - v_f)/v_f + \Psi(v_f - v_c)/v_f + d/v_f & \text{if } \Psi - d/v_c < t < \Psi, \\ d/v_f & \text{if } t \geq \Psi \end{cases} \tag{15.40}$$

for a given start time t. To estimate emissions, (15.1) with parameters $(\zeta_0, \ldots, \zeta_6) = (1576, -17.6, 0, 0.00117, 0, 36067, 0)$ is used, which prescribes an optimal free-flow speed of 71 km/h, minimizing emissions. Jabali, Van Woensel, and de Kok [34] describe a tabu search heuristic for the solution of the problem, which is tested on standard benchmark instances. Their results suggest that achieving reducing CO_2 emissions of about 11.4% implies a 17.1% increase in travel times, on average, using a congestion speed of 50 km/h and an upper speed limit of 90 km/h.

The PhD dissertation by Qian [46] studies a VRP with time-dependent travel data with an aim to minimize fuel consumption that is based on speed. The author first develops a dynamic programming algorithm and a heuristic solution procedure to optimize speeds on each segment of a route. The sequence of customers to be visited is fixed, but the route between the customers and the speeds on the road segments are determined by the algorithm. Qian [46] uses a real road network, where each road junction is modeled as a node. For instance, one of the data sets considered in this work is a Bristol data set of a single depot and 14 customers, which, when transformed into a full network, results in 9,256 nodes (customer nodes and road junctions) and 6,643 arcs. Results on this network indicate that average savings of 6–7% in fuel emissions can be achieved, though at the cost of increasing the trip time by around 9–10%. The speed optimization procedure is then incorporated into a column-generation framework to optimize the routes as well as speeds. Tests of this method on a London data set with 208,488 nodes and 477,411 arcs and time-varying speeds show the importance of looking at route optimization in addition to speed optimization. Furthermore, allowing drivers to wait at customer nodes is shown to reduce fuel emissions by avoiding congestion. Qian [46] suggests that if idle waiting at customers is to be used as an option, driver costs should be considered.

Following a similar line of research, Franceschetti et al. [28] look into a similar problem where time dependency is modeled as in Jabali, Van Woensel, and de Kok [34]. In this work, the costs of fuel, emissions, and drivers are explicitly taken into account by extending the modeling approach of Bektaş and Laporte [5]. The authors describe a mathematical formulation of the problem and a complete characterization of optimal solutions on a single-link version, which offers insights as to when it is profitable to wait idle at customer nodes in order to minimize the total cost. The authors also present a procedure on fixed routes, which not only optimizes the speed on each segment of the route, but also the departure times from each node which might be *later* than the service completion time, in order to avoid congestion.

15.4 ▪ Speed Optimization on Fixed Routes

Most approaches described above for modeling or solving "green" VRPs are either variations or extensions of the existing body of work on the VRP, e.g., incorporating emissions functions within VRP models or algorithms. However, there is one other interesting problem type, namely schedule optimization for a fixed route with (linear or convex) inconvenience costs (see, e.g., Dumas, Soumis, and Desrosiers [17] and Fagerholt [22]). This problem has now been applied to the Speed Optimization Problem (SOP) on a given route. The SOP is defined on a given route of customers indexed by $k = 1, 2, \ldots, n$, who have (hard) time windows $[a_k, b_k]$ in which the service needs to start, and consists of determining the speed on each leg of the route so as to minimize the total fuel consumption. Fagerholt, Laporte, and Norstad [23] present, to our knowledge, the first description of SOP in the context of shipping and describe mathematical models for the problem along with a solution algorithm. One of these models uses speed as a primary decision variable, defined as $v_{k,k+1}$ on each arc $(k, k+1)$ of length $d_{k,k+1}$ for $k = 1, 2, \ldots, n-1$, using which one can calculate the travel time on an arc $(k, k+1)$ as $t_{k,k+1} = d_{k,k+1}/v_{k,k+1}$. The model is presented below:

$$\text{minimize} \quad \sum_{k=1,\ldots,n-1} d_{k,k+1} f(v_{k,k+1}) \tag{15.41}$$

$$\text{s.t.} \quad T_{k+1} - T_k - d_{k,k+1}/v_{k,k+1} \geq 0 \qquad \forall\, k = 1, \ldots, n-1, \tag{15.42}$$

$$a_k \leq T_k \leq b_k \qquad \forall\, k = 1, \ldots, n, \tag{15.43}$$

$$v_{\min} \leq v_{k,k+1} \leq v_{\max} \qquad \forall\, k = 1, \ldots, n-1. \tag{15.44}$$

The objective function (15.41) minimizes the total fuel consumption on the given route, where $f(v)$ is the fuel consumption as a function of speed v. Constraints (15.42) are used to restrict the start time of service at a given node only after the ship has arrived to that node. Time-window restrictions are modeled through constraints (15.43), whereas the last set of constraints (15.44) enforce minimum and maximum speed limits on each arc as $v_{\min}$ and $v_{\max}$, respectively. As $f(v)$ is, in general, a quadratic convex function for ships, this model is non-linear in the objective function and the constraints. Fagerholt, Laporte, and Norstad [23] show that, by using traveling time as a primary decision variable, the non-linearity in the constraints can be avoided. Furthermore, by discretizing the arrival times at each node and replicating each node as many times as the number of discretizations, the SOP can be modeled and solved as a shortest path problem on a directed acyclic graph. Norstad, Fagerholt, and Laporte [41] later on present a recursive smoothing algorithm for the SOP that is based on the convexity of the fuel consumption function which runs very fast, and later on was shown to be optimal by Hvattum et al. [32].

This algorithm was later on adapted to the PRP by Demir, Bektaş, and Laporte [15] and reported to result in an average improvement of 3%, with respect to fuel consumption, on fixed vehicle routes. A similar algorithm appears in Figliozzi [25] which optimizes departure times at each node on a fixed route by taking into account time-window constraints and emissions.

15.5 ▪ Multicriteria Analysis

Minimizing emissions in VRPs might sometimes conflict with the traditional objective of minimizing total travel distance or time. One way of dealing with multiobjective VRPs in which some objectives are environmental (e.g., CO_2 emissions) and others are operational (e.g., financial) is to use a weighted combination of the multiple objectives to convert the problem into a single objective problem. However, the solutions produced through such an approach heavily depend on the weights assigned to the objectives. An alternative way to overcome this difficulty, as well as to capture the tradeoffs between several objectives, is to use multiobjective programming techniques. One example of the use of such an approach is described by Jemai, Zekri, and Mellouli [35], who describe an evolutionary algorithm to solve a bi-objective VRP where one objective minimizes the total distance traveled whereas the other minimizes CO_2 emissions. In a similar vein, Demir, Bektaş, and Laporte [16] study the bi-objective PRP in which the two objective functions pertaining to minimization of fuel consumption and driving time are conflicting and are thus considered separately. Four a posteriori methods, namely the weighting method, the weighting method with normalization, the epsilon-constraint method, and a new *Hybrid Method* (HM), are evaluated and compared with one another.

15.6 ▪ Routing in Other Modes of Transport

This chapter has so far focused on environmental hazards of routing vehicles for road transportation. Similar studies exist in other domains of transportation, and shipping is one which has been given particular attention in the literature given the size of ships and the significant amount of freight transported on this mode of transport. Fuel consumption for vessels can be described by a function which, among other technical factors, is linear in the distance of travel and cubic in the speed (see Corbett, Wang, and Winebrake [10]). For container ships running on diesel engines, reducing speeds from design speed to slow steaming is shown to have reduced emissions by around 11% between 2008 and 2010 (see Cariou [8]). Furthermore, the approach described by Fagerholt, Laporte, and Norstad [23] to optimize speeds for ships has been shown to yield savings in fuel consumption by 21% on average. However, reduction in speed may have undesirable consequences, including increased fleet size and inventory costs (see Psaraftis, Kontovas, and Kakalis [45]).

Few studies combine routing decisions with environmental considerations in rail transportation planning. The study by Bauer, Bektaş, and Crainic [4] looks at an intermodal rail transportation system operating over several countries where intermodality arises due to the need to transfer containers between rail services of different characteristics at borders. In this study, rail fuel consumption is modeled using the emissions function introduced by Ross [48] and used later by Barth, Younglove, and Scora [3] assuming constant speed. The authors present two variants of an integer programming formulation for the service network design problem, one to minimize service time and the other to minimize emissions. Using the model on case study data, the authors present results of computational experiments that capture the tradeoff between minimizing time and emissions.

Environmental concerns are gradually being introduced into other variants of the VRP. One particular study is due to Treitl, Nolz, and Jammernegg [55], who look at a multi-period inventory-routing problem arising in a case study in the petrochemical industry. The particular problem the authors consider has deterministic demands and no inventory costs, as the retailers and the suppliers belong to the same company. Instead they model emissions resulting from electricity usage for inventory transfer at customer nodes, as well as emissions due to the routing itself modeled in the spirit of Bektaş and

Laporte [5], and minimize emission costs along with the usual routing costs. The authors also introduce a carbon cap for the total amount of emissions. An integer linear programming formulation of the problem is tested on case study data of a single depot and 45 customer nodes, and results indicate that not only can the total routing distance (loaded and empty) be significantly reduced, but also the average load on the vehicles can be increased. The authors also mention that, given the current low costs of carbon in the EU ETS, the solution is not affected by consideration of CO_2 emissions. This conclusion parallels those of Bektaş and Laporte [5] and Jabali, Van Woensel, and de Kok [34].

15.7 ▪ Alternative Fuel-Powered Vehicles

For many years, vehicles have mainly been powered by petroleum-based fuels. Environmental concerns have encouraged the development and use of alternative fuels that have reduced environmental impact. Examples include electricity and ethanol. In many cases, the use of an alternative fuel will not affect the structure of the associated VRP, but in some cases an alternative fuel can have a significant effect.

A good example is given by Erdoğan and Miller-Hooks [20], who describe a VRP that applies to alternative fuel vehicles that have limited range and where there are limited locations for the alternative fuel stations where the vehicles may refuel. They define a "Green Vehicle Routing Problem" where the objective is to minimize the total distance covered by a vehicle fleet, with the additional constraint that no vehicle must exceed its maximum range without refuelling and vehicles may only refuel at alternative fuel stations located in specific places. The problem is formulated as a mixed integer program, and heuristics are developed for its solution. Tests are carried out based on locations for publicly available fuel stations for biodiesel in an area of the USA showing how the total distance for a fleet of vehicles may depend on the number of fuel stations and the range of the vehicles.

15.8 ▪ Conclusions and Future Research Directions

This chapter has presented a review of the state of the art in green vehicle routing, an emerging area of research within vehicle routing attracting growing interest from the scientific community. The review presented the available fuel consumption and emissions models in the literature, and ways in which these models could be integrated into the existing formulations or approaches for the VRP. In particular, we have presented a classification whereby problems are differentiated with respect to time dependency and whether speed is considered as a decision variable. The paper has also briefly touched on the "green" literature for other modes of transport, as well as relevant areas such as alternative fuel-powered vehicles.

The review has revealed several interesting characteristics of the relevant body of green vehicle routing literature, listed below, along with suggestions for further research:

- Of the various externalities of transportation including noise and accidents, the VRP-related literature mainly focuses on minimizing GHG emissions and fuel consumption. This is not surprising for several reasons. First, there is rich literature on analytical expressions for emissions, but this is not so much the case for other externalities. Second, externalities such as accidents are difficult to model analytically and are usually the subject of other areas of research, such as accident prevention and policy making.

- The emphasis of the existing research is predominantly on new problem definitions, such as the EVRP, rather than new solution techniques. In fact, most new problems of green vehicle routing can be solved by variations of the existing techniques available for the traditional VRP. However, one novel problem that has been identified in this context is the speed optimization problem on fixed routes, which has previously been studied primarily for theoretical interest, but has now found applications in a more relevant domain of research.

- An accurate estimation of fuel consumption (and emissions) requires significantly more parameters than what has previously been used in the VRP literature. Travel speed, elevation and inclination, and time-dependent data are but a few examples. This might sound too difficult a task, but the recent developments in GIS and traffic system management software (see, e.g., Hansen et al. [30]) might facilitate gathering such data and in sufficient detail to be used as input to some of the methods described in this chapter.

- Whereas some studies report that environmental objectives (e.g., minimizing emissions) are in conflict with those that aim to reduce operational costs, this is not always the case. As some of the results mentioned in this chapter suggest, there are cases where minimizing fuel consumption also leads to minimizing the total distance. In some cases, this is due to using rural roads as opposed to highways, which require slower speeds but often provide direct routes. In other cases, this might be due to avoiding congestion or using fewer vehicles. Whether the two objectives are in conflict or not depends on the particular application and the decisions involved, and our view is that this will become more evident as more studies are conducted in this area of research and will provide further evidence into the tradeoffs.

- Apart from road-based transportation, one other area of green logistics that has received particular attention is in maritime transportation. To the best of our knowledge, little work has been done on how vehicle routing aspects in rail or air transportation are affected by environmental considerations.

- Of the problems hitherto addressed, those assuming time independency seem to have been sufficiently well studied. The green vehicle routing literature is gradually moving towards the time-dependent setting, and this is an area that needs further investigation. Phenomena such as congestion are one of the primary causes of pollution, particularly for urban transportation. Although one type of congestion can be predicted (e.g., peak hours), allowing for vehicle routes to be planned in advance, other types of congestion arising due to unforeseen events warrant research into stochastic, dynamic, or real-time vehicle route planning to minimize the impact on the environment. This is an open research direction.

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