The accuracy of carbon emission and fuel consumption computations in green vehicle routing

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Abstract

Many recent green vehicle routing papers have presented mathematical models designed to minimize fuel consumption and the environmentally damaging carbon emissions in the routing decisions related to route choice, the load on the vehicle, and the speed. A popular model for computing such impact is the Comprehensive Modal Emissions Model (CMEM) that can compute fuel consumption and carbon emissions for a vehicle with a given speed and load. However, the CMEM requires that input parameters are specified for every second of a haul. To avoid this, computations are used in which the vehicle is assumed to travel at a fixed speed. This paper investigates the extent to which such fixed speed computations in the CMEM are suitable for actual driving conditions with fluctuating speeds. In our numerical experiments, we find that the CMEM results under fixed speeds are sometimes less than half of those computed under realistic driving conditions, depending on the type of conditions. This indicates that we cannot take for granted that fixed speed computations are sufficiently accurate to be used in green routing and validation of these computations is necessary.

Keywords: OR in environment and climate change, green vehicle routing, fuel consumption, carbon emissions.

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1. Introduction

A frequently given motivation for green routing is that it can help reduce the emission of greenhouse gases, such as carbon dioxide, the *carbon emissions*. Transportation is a major source of carbon emissions worldwide, contributing to about 26% of all carbon dioxide emissions in 2000 and road transport causes about 65% of those emissions (Chapman, 2007). It is widely agreed that carbon (dioxide) emissions contribute to global warming through the enhanced greenhouse effect (Lashof and Dilip, 1990). One of the suggested ways of reducing the carbon emissions and fuel consumption is through improved routing decisions on how often and when customers should be visited; see also Dekker et al. (2012) and McKinnon et al. (2015). This is the field of *green vehicle routing*, where one aims to reduce the environmental impact of routing decisions, usually measured in the amount of carbon emissions (Demir et al., 2014).

Green vehicle routing emanates from the well-established field of Vehicle Routing Problems (VRPs), where one minimizes the sum of the distances or the costs of the routes from a depot to a given set of customers (Toth and Vigo, 2014)[1]. In Bektas and Laporte (2011), the minimization of the environmental impact of routing is called the Pollution Routing Problem (PRP), but we use the term *green vehicle routing*. Under this term, we also include papers that minimize fuel consumption from routing decisions, such as Franceschetti et al. (2013) and Demir et al. (2014), as fuel consumption is more or less proportional to carbon emissions for a given vehicle; see e.g. Kellner and Otto (2012). Literature reviews on green vehicle routing are given in the papers by Demir et al. (2013) and Lin et al. (2014). Green vehicle routing has been used recently for purposes such as assigning different vehicles to delivery areas in order to reduce carbon emissions (Velazquez-Martinez et al., 2016) or routing a heterogeneous fleet of vehicles in city logistics (Koc et al., 2016).

Green vehicle routing is presented as an alternative to regular vehicle routing models. Although the minimization of objectives such as cost or distance can lead to routes with low carbon emissions, it is argued that carbon emissions also depend on the speed of the vehicle (Demir et al., 2013), the load on the vehicle (Bektas and Laporte, 2011; Kara et al., 2007), the inclination

[1]Green vehicle routing can also denote the routing of electric vehicles, but this is not considered in our article.

(slope) of the road (Tavares et al., 2008), and the level of congestion (Maden et al., 2010) so that the shortest or cheapest route may not be optimal with respect to carbon emissions or fuel consumption. Some papers, such as Demir et al. (2014) or Franceschetti et al. (2013), enable a trade-off between the cost or distance and carbon emissions or fuel consumption through multi-objective approaches. Such approaches typically provide the decision maker with a set of so-called efficient routes (where one objective cannot be improved without causing deterioration to another), so that he or she can, for example, decide to accept a slight increase in costs if this leads to a large decrease in carbon emissions compared to the minimum cost route.

Green vehicle routing depends on correct computation of the carbon emissions in order to generate routes that are truly greener than the distance or cost minimizing route (a similar argument can be made for fuel consumption levels). To that end, green vehicle routing studies use different types of carbon emissions and fuel consumption computations; see also Demir et al. (2013). The most straightforward method is to use actual measurements for the given vehicle. Ubeda et al. (2011) use fuel consumption measurements in the case company Eroski in which the vehicle drives with a different load factor (roughly, the amount of capacity on the vehicle occupied). Some papers such as the studies by Maden et al. (2010) and Qian and Eglese (2016) rely on measurements reported by environmental or transport agencies, e.g., the Swedish Network for Transport and Environment (NTM) or the British National Atmospheric Environmental Inventory (NAEI). Advantages of using measurements are that they are relatively easy to use and that they are accurate for the vehicle at hand when the measurements have been obtained under representative circumstances.

A limitation of actual measurements is that they are not sufficiently detailed to take variations in variables such as the speed of the vehicle or the load on it (also called the net payload) into account. Many green routing studies, however, vary the speed or the load on the vehicle in the decisions. Therefore, these studies resort to so-called *engine emission models*. Engine emission models are based on regression results on observed tailpipe emissions and allow a user to compute the expected carbon emission levels for given values of input parameters. The study by Boulter et al. (2009) differentiates between two types of engine emission models: average speed models and instantaneous emission models (referred to as macroscopic and microscopic models, respectively, in Lin et al. (2014)).

In *average speed models*, emissions are related to the vehicle's average speed. Examples of papers in green routing that use average speed models are Figliozzi (2011), and Tavares et al. (2008); they both apply the so-called COPERT model from Ntziachristos and Samaras (2000) to compute fuel consumption levels. Other average speed models include ARTEMIS, MEET, and HBEFA (Lin et al., 2014).

For cases where not only the average speed, but also other parameters such as the type of vehicle and the mass of the vehicle can vary, *instantaneous emission models* are used to compute fuel consumption and carbon emission levels. Average speed models cannot compute, for example, the carbon emissions that result from transporting 5 tons (t.) of load on the connection from A to B at 10 am in the morning. Some instantaneous emission models can compute the emissions of a vehicle driving at a given speed and with a given acceleration, having a given load or mass, and inclination (slope) of the road (Demir et al., 2011).

The most popular instantaneous emission model in green vehicle routing is the Comprehensive Modal Emissions Model (CMEM) by Barth et al. (2005). This model, designed for heavy duty vehicles (Franceschetti et al., 2013), relates the fuel consumption and carbon emissions to the relevant logistics decisions of the route choice and the resulting driving distance, the vehicle speed, and the weight of the load on the vehicle. The original application of the CMEM to green vehicle routing is presented in the paper by Bektas and Laporte (2011) on the PRP. The papers by Demir et al. (2012), Franceschetti et al. (2013), Demir et al. (2013), and Kramer et al. (2015) consider multi-objective versions of this problem where the emissions or fuel consumption is one of the objectives. The paper by Ramos et al. (2012) computes the emission from recyclable waste transport using the CMEM. The paper by Koc et al. (2014) extends the problem formulation from Franceschetti et al. (2013) to a situation with heterogeneous vehicles. The paper by Soysal et al. (2015) uses CMEM computations in an Inventory Routing Problem where one not only decides on the construction of the routes, but also on the days on which deliveries are made.

One challenge with the use of instantaneous emission models such as the CMEM is that in order to obtain total emissions on a given connection from A to B, one has to specify the values of all input parameters and variables on a moment-to-moment basis, typically second by second. All the aforementioned papers that use the CMEM assume that the speed of the vehicle remains the same during the haul. We call such computations *fixed speed* computations (in the literature, the term *steady state speed* is used as well).

The usage of instantaneous emission models such as the CMEM has been validated to some degree for a vehicle traveling at a steady fixed speed in Demir et al. (2011). In reality, a vehicle is unlikely to maintain fixed speeds for longer periods of time: traffic conditions force the driver to adopt lower or higher speeds and sometimes come to a full stop, e.g., at a traffic light or at a customer. The speed of the vehicle on a second-to-second basis thus depends on traffic conditions and on the driving style of the driver. It is therefore standard practice in transportation science to model driving conditions with fluctuating speeds, usually in the form of so-called *driving cycles* (also called *drive cycles*), which contain a sequence of driving speeds over time; see e.g. André et al. (2006) and Boulter et al. (2009). For example, the study by Rizet et al. (2012) determines fuel consumption levels for given average speeds of 20, 50, and 80 km/h, but the corresponding driving cycles have fluctuating speeds.

One can replace these fluctuating speeds with average speed during a haul. For example, Franceschetti et al. (2013) model congested traffic conditions with a low and fixed average speed. We do not know, however, whether such fixed speed computations are appropriate for driving conditions with fluctuating speeds; we only know from the calibration of the CMEM in Barth et al. (2005) that the measured engine emissions match the computed ones if the input parameters, most importantly speed, are inserted on a second-to-second basis. On the other hand, there are, to the best of our knowledge, no studies in transportation science validate the usage of fixed speeds in instantaneous emission models such as the CMEM, as we discuss in Section 2. Thus, we do not know whether the fixed speed CMEM computations used in green vehicle routing problem papers are sufficiently accurate under realistic driving conditions.

The objective of the present paper is to measure the error of fixed speed CMEM computations when modeling realistic driving conditions with unavoidable speed fluctuations. To that end, we start by summarizing papers from transportation science and routing on the effect of speed fluctuations in Section 2 and conclude that further experiments are needed. We perform numerical experiments in which we test the CMEM results under driving conditions with fluctuating speeds. In these experiments, we simulate realistic driving conditions with driving cycles, as is common practice in transportation science. For each driving cycle, we use the CMEM to compute the fuel consumption levels both using fluctuating speeds according to the driving cycle and using the driving cycle's average speed as a steady speed. We then compare these results and determine the conditions under which the difference in results between the two types of computations is most significant.

Our experiments can have important implications for green vehicle routing approaches. If we find large differences between fuel consumption levels with fixed and fluctuating speeds and if the size of these differences varies across driving conditions, it is far from sure that a route that is relatively green according to fixed speed computations has low carbon emissions in reality as well. We provide examples of such situations in Section 5. Another implication relates to the design of models and solution approaches to green vehicle routing: if we find that fixed speed CMEM fuel consumption and carbon emission computations are inaccurate, it may be necessary to abandon some of the nice mathematical properties of fixed speed engine emission models. For example, the Speed Optimization Procedure by Demir et al. (2012) and the Departure-time SOP by Franceschetti et al. (2013) use the property that fuel consumption forms a continuous and convex function of the given fixed speed in the CMEM (see Section 3). If our results indicate that fixed speeds are too inaccurate and driving conditions should be included, the resulting fuel consumption computations may no longer be convex or even continuous.

The paper is set up as follows. Section 2 provides an overview of studies in transportation science on emission of fuel computations that compare fixed and fluctuating speeds. In Section 3, we describe the fuel consumption computations in the CMEM. The numerical experiments are presented in Section 4, and Section 5 illustrates cases in which this could lead green vehicle routing problems to return poor solutions. Finally, Section 6 discusses the implications as well as possible solutions, gives the limitations of the experimental results, and outlines directions for future research.

2. The impact of driving conditions on fuel consumption: existing results

In transportation science, it is well known that driving conditions are an important determinant of fuel consumption and carbon emissions. We briefly review experiments on the impact of speed fluctuations. Most of the results, however, are for passenger cars; research on Heavy Goods Vehicles (HGVs, i.e., trucks) with different payloads is relatively scarce.

What is the effect of choosing average speeds to compute fuel consumption under driving conditions with fluctuating speeds? Previous research indicates that the use of fixed average speeds is likely to lead to *underestimation* of actual emissions, firstly because the contribution of acceleration to fuel consumption is much larger than the savings from deceleration; see Ericsson (2001). Secondly, since the fuel consumption is a convex function of a vehicle's speed, it follows that driving at different speeds costs more energy than driving at the average of these speeds; see Section 3. The degree of underestimation may vary between driving conditions as some roads have relatively free-flowing conditions and others have large speed fluctuations and possibly many phases with strong acceleration, for instance.

Some studies have observed the underestimation of emissions in real-world driving conditions for passenger cars and/or LDVs. For passenger household vehicles, Barth and Boriboomsin (2009) find that the measured fuel consumption in actual traffic is consistently up to 40% higher than predicted by the CMEM under fixed speeds; see also Figure 1 in Figliozzi (2011). Regression studies of vehicle fuel consumption determinants in transportation science confirm this result: Fuel consumption is positively and significantly affected by factors such as acceleration and 'speed oscillation' (the effect of having different velocities during a trip) in Ericsson (2001). For the engine emission model IFCM, the PhD thesis by Palmer (2007) computes carbon emissions with the speed fluctuating according to artificial driving conditions. It is found that for a light duty vehicle (LDV) with a mass of 3.5 t., the fuel consumption levels computed with the ICFM with fluctuating speeds are about 20 to 40% higher than computed with fixed speeds, but there is no comparison with actual measurements.

For HGVs, the impact of the vehicle mass on total emissions should be taken into account. It is therefore not possible to simply aggregate the observations of HGVs traveling at average speeds, but the experiment should also distinguish between different vehicle weights, because of the load on the vehicle, for instance. Ligterink et al. (2012) argue that studies from the area of transportation science tend to aggregate their results and to ignore the impact of the actual payload. Ligterink et al. (2012) determine the average power usage per ton-kilometer linked to a vehicle's speed over a wide range of driving conditions and find that the power usage per ton-kilometer depends on the vehicle's actual speed, whereas fixed speed computations give the same fuel consumption per ton for each (fixed) speed; see Section 3. The paper by Walnum and Simonsen (2015) uses regression to determine the impact of individual factors such as the load, the average speed, and the number of stops per 100 km on certain roads in Norway and find that the average speed of a haul is the major determinant of fuel consumption. However, if the fuel consumption is measured for a vehicle driving at a given average speed, say 50 km/h, this allows for speed fluctuations and cannot be used to argue that fixed speeds can be used. To the best of our knowledge, no study has yet determined the accuracy of using fixed speed computations for HGVs with different vehicle mass and payloads. In our study, we fill this gap by considering the most frequently used instantaneous engine emission model in green vehicle routing, the CMEM.

3. The Comprehensive Modal Emissions Model (CMEM)

This section discusses the Comprehensive Modal Emissions Model (CMEM) from Barth et al. (2005) and its use in green vehicle routing. The CMEM can take many factors into account that depend on routing decisions, such as the load on the vehicle (which determines the vehicle mass), the speed of the vehicle, and the inclination of the road (see also Demir et al. (2011)). It further includes a wide range of parameters, mostly related to the vehicle at hand. We use the CMEM specification from Franceschetti et al. (2013) to set values for most input parameters and complement this with the specification from Barth et al. (2005), where necessary.

The CMEM computations are broadly as follows. For each second, it computes the amount of fuel needed during that second: the *fuel rate*. The fuel consumption in kg per km is then determined by adding all fuel rates computed for the duration of a driving cycle and dividing this by the distance covered during the driving cycle. In the first step, the CMEM computes the power usage P_t in kW at second t as follows:

$$P_t = 0.5 C_d \rho A v_t^3 + M v_t (g \sin\phi + g C_r \cos\phi + a_t). \quad (1)$$

In our usage of Eq. (1), the variables are the vehicle velocity v_t, the acceleration a_t, the vehicle mass $M = \mu + f$ in kg (with the weight of the empty vehicle weight μ and the weight of the load on the vehicle f). In comparison to the model formulation from Franceschetti et al. (2013), we add the subscript t to distinguish the speed at different time points t and we add a_t, which is the positive difference between v_{t+1} and v_t; see also Barth et al. (2005). The input parameters are set to the values reported in Table 1 from Franceschetti et al. (2013): the coefficient of aerodynamic drag $C_d = 0.7$, the air density $\rho = 1.2041$, the frontal surface of the vehicle $A = 4$, the gravitational constant $g = 9.81$, the declination of the road $\phi = 0$, and the rolling resistance $C_r = 0.01$.

The power usage P_t forms the main input of the computation of the fuel rate in grams during second t as follows:

$$FR_t = \frac{\zeta}{\kappa}(kN_eV + \frac{P_t}{1000\epsilon\bar{\omega}}). \tag{2}$$

The parameter $\zeta = 1$ denotes fuel-to-air mass, κ is the heating value of a typical diesel fuel, $k = 0.2$ the engine friction factor, N_e the engine speed, $V = 5$ the engine displacement, $\bar{\omega} = 0.9$ the efficiency parameter for diesel engines, and $\epsilon = 0.4$ the vehicle drive train efficiency. Note that Equation 1 in Franceschetti et al. (2013) computes the fuel consumption in liters per km and includes a conversion factor from grams to liters (ψ). We keep the fuel consumption in grams and do not need this factor.

In Franceschetti et al. (2013), the value of κ is set to the constant of 44. However, in Barth et al. (2005), the value of $1/\kappa$ is computed as $\frac{1}{43.2}(1 + b_1(N_e - N_0)^2)$, where the term $(N_e - N_0)$ denotes the deviation of normal engine speed in revolutions per second (rps) N_e from the stationary engine speed $N_0 = 23.2379$, where N_e is set to 40 following Demir et al. (2011) and $b_1 = 0.0001$ is a constant. This modification enables us to use the model for situations where the number of rps varies, e.g. as a consequence of speed variations. In the experiments, we assume a fixed value of N_e, but we perform a sensitivity analysis to assess the impact of variations in its value.

As the vehicle mass M plays an important role, we divide the fuel rate at time t into a term linearly related to M and the term $FR_t(M)$ to obtain:

$$FR_t(M) = \frac{\zeta}{\kappa} \times \frac{v_t(gsin\phi + gC_rcos\phi + a_t)}{1000\epsilon\bar{\omega}}M + FR_t(0) \tag{3}$$

The term $FR_t(0)$ represents the emissions unrelated to the vehicle mass and contains, among others, the term $0.5C_dAv_t^3$ from Eq. (1).

Now we wish to compute the fuel consumption of a given driving cycle dc, described by the vehicle's speed v_t during every second $t = 1, \ldots, T(dc)$, where $T(dc)$ denotes the drive cycle's duration and $dist(dc)$ the covered distance in meters. In the case of fluctuating speeds, the driving cycle dc describes how the speed v_t varies. For the corresponding fixed speed case, we construct the corresponding driving cycle $\bar{dc}$ such that $T(\bar{dc}) = T(dc)$ and $v_t = v = dist(dc)/T(dc)$ for all $t = 1, \ldots, T(dc)$, i.e., the same distance is covered as in dc.

We determine the fuel consumption in kg of the vehicle independent of its mass, denoted by $FUEL1(dc)$, and per additional ton, denoted by $FUEL2(dc)$ of driving cycle dc as follows:

$$FUEL1(dc) = \sum_{t=1}^{T(dc)} FR_t(0)/dist(dc) \tag{4}$$

$$FUEL2(dc) = \sum_{t=1}^{T(dc)} [FR_t(1000) - FR_t(0)]/dist(dc) \tag{5}$$

The total fuel usage of a vehicle with M t. mass is then $FUEL1(dc) + M \times FUEL2(dc)$. Note that $FUEL2(dc)$ can be computed as $FR_t(M + 1000) - FR_t(M)$ for any vehicle mass $M \geq 0$.

Figure 1 illustrates the effect of velocity on total fuel consumption for a 12 t. vehicle: the fuel consumption per km is high for very low speeds, decreases with the velocity, is low at the ideal speed of about 50 to 60 km/h, and then increases slowly again as velocity increases. Given a driving cycle $\bar{dc}$ with fixed speed v, the fuel consumption per km is simply the fuel consumption per second multiplied by the number of seconds per meter (i.e., $1/v$). Interestingly, the term containing the vehicle mass M is multiplied by v in Eq. (3) and is then divided by v in order to compute the fuel consumption per km. The result is therefore that the fuel consumption per additional ton of mass $FUEL2(\bar{dc})$ is the same for any fixed speed driving cycle $\bar{dc}$, that is, for any fixed velocity v.

In case of fluctuating speeds, the speed of the vehicle and its acceleration can vary on a second-to-second basis during a driving cycle. This also means that the fuel consumption per second fluctuates on a second-to-second basis and the values of $FUEL1(dc)$ and $FUEL2(dc)$ can only be computed by taking the sum of the fuel consumption during the whole driving cycle dc. Moreover, since the mass of the vehicle is multiplied by the acceleration a_t in Eq. (3), the fuel consumption per additional ton $FUEL2(dc)$ varies between different driving cycles dc.

To give an example of the computations: assume that a vehicle weighing 7 t. has a speed of 0 m/s at second $t = 0$ and of 3 m/s at second $t = 1$. During this first second, we use $v_1 = 0$ m/s and $a_1 = 3$ m/s^2. Using Eq. (2), we obtain that the vehicle uses 4.05 g of fuel during that second; adding a ton leads to the consumption of 0.19 additional grams of fuel. If it then

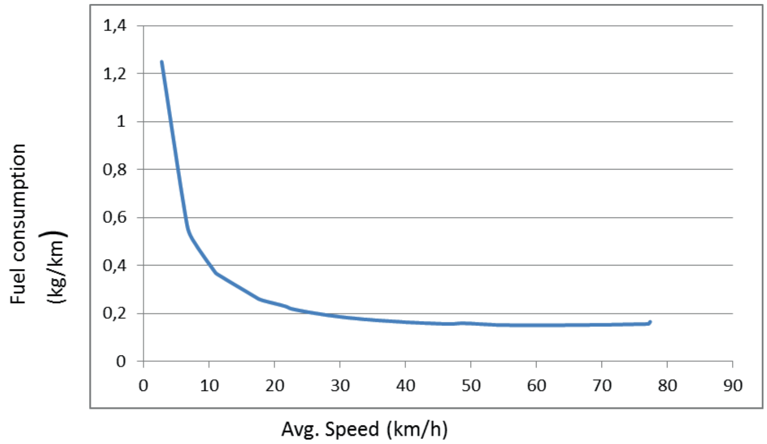

Figure 1: Fuel consumption according to CMEM with fixed speed as a function of velocity and vehicle mass 12 t

decelerates from 3 to 0 m/s during second t, we set $v_t = 1.5$, but $a_t = 0$.

In the numerical experiments, we use the fuel consumption in kg per km, but this can easily be transformed into liters of fuel and carbon emissions in kg. For instance, the conversion factor of British DEFRA from 2010 for combustion of diesel is 3.164 kg of carbon per kg, 3.201 kg of CO_2-equivalents (CO_2eq; this measure includes the impact of all greenhouse gases normalized to units of CO_2), and 0.607 additional kg of CO_2eq in order to obtain the emissions from well-to-tank (including extracting and producing fuel); see Defra (2010).

4. Numerical experiments

In the numerical experiments, we wish to compare the fuel consumption levels computed with fluctuating speeds and with fixed average speeds under different driving conditions using the CMEM from Section 3. This is similar to the comparison in Palmer (2007) for the IFCM, but we include a much broader set of driving conditions and different vehicle masses for the CMEM.

This numerical experiment requires that the CMEM gives fuel consumption levels on a second-to-second basis and that the driving cycles are representative of actual driving conditions. For our numerical experiments of varying vehicle mass and payloads we rely on the laboratory driving results presented in Barth et al. (2005) that validate the model for fluctuating speeds on a second-to-second basis. We then determine the differences between the results concerning emissions from the average speed to those measured under realistic driving conditions and we determine the impact by factors such as the vehicle mass on the results. We also discuss the type of experiment needed to validate CMEM computations in green vehicle routing using an experimental study from Coyle (2007).

The experiments are operationalized as follows. For each driving cycle dc, introduced below, we compute the fuel consumption of a vehicle with a given mass of 7 t. as $FUEL1(dc)+7\times FUEL2(dc)$ and the fuel consumption of each ton that is added to (or subtracted from) the vehicle $FUEL2(dc)$; see Eq. (4) and (5). Note that the fuel consumption of any vehicle and any load with similar parameter values as in Section 3 can be computed from our results for the 7 t. vehicle by adding or subtracting the fuel consumption of the additional tons. For instance, the ratio of a 22 t. vehicle can be obtained by adding the fuel consumption of a vehicle of 7 t. and the fuel consumption of 15 additional tons. Likewise, the fuel consumption of a 4.5 t. vehicle can be obtained by subtracting the fuel consumption of 2.5 additional tons. For each driving cycle, the fuel computations are performed twice: first, the vehicle follows the *fluctuating speed* patterns as given in the driving cycles, and in the second computation, the vehicle maintains the *fixed average speed* for the entire duration of the driving cycle.

In addition to the absolute fuel consumption levels per km, we determine the ratio between fuel consumption levels under fluctuating and fixed speeds. Any fuel consumption level in kg per km with speeds fluctuating according to the driving cycle is denoted by $FFluct$ and any fuel consumption level under fixed speeds by $FFixed$. The ratio between fuel consumption under fluctuating speeds and fuel consumption under fixed speeds is denoted by $RTOT$ and computed as $RTOT = FFluct/FFixed$. As it holds that $RTOT \geq 1$, this ratio represents the *degree of underestimation* from fixed speed computations in the experiments.

In our computations, we model realistic driving conditions by using many publicly available driving cycles for heavy goods vehicles. We use 12 freely and publicly available driving cycles from the US Environmental Protection Agency (EPA)[2]; three artificially generated driving cycles; and 25 driving

[2]The test procedures can be found on `http://www.epa.gov/nvfel/testing/dynamometer.htm`

cycles from Dieselnet[3]. These driving cycles cover a wide range of driving conditions such as urban roads, rural roads, congested roads, arterial roads, and highways. To the extent possible, we have selected driving cycles that are realistic for commercial vehicles, which excludes driving cycles with high speeds (more than 120 km/h) and strong acceleration. In addition to these freely available driving cycles, we have generated the 'Up-to-50' and 'Up-to-80' cycles, where the vehicle accelerates to 50 or 80 km/h, stays there for five minutes, and then decelerates to 0 km/h again, and the 'Truncated Highway' cycle, from which the acceleration from 0 to 64 km/h in the beginning and the deceleration from 64 to 0 km/h at the end have been removed to model long hauls on highways. The key properties of these driving cycles are given in Table 8 in the Appendix.

To illustrate these cycles, we visualize four types of common driving circumstances in Figure 2, all from the EPA: the *Highway* driving cycle with highway conditions; the *NYC* driving cycle with stop-and-go driving conditions in New York City; the *Heavy urban (Urban)* driving cycle with driving conditions of a heavy duty vehicle in an urban environment; and the *(Rural)* driving cycle used to model driving conditions on rural roads with relatively free flowing traffic (also known as 'Extra-Urban'). For example, the Urban driving cycle has intervals where speeds are positive (e.g., from $t = [20, 150]$), interspersed with stationary intervals (e.g., $t = [150, 200]$) that could correspond to traffic lights or busy junctions. After 600 seconds, the vehicle uses a road where speeds in excess of 80 km/h are attained and where fluctuations are small, presumably on a highway or motorway crossing the city. Finally, as in all intervals, the speed is 0 km/h at the end ($t = 1060$). Table 8 in the Appendix shows that this driving cycle is characterized by a relatively low average speed, many stationary intervals, and some phases with strong acceleration (though not very strong).

We firstly determine the fuel consumption levels for all driving cycles. Using four representative driving cycles we then evaluate the factors that have an impact on the degree of underestimation when we include speed fluctuations and assess the influence of vehicle mass. Finally, we use these driving cycles to illustrate issues in the validation and implementation of CMEM computations in green vehicle routing under realistic driving conditions.

[3]These can be found on `http://www.dieselnet.org`

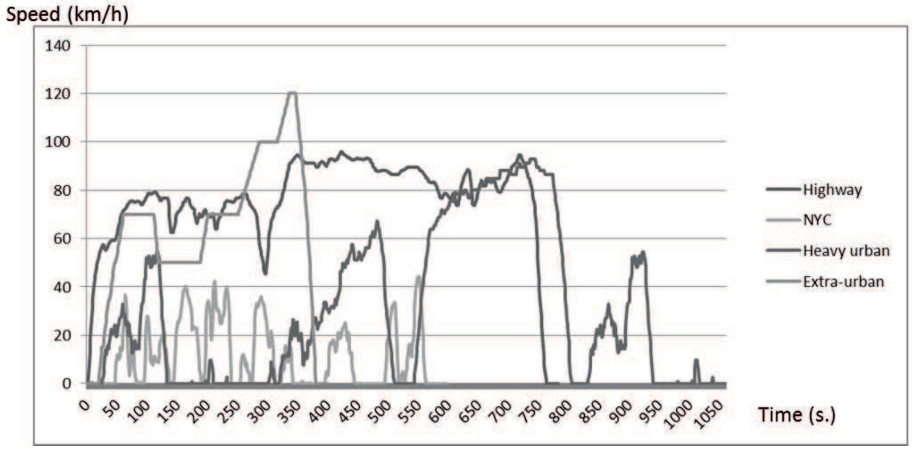

Figure 2: The velocities in km/h of vehicles in the four driving cycles during each second

4.1. Fuel consumption levels computed with the CMEM

For all driving cycles introduced in the previous part, we compute the fuel consumption level of the 7 t. vehicle and for each additional ton per km for fluctuating and fixed speeds. We also report the ratios $RTOT$ between the results for fluctuating and fixed speeds in Table 1. For example, the ratio of 1.2612 for the 7 t. vehicle on a Highway driving cycle indicates that the fuel consumption with fluctuating speeds in the Highway driving cycle is 1.2612 times higher than in case of a fixed average speed of 48 mph (77.1 km/h). The four driving cycles in boldface are used in the detailed experiments below.

The results reported in Table 1 indicate that, for the vehicle with a mass of 7 t., there are large fluctuations between different driving cycles. Fuel consumption levels are high for congested driving cycles and low for highways and arterial roads. However, fixed speed fuel consumption levels for low average speeds are also high. As a result, the ratios are close to 1 for driving cycles with low fixed average speeds, such as the HHDDT creep cycle and for cycles with relatively little speed fluctuation, such as Up-to-80 and Up-to-50. Ratios increase to around 1.2 to 1.4 for relatively free-flowing conditions, e.g., Highway. The highest values are obtained for driving cycles such as the Aggr. and the AUS NB cycles, which contain much strong acceleration and are designed for light duty vehicles.

When we consider the fuel consumption per additional ton in Table 1, the fixed speed computation returns the same amount of 0.0057 kg per km for all fixed speeds as explained in Section 3. For fluctuating speeds, however,

Table 1: CMEM fuel consumption in kg per km for a 7 t. vehicle and for each additional t. of mass and ratios between fixed and fluctuating speeds, for all driving cycles

Driving cycle	Av. speed km/h	Fluctuating speed $FFLUCT$ 7 t.	Fluctuating speed $FFLUCT$ add. t.	Fixed speed $FFIXED$ 7 t.	Fixed speed $FFIXED$ add. t.	Ratios $RTOT$ Gross 7 t.	Ratios $RTOT$ Add. t.
FTP	33.9	0.2293	0.0152	0.1471	0.0057	1.56	2.67
Highway	**77.1**	**0.1613**	**0.0097**	**0.1279**	**0.0057**	**1.26**	**1.70**
NYC	**11.3**	**0.4490**	**0.0214**	**0.3355**	**0.0057**	**1.34**	**3.75**
Aggr.	76.7	0.2379	0.0171	0.1279	0.0057	1.86	3.00
Urban	**30.1**	**0.2380**	**0.0132**	**0.1577**	**0.0057**	**1.51**	**2.32**
Maint.	46.8	0.2211	0.017	0.1553	0.0057	1.42	2.98
LA	39.4	0.2481	0.0181	0.1368	0.0057	1.80	3.18
Elem.	18.3	0.2860	0.0136	0.2254	0.0057	1.70	2.39
Rural	**62.4**	**0.1809**	**0.0110**	**0.1228**	**0.0057**	**1.47**	**1.93**
JPN10	17.6	0.306	0.0158	0.2324	0.0057	1.30	2.77
JPN15	33.9	0.2211	0.0139	0.1475	0.0057	1.50	2.44
JPN10-15	25.6	0.2510	0.0145	0.1754	0.0057	1.40	2.54
WLTP Class 1 v.1.4	28.3	0.2058	0.0104	0.1640	0.0057	1.25	1.82
WLTP Class 2 v.1.4	35.7	0.2080	0.013	0.1431	0.0057	1.45	2.28
WLTP Class 3 v.1.5	46.5	0.2226	0.0144	0.1281	0.0057	1.74	2.53
WVU 5-Peak (Truck)	32.1	0.1848	0.009	0.1518	0.0057	1.22	1.58
WHVC	40.1	0.1971	0.0116	0.1353	0.0057	1.46	2.04
CBD (SAE J1376)	21.6	0.2672	0.0145	0.2023	0.0057	1.32	2.54
City Suburban	22.6	0.2687	0.0152	0.1914	0.0057	1.40	2.67
HHDDT Cruise	70.7	0.1635	0.0081	0.1248	0.0057	1.31	1.42
HHDDT Transient	24.6	0.2512	0.014	0.1804	0.0057	1.39	2.46
HHDDT Creep	2.8	1.2431	0.0088	1.2212	0.0057	1.02	1.54
Artemis Urban	17.7	0.3545	0.0222	0.2315	0.0057	1.53	3.89
Artemis Rural	57.5	0.2054	0.0156	0.1229	0.0057	1.67	2.74
Aus NC Cong.	8.0	0.5323	0.0159	0.4600	0.0057	1.16	2.79
Aus NC Minor	32.4	0.2110	0.0135	0.1510	0.0057	1.40	2.37
Aus NC Arterial	31.5	0.2437	0.0175	0.1533	0.0057	1.59	3.07
Aus NC Highway	54.2	0.1785	0.0122	0.1237	0.0057	1.44	2.14
AUS NB Cong.	10.9	0.4185	0.0158	0.3461	0.0057	1.21	2.77
Aus NB Minor	35.8	0.2523	0.0204	0.1429	0.0057	1.77	3.58
Aus NB Arterial	29.9	0.2652	0.0191	0.1585	0.0057	1.67	3.35
Aus NB Highway	54.5	0.2087	0.0169	0.1236	0.0057	1.69	2.96
Aus NCH Cong.	6.7	0.6117	0.0159	0.5378	0.0057	1.14	2.79
Aus NCH Minor	32.6	0.2315	0.0164	0.1505	0.0057	1.54	2.88
Aus NCH Arterial	28.1	0.2384	0.0147	0.1647	0.0057	1.45	2.58
Aus NCH Highway	64.4	0.1734	0.0106	0.1231	0.0057	1.41	1.86
FIGE	59.0	0.1669	0.0096	0.1228	0.0057	1.36	1.68
Up-to-80	77.4	0.1440	0.0067	0.1374	0.0057	1.05	1.18
Up-to-50	48.9	0.1370	0.0063	0.1309	0.0057	1.05	1.11
TruncHwy	80.9	0.1579	0.0093	0.1239	0.0057	1.27	1.63

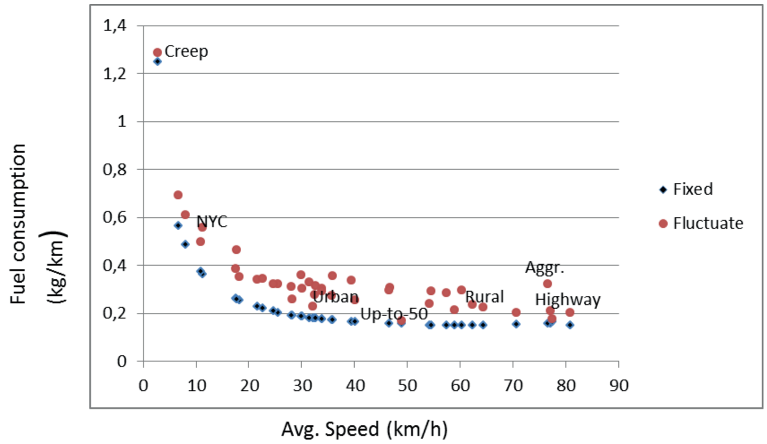

Figure 3: Fuel consumption of a 12 t. vehicle computed with the CMEM under fixed speeds (black dots) and fluctuating speeds according to driving cycles (lighter dots)

the fuel consumption levels per additional ton are often much higher and the resulting ratios can take values of over 3 for driving cycles such as the NYC and the Artemis Urban driving cycles.

One explanation may be that in Eq. (3) the vehicle mass M is multiplied by a term that contains the acceleration at time t a_t and the driving cycles in question contain relatively many phases of strong acceleration; see Table 8 in the Appendix. The ratios $RTOT$ therefore increase with the vehicle mass and with the addition of payload to a vehicle and this effect is sometimes very strong.

Figure 3 illustrates the difference between fuel consumption levels computed with fixed and fluctuating speeds of a 12 t. vehicle, a case that is similar to the 6.35 t. vehicle with 6 t. load capacity presented in Franceschetti et al. (2013). The computations, illustrated with the Highway driving cycle, are as follows. The fluctuating speed fuel consumption $FFluct$ of a 12 t. vehicle in a Highway driving cycle is $0.1613 + (12 - 7) \times 0.0097$ and for fixed speeds $FFixed$, it is $0.1279 + (12 - 7) \times 0.0057$, giving the ratio of 1.3419. The dark dots indicate the fixed speed fuel consumption and correspond to the results in Figure 1 and each light dot represents a fluctuating speed result of a given driving cycle; some striking driving cycles are tagged. The figure shows that there is a broad band of possible fuel consumption levels above the line representing fixed speed fuel consumption levels. This band widens as the average speed decreases from 80 to 40 km/h and then narrows as the

Table 2: Ratios $RTOT$ between fuel consumption computed with fluctuating and fixed speeds for different driving cycles and vehicles

	Highway	NYC	Urban	Rural
Av. speed	76.8 km/h	11.3 km/h	30.1 km/h	62.4 km/h
22 t.	1.4387	1.8305	1.7954	1.6632
12 t.	1.3419	1.5295	1.6349	1.5608
7 t.	1.2612	1.3406	1.5111	1.4740
5 t.	1.2179	1.2557	1.4481	1.4268

speed decreases even further. This could mean that a haul of this vehicle with an average speed of, say, 40 km/h does not have a fuel consumption of precisely 0.19 kg/km as predicted by the fixed speed computations, but more likely between 0.19 and 0.37 kg/km, depending on the driving conditions.

4.2. The effects of vehicle mass, acceleration, and varying speeds

The differences between the fixed and fluctuating speed results $FFixed$ and $FFluct$ are caused by several factors (see Section 3): the vehicle mass and the effects of acceleration and different speeds. We determine the effect of these factors for the Highway, the NYC, the Urban, and the Rural driving cycles, presented in Figure 2 to model highway, stop-and-go, urban, and rural driving conditions, respectively.

We compute the ratios $RTOT$ for vehicle masses of 22, 12, 7, and 5 t. using the results from Table 1. The results in Table 2 show that if the fluctuating speed computations are accurate, the degree of underestimation increases from around 20 to 45% for 5 t. vehicles to 60 to 80% for 22 t. vehicles. The effect of vehicle mass is notable for the Urban and NYC cycles and less so for the Highway and Rural driving cycles. The high values of the ratio $RTOT$ demonstrated for heavy vehicles in urban driving conditions may mean that green vehicle routing approaches are likely to underestimate the fuel consumption or the carbon emissions that result from sending such a vehicle through such driving conditions.

As we have seen in Section 3, two factors are at the root of the underestimation $RTOT$: the effect of having varying speeds and the effect of acceleration. In order to determine the size of these effects for a given driving cycle, we compute the fuel consumption denoted by $FNoAcc$ with the CMEM as follows: the speed v_t fluctuates according to the driving cycle dc, but the acceleration parameter a_t is set to 0 during every second t. We compute the values of $FNoAcc$ using a modified version of the CMEM and obtain 0.1332, 0.3399, 0.1856, and 0.1437 kg per km for the 7 t. vehicle for

Table 3: The total effect, acceleration effect, and effect due to varying speeds for different driving cycles and vehicles

Effect	Highway	NYC	Urban	Rural
	22 t. gross weight truck			
Acceleration	1.4047	1.8122	1.6113	1.5125
Varying speeds	1.0242	1.0101	1.1143	1.0996
Total ($RTOT$)	1.4387	1.8305	1.7954	1.6632
	12 t. gross weight truck			
Acceleration	1.2985	1.5115	1.4221	1.3720
Varying speeds	1.0334	1.0119	1.1496	1.1376
Total ($RTOT$)	1.3419	1.5295	1.6349	1.5608
	7 t. gross weight truck			
Acceleration	1.2114	1.3234	1.2840	1.2600
Varying speeds	1.0412	1.0130	1.1769	1.1699
Total ($RTOT$)	1.2612	1.3406	1.5111	1.4740
	5 t. gross weight truck			
Acceleration	1.1651	1.2390	1.2161	1.2017
Varying speeds	1.0453	1.0135	1.1907	1.1874
Total ($RTOT$)	1.2179	1.2557	1.4481	1.4268

the Highway, NYC, Urban, and Rural driving cycles, respectively, and the fuel consumption per additional ton is 0.0057 kg per km for all driving cycles. We can rewrite $RTOT$ as:

$$RTOT = FFluct/FFixed = (FFluct/FNoAcc) \times (FNoAcc/FFixed) \quad (6)$$

where $(FFluct/FNoAcc)$ is a measure of the effect due to acceleration and $(FNoAcc/FFixed)$ is a measure of the effect due to varying speeds.

Table 3 reports the sizes of the effects for vehicles with 22, 12, 7, and 5 t. of mass. The results show that 1) the effect due to acceleration is often much larger than that caused by varying speeds; and 2) the effect of acceleration increases with the mass of the vehicle, whereas the effect due to varying speeds decreases with the vehicle mass. The explanation is that the vehicle's acceleration is multiplied with the mass of the vehicle in Eq. (1), whereas the effect due to varying speeds stems mainly from the term related to v^3 that does not contain the vehicle mass; this effect is largest when the mass of the vehicle is low. As a consequence, driving cycles with much acceleration, such as the NYC driving cycle, have the strongest effect due to acceleration, whereas driving cycles with large speed fluctuations, such as the Urban and Rural cycles, have a relatively strong effect due to varying speeds.

As any fixed speed choice assumes zero acceleration, the effect due to acceleration remains as in Table 3. The effect due to varying speeds, however, can be quite different from those in Table 3. For example, if we choose the speed limit of a road as our fixed speed, as is done in Harris et al. (2011), the effect could be smaller than 1 if the maximum speed fuel consumption is larger than those of most observed speeds in the driving cycle, but it could attain a very large value for a very congested road with a speed limit of the road of, say, 50 km/h. Alternatively, if we split connections into segments and use fixed average speeds for all these segments, the effect due to acceleration remains as large as in the case with only one segment. Thus, this choice can only reduce the effect due to varying speeds but not the often more sizeable effect due to acceleration.

4.3. The effect of CMEM parameters

In our implementation of the CMEM, we have mainly fixed the parameter values as in Barth et al. (2005) and Franceschetti et al. (2013). This section performs a brief sensitivity analysis on the effect of changes in two key parameter values: the number of revolutions per second (rps) N_e and the frontal surface of the vehicle A. We do not consider any effects of other parameters, such as efficiencies or the declination of the road.

In our computations, we have so far assumed a fixed value of $N_e = 40$. In reality, N_e may attain high values in acceleration phases before a gear shift takes place and it may attain low values during phases of deceleration, giving low energy usage during deceleration phases. According to Barth et al. (2005), N_e can vary between $N_e = 23.2379$ under stationary conditions and has a maximum value of 60 rps (3,600 per minute).

We consider two crude modifications of our CMEM approach to assess the effect of variations of N_e on the fuel consumption per km; see Table 4. Modification 1 takes into account that vehicles may be stationary during driving cycles and modification 2 measures the effect of a low power usage during deceleration and stationary intervals and a high power usage for acceleration. The setting of $a > 0.1m/s^2$ and the deceleration of $0.1m/s^2$ is taken from Ericsson (2001).

The results in Table 5 indicate that variations in N_e can have an influence on the fuel consumption levels of the 7 t. vehicle for urban cycles, in particular the NYC driving cycle with its frequent and lengthy stationary intervals, but the effect on the fuel consumption per additional ton is minimal. The consequence is that $RTOT$ may be lower than in Table 2 for urban driving cycles, but the ratio decreases with the vehicle mass. The effect of the acceleration, which is related to the mass of the vehicle, remains as strong as

Table 4: Tested CMEM computations with varying N_e

$FFluct$:	fuel consumption of the standard CMEM with fluctuating speeds using fixed $N_e = 40$
Modification 1:	set $N_e = 40$ if the vehicle is in motion and $N_e = 23.2379$ if it is stationary ($v = 0$)
Modification 2:	in addition to modification 1, set $N_e = 50$ if $a > 0.1m/s^2$, $N_e = 23.2379$ (i.e., the value for stationary vehicles N_0) if the degree of deceleration is larger than $0.1m/s^2$, and $N_e = 40$ otherwise
$FFixed$	fuel consumption of the fixed speed approach (with $N_e = 40$).

Table 5: Fuel consumption in kg/km for the different modifications

Variant	Highway	NYC	Urban	Rural
	For the 7 t. vehicle			
$FFluct$	0.1613	0.4493	0.2382	0.1809
Modification 1	0.1611	0.4065	0.2228	0.1787
Modification 2	0.1607	0.3920	0.2199	0.1801
$FFixed$	0.1279	0.3355	0.1577	0.1228
	Per additional ton			
$FFluct$	0.0097	0.0214	0.0132	0.0110
Modification 1	0.0097	0.0214	0.0132	0.0111
Modification 2	0.0097	0.0215	0.0133	0.0111
$FFixed$	0.0057	0.0057	0.0057	0.0057

observed in Table 3.

Even if the choice of a fixed value of N_e during a haul could be justified, it is probably incorrect to apply the same fixed value of N_e for all driving conditions and speeds and thus further research on appropriate values of N_e for different speeds and driving conditions could be conducted.

Another factor that can play a role is the front size of the vehicle, denoted by A; we choose a value of 4, but according to Demir et al. (2011), it can vary between 2.1 and 5.6. Since A is multiplied by the term v^3 but not with the vehicle mass M in Eq. (1), its value does not influence the fuel consumption per ton added $FUEL2(\bar{d}c)$.

Table 6: Fuel consumption in kg/km and ratios for different frontal surface sizes A for a 7 t. vehicle

Variant	$FFluct$		$FFixed$		$RTOT$	
	$A = 5.6$	$A = 2.1$	$A = 5.6$	$A = 2.1$	$A = 5.6$	$A = 2.1$
Highway	0.1813	0.1375	0.1460	0.1068	1.24	1.29
NYC	0.4521	0.4470	0.3359	0.3350	1.35	1.33
Urban	0.2523	0.2217	0.1604	0.1544	1.57	1.44
Rural	0.2012	0.1571	0.1346	0.1088	1.49	1.44

In Table 6, we present the fuel consumption levels $FFluct$ and $FFixed$ as well as the ratios $RTOT$ for a 7 t. vehicle. The value of A has the largest effect on absolute fuel consumption levels for the Highway driving cycle, but has little effect on $RTOT$. For the other driving cycles, the value of $RTOT$ can increase strongly with A, in particular for the Urban one. This effect, however, decreases with the vehicle mass. This also implies that a light weight vehicle with small frontal surface may not be much affected by speed fluctuations.

In conclusion, changes in the front size A and the number of rps N_e can have significant effects in case of relatively light weight vehicles, but additional experiments not presented here indicate that this effect decreases with the vehicle mass.

4.4. Challenges in the validation and the implementation

A natural question is whether the CMEM computations can be validated using actual observations. This section shows that this is in fact quite challenging.

The complications are the following. In green routing, we presume that we can attribute the fuel consumption or carbon emissions of a vehicle accurately to our decisions on the route choice, the load on the vehicle, and the time of the day or expected speed of the vehicle. Therefore, empirical observations should include detailed measurements on the fuel consumption, the mass of the vehicle, and the precise speed profiles.

To the best of our knowledge, the study by Coyle (2007) provides empirical results that are the most relevant for our specific requirements. The study reports the fuel consumption of three tipper vehicles and two articulated vehicles (i.e., vehicles with a joint) in an experiment where each vehicle is driven on a given route several times with varying payloads. Each observation contains the fuel consumption measured in miles per gallon and the precise mass of the vehicle, including the load. The relationship between the number of miles per gallon and the mass of the vehicle is determined using linear regression. We use this study to illustrate the challenges related to the validation and implementation of CMEM computations. For both types of vehicles, Coyle (2007) reports the composition of the entire haul: the tipper vehicles drive over a mixture of urban roads and single and dual carriageways, and the articulated vehicles over single and dual carriageways and over motorways. The problem is that we do not know the precise driving circumstances and that they may vary between test runs.

One course of action is to use these measurements and approximate driving conditions, e.g., assume that the Urban driving conditions and corresponding average speeds apply to an experiment and use these to estimate fuel consumption with fluctuating and fixed speeds. When computing fuel consumption using the CMEM, there are several sources of error: the fuel consumption level computed with the CMEM may be inaccurate even if the precise driving conditions are inserted, as the CMEM is formed through regression on observed data points and there is variation around the regression line. Secondly, the unknown driving conditions have an influence on fuel consumption. For example, for a single run, it can be that the first effect, the error in the CMEM, may even out the impact of driving conditions, but this is no proof that fixed speed computations work as intended. To determine the validity of fixed speed computations under different driving conditions we therefore have to be able to separate the two effects. This is not possible with the results from Coyle (2007).

To separate these sources of error, experiments are needed in which an observer keeps track of both the precise mass of the vehicle and of the speed of the vehicle at any given moment in order to distinguish between the possible error in the CMEM, the choice of a given average speed, and the effect of speed variations and acceleration. Moreover, in order to ensure that computations are correct, these experiments should also contain a wide range of representative driving conditions. To the best of our knowledge, no such results have been reported; even the most detailed studies in transportation science studies, such as those in Coyle (2007) or Walnum and Simonsen (2015), do not contain such detailed experiments.

The suggested validation exercise is very extensive. An alternative is to determine in which cases fixed speed computations can lead to poor green vehicle routing decisions; if these decisions are avoided, such solutions might be useful even if the fuel consumption computations have not been properly validated. We provide examples of such poor decisions in the next section.

5. Numerical examples

The results in Section 4 indicate that the use of fixed speed CMEM computations to model realistic driving conditions can lead to underestimation of actual fuel consumption. This section illustrates the problems that this finding can give in green vehicle routing, namely that some types of driving conditions may incorrectly be identified as green and that such computations are unable to model the differences in impact of an additional ton of

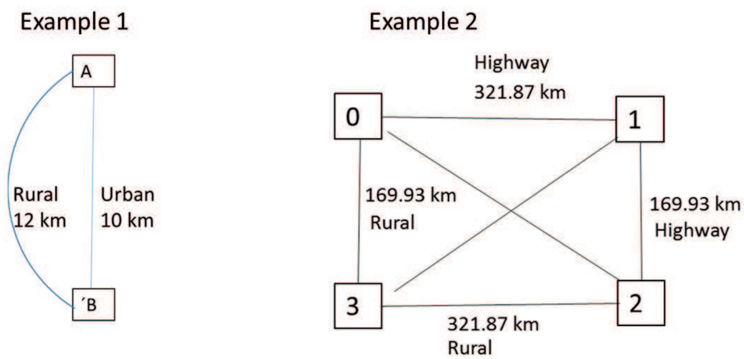

Figure 4: Schematic overview on the choice of routes in the two examples in the section: the choice between urban and rural routes (example 1) and between two routes in a four city setting (example 2)

mass under different driving conditions. The decisions in the examples are represented schematically in Figure 4.

The first example illustrates the risk that green vehicle routing approaches may label an option as having low fuel consumption assuming fixed speeds, but that they fail to take into account that the degree of underestimation varies between different driving conditions.

Example *Assume that we have a 12 t. vehicle (including load) which we wish to send from A to B. Two options are available: an urban road of 10 km and a rural road of 12 km; see the left-hand part of Figure 4. We assume that the Urban and Rural driving cycles apply to these roads. We can compute the fuel consumptions under fixed speeds and find 1.816 kg for the rural road and 1.862 kg for the urban road, suggesting that the rural road gives the lowest fuel consumption. The fluctuating speed computations find a fuel consumption of 2.831 kg for the rural road and 2.667 kg for the urban road, leading to a preference for the urban road. The reason for this result is that the underestimation is lower for the Urban driving cycle than for the Rural one.*

One may argue that the rural road is the greener choice when it leads to avoidance of congestion, noise, and the emissions of local pollutants such as Particulate Matter on urban dwellers. However, this 'right' result is then obtained by choosing the wrong objective (as it ignores the apparently important local pollutants) in combination with a possibly incorrect computation *method.*

The second example illustrates the effect of the vehicle mass. In fixed speed models, this effect is independent of the given speed, but it varies significantly in the fluctuating speed computations. To that end, we use the small numerical example presented in Table 2 of Bektas and Laporte (2011), see the left hand side of Figure 4.

Example *The example discusses the problem of finding the shortest route and the route with the lowest fuel consumption in a network with the starting node 0 and the three nodes 1, 2, and 3. In this routing instance, the connections between 0 and 1 and between 2 and 3 and vice versa have a length of 200 miles (321.87 km), whereas the lengths of connections between 0 and 3 and between 1 and 2 and vice versa have a length of 100 miles (160.93 km); see the right-hand part of Figure 4. The lengths of the diagonal connections between 1 and 3 and between 0 and 2 are 223.61 miles (360 km). As in Table 2 of Bektas and Laporte (2011), demand at nodes 1 and 3 is 0.25 t. each and demand at node 2 is 3.50. Node 0 is the location from which the vehicle is dispatched and to which it returns. The vehicle weighs 3 t. and can carry the total demand of 4 t. The shortest routes are* $0-1-2-3-0$ *(Route 1) or the reverse route* $0-3-2-1-0$ *(Route 2) with a length of 965.61 km. Route 2 has fewer ton-kilometers (1,891) than Route 1 (1,971). Hence, Bektas and Laporte (2011) find that Route 2 is greener.*

We modify the example such that the vehicle travels according to the Highway driving cycle on the connections from 0 to 1 and from 1 to 2, and according to the Rural driving cycle on the other connections. From Table 1, we can compute that the fuel consumption of the vehicle is 0.1051 and 0.1000 kg using the fixed average speeds of the Highway and Rural driving cycles, respectively. For each additional ton, fuel consumption is 0.0057 kg irrespective of the chosen average speed. If the speeds fluctuate according to the Highway driving cycle, the computed fuel consumption is 0.1225 kg for the vehicle and 0.0097 per ton; the corresponding amounts for the Rural driving cycle are 0.1369 kg for the vehicle and 0.011 kg per ton. Table 7 shows the computation of the fuel consumption $FFixed$ *and* $FFluct$ *of the routes 0-1-2-3-0 (Route 1) and 0-3-2-1-0 (Route 2).*

The fixed speed computations suggest that Route 2 is greener than Route 1 because it has fewer ton-kilometers. This holds for any vehicle speed since the fuel consumption per additional km is independent of the speed. How-

Table 7: Computation of the fuel consumption of the route 0-1-2-3-0 (Route 1) and 0-3-2-1-0 (Route 2)

			Route 1			Route 2		
Arc	Distance	Conditions	Load	*FFluct*	*FFixed*	Load	*FFluct*	*FFixed*
(0,1)	321.87	Highway	3 + 4	51.92	41.17	3+ 0	39.43	33.83
(1,2)	160.94	Highway	3 + 3.75	25.57	20.35	3 + 0.25	20.10	17.14
(2,3)	321.87	Rural	3 + 0.25	44.95	32.65	3 + 3.75	57.34	39.07
(3,0)	160.94	Rural	3 + 0	22.03	16.09	3 + 4	29.11	19.76
			Total	144.47	110.26	*Total*	145.99	109.80

ever, the fluctuating speed computations suggest to use Route 1 and send the heavily loaded vehicle across the highway connections as we find that it takes more fuel to transport a ton over rural road (0.0110 kg) than over a highway (0.0097 kg). Note that the selection of a heavier vehicle of, say, 8 t., does not alter the conclusions: this amounts to sending an additional 5 t. through all connections and raises the fuel consumption of both routes by the same amount.

These examples illustrate two ways in which fixed speed computations may lead green routing methods to the incorrect choices: firstly, because these computations may suggest types of connections for which actual fuel consumption levels are higher than the computed ones, such as the Rural connection in Example 1, and secondly, because these computations may ignore that sending extra units of load across certain connections, e.g. Rural in Example 2, can cause larger fuel consumption than sending them through other connections, e.g. Highway. It also holds that if green vehicle routing solutions contain only connections with minor speed fluctuations, these incorrect choices are avoided. This can be used in the validation of green vehicle routing solutions.

6. Conclusions and future research

This paper investigates an important part of green vehicle routing models, namely the computation of carbon emissions and fuel consumption by means of the frequently used CMEM. This model can measure the effect of relevant routing decisions, such as the load on the vehicle or the chosen speed, on the fuel consumption or carbon emissions. However, the CMEM is difficult to implement, as its proper usage requires driving conditions on a second-to-second basis. Green routing papers that use the CMEM simplify the fuel consumption computations by assuming that these conditions are in a steady-state and that the vehicle travels at a fixed average speed.

Modeling always involves a simplification of the real world. However, the simplification should be such that key properties of reality are preserved in the model. In green vehicle routing, such a key property is formed by the driving conditions faced by a truck or van. However, no validation has been made on the assumption that driving conditions with fluctuating speeds can be replaced by an average speed in the fuel consumption and carbon emissions computations. As a consequence, we can only use such computations safely if speed fluctuations are negligible, but studies in transportation science do not find this very realistic.

It follows from previous studies in transportation science (Section 2) and from the formulation of the CMEM (Section 3) that fixed average speed computations are likely to underestimate the fuel consumption under fluctuating speeds. In order to determine the size of this underestimation, we perform numerical experiments in Section 4 in which we compute fuel consumption levels using the CMEM with speeds fluctuating according to driving cycles as well as with the average speeds. These results indicate that fixed speeds results are close to those under fluctuating speeds if traffic is free-flowing and the vehicle can stay at the same speed; if the time spent at the fixed speed is sufficiently large, the acceleration to and the deceleration from this speed have little effect. Additionally, fixed speed computations are most accurate if 1) the mass of the vehicle is low as each additional ton increases the degree of underestimation; and 2) the average speed is very low in which case the fuel consumption is very high, meaning that the underestimation as a fraction of total fuel consumption is quite small as well. However, our experiments indicate that there are other conditions where the fuel consumption computed with the fluctuating speeds can easily be up to 80% higher than those under fixed speeds, namely for high vehicle masses and for driving cycles with large amounts of acceleration. Even for the relatively steady state Highway driving cycle, the fixed speed results are 30 to 40% lower than the steady state results.

We find that there are two causes of the underestimation from fixed speeds. We find that the main cause is often that much fuel is used for accelerating vehicles when speeds fluctuate, i.e., the effect due to acceleration. This effect appears to increases with the mass of the vehicle. Another cause is that fuel consumption is a convex function of a given vehicle's speed and that the fuel consumption is therefore lower for the average speed than the average of the actual speeds (weighted according to how long each speed is maintained), i.e., the effect due to varying speeds. This effect is most prominent for light vehicles but decreases with the vehicle mass. A consequence of this finding is that if one tries to improve computations by taking fixed speeds over smaller intervals, this does little to reduce the effect due to acceleration.

Our results indicate that green vehicle routing approaches with fixed speed CMEM computations may produce solutions that perform badly on both greenness and cost; see Section 5. If a decision maker makes the trade-off between the cheapest solution and a routing solution with higher costs but lower fuel consumption or carbon emissions, e.g., in a multi-objective setting, the choice of such a greener route is hard to motivate if the fuel consumption or carbon emission savings from using this green option are highly uncertain. The question is even whether the applied green vehicle routing model provides greener solutions than a model that minimizes distance or costs. This requires actual fuel consumption or carbon emission measurements.

Our experiments are by no means been complete as factors such as the impact of declination of roads have not been taken into account. Moreover, our experiments have been limited to the CMEM. A direction of future research is to extend our experiments to these parameter values and to other instantaneous emission models, such as the PHEM (Boulter et al., 2009).

Experimental validation is necessary to ensure that CMEM computations in green vehicle routing are also valid under realistic driving conditions. Comparing observed fuel consumption level or carbon emissions of the efficient solutions suggested by green routing with the computed level is insufficient proof of validity as this does not exclude that (many) less costly routing options might actually be greener than the solution obtained.

In principle, the fixed speed CMEM computations should be correct for all types of decisions in green vehicle routing, i.e., for every combination of the load of the vehicle, the desired speed of the vehicle, and for every possible connection in Franceschetti et al. (2013), and in addition for each type of vehicles considered in Koc et al. (2014). Validation with actual observations is very challenging as it may require a vast number of observations. An easier approach is to determine conditions under which the CMEM computations with the fixed speed assumption indeed find appropriate solutions. Our findings predict that this is so if the obtained solutions consist of connections with free-flowing traffic conditions.

An interesting direction of future research is to include the speed fluctuations in actual driving conditions into green vehicle routing approaches, as the CMEM computations have been calibrated and validated under such conditions. For relatively light vehicles, one may achieve this by taking short segments, as in Maden et al. (2010). The question is how we approximate the driving conditions on each connection. We can follow the approach suggested in Palmer (2007) and take a *discrete set of driving cycles* corresponding to different driving conditions (e.g., congested roads or urban roads) and determine the driving cycle with the best fit to each connection under consideration. However, without measurements on actual driving conditions or fuel consumption, we cannot be sure that the selected driving cycles are close to the actual driving conditions; see also Section 4.4. This is aggravated by the fact that driving conditions and driver behavior, which cause the speed fluctuations, are variable and unpredictable. A conceptually more appropriate approach may be to use *robust optimization* in order to reflect the large uncertainty in the fuel or carbon computations due to driving conditions.

A different way forward in green vehicle routing is to use average speed engine emission models instead of instantaneous ones. Because fuel measurements are determined under various actual driving conditions, average speed models have the advantage that they are based on typical driving conditions and therefore include speed fluctuations. A recent approach by Ligterink et al. (2012) computes average speed power usage per ton of mass, which can be transformed into kg per km.

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Appendix

In Table 8, we report the following properties of the 40 driving cycles that are used in the numerical experiments, namely the duration of and distance covered in the driving cycle, the average speed, maximum speed, the standard deviation in speed (to measure variation in velocity), the duration of the intervals at which a vehicle is stationary (at speed $v = 0$), and the occurrence of strong acceleration of more than 5 km/h per second (1.39 m/s^2) and 10 km/h per second (2.78 m/s^2). The fuel consumption per km can then be related to the properties of the driving cycles. For example, a stop-and-go driving cycle such as the NYC is characterized by low average and maximum speeds and a large proportion of stationary intervals. Some driving cycles, most notably the Aggr., Maint., and the Aus NB driving cycles, contain high maximum speeds or many phases with strong acceleration and are not suitable for heavy HDVs.

Table 8: Properties of the selected driving cycles

Driving cycle	Dist. (meter)	Duration Total (s.)	Stationary (s.)	Speed Avg (km/h)	St. dev (km/h)	Max (km/h)	Acc. over $> 5(10) km/hs$ (s.)
FTP	17667	1874	355	33.9	15.9	90.7	75
Highway	16411	765	6	77.1	10.2	95.8	3
NYC	1887	598	210	11.3	8.0	44.3	22
Aggr.	12813	600	45	76.7	24.6	128.5	50 (10)
Urban	8883	1060	353	30.1	19.8	92.8	13
Maint.	3134	240	12	46.8	15.8	90.7	7
LA	15706	1435	234	39.4	19.7	107.5	47 (2)
Elem.	994	195	64	18.3	10.7	50.0	0
Rural	6955	400	42	62.4	19.7	120.0	0
JPN10	664	135	39	17.6	14.7	40.0	0
JPN15	2174	231	77	33.9	27.5	70.0	0
JPN10-15	6339	891	291	25.6	23.8	70.0	0
WLTP Class 1 v.1.4	8091	1028	205	28.3	20.4	64.4	0
WLTP Class 2 v.1.4	14664	1477	233	35.7	24.7	85.2	0
WLTP Class 3 v.1.5	23262	1800	235	46.5	36	131.3	14
WVU 5-Peak (Truck)	8023	900	163	32.1	21.6	64	0
WHVC	20072	1800	245	40.1	29.5	87.8	3
CBD (SAE J1376)	3273	560	99	21	13.1	32	0
City Suburban	10689	1700	396	22.6	20.9	70.1	0
HHDDT Cruise	36783	2083	39	70.7	30.1	94.9	1 (1)
HHDDT Transient	4562	668	104	24.6	21.4	76	0
HHDDT Creep	199	253	104	2.8	3.3	13.1	0
Artemis Urban	4870	993	282	17.7	17	57.7	41 (1)
Artemis Rural	17272	1082	33	57.5	24.6	111.5	18
Aus NC Cong.	726	328	69	8	6.8	28.2	6
Aus NC Minor	4577	509	24	32.4	15.8	57.2	8
Aus NC Arterial	3776	431	76	31.5	19.4	63.3	7 (1)
Aus NC Highway	7956	528	29	54.2	21.8	82.9	5 (1)
AUS NB Cong.	970	319	24	10.9	8	30.9	13 (1)
Aus NB Minor	4029	405	13	35.8	16.8	68.7	33 (3)
Aus NB Arterial	3234	390	106	29.9	23.8	73.7	11 (2)
Aus NB Highway	12357	591	0	75.3	20.6	91.6	2
Aus NCH Cong.	679	364	94	6.7	7.8	33	0
Aus NCH Minor	4313	477	8	32.6	16.8	60.3	0
Aus NCH Arterial	3469	444	91	28.1	21.8	59	1 (1)
Aus NCH Highway	7071	390	12	64.4	29	96.1	1 (1)
FIGE	29492	1800	0	59	28.7	91.1	1 (1)
Up-to-50	13778	640	2	77.4	11.7	80	0
Up-to-80	8715	640	2	48.9	6	50	0
TruncHwy	15623	694	0	129.5	9.7	95.8	0