Incorporating Driving Cycle Based Fuel Consumption Estimation in Green Vehicle Routing Problems

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Abstract

Traditionally, vehicle routing problems (VRP) were solved with the objective of minimizing total distance traveled. The rationale behind minimizing distance was perhaps that fuel consumption depends on distance traveled. Fuel consumption depends on several other factors besides distance. Recently, several authors have focused on directly minimizing total fuel consumed considering load carried and/or speed. However, it is surprising that none have considered the significant effect of acceleration on fuel consumption. Since fuel cost represents a significant fraction of operating cost, incorrect fuel consumption estimation may result in suboptimal routes and schedules. Here, we estimate fuel consumption while considering the effect of load, speed, and acceleration. We achieve this by using driving cycles (speed-time profile of a vehicle) that can be easily obtained from Global Positioning System (GPS) data. Modified versions of several standard VRP instances are used to test the effect of estimated fuel consumption using driving cycles. Test results show that using driving cycles results in an average fuel savings of 8-12% compared to using average speed

Keywords: Driving cycles, Fuel consumption minimization, Acceleration, Green vehicle routing problem

1. Introduction and Background

The World Health Organization certified that 98% of the cities in developing countries and 56% of the cities in developed countries having more than 100,000 inhabitants do not meet air quality standards. Another report by the US Environmental Protection Agency (CAR, 2014) estimated 33 percent of CO_2 emissions in 2011 were from the transportation sector, of which nearly 63 percent of the emissions were from road transport. Freight transport is one of the major contributors to these emissions, especially in cities. Emissions from urban freight transport can be reduced by acting at either the strategic level (Kin et al., 2017) or the operational level. Our study is on the operational level. We determine "green" routing strategies with an aim to reduce fuel consumption and, as a result, CO_2 emissions. Fuel cost contributes approximately 30-60% of operational costs for logistics operators (Martino et al., 2009; Sahin et al., 2009; Hooper and Murray, 2017). Therefore, reducing fuel consumption achieves the twin goal of lessening the cost for the operators as well as reducing the impact on the environment.

The Vehicle Routing Problem (VRP) is an important problem for every logistics and distribution company. The objective is to find optimal vehicle routes from one or more depots to customers who are geographically spread out (Laporte, 1992). Most variants of the VRP have evolved by modifying the constraints set of the formulation. Examples of variants of the VRP include Capacitated VRP (CVRP) (Vigo, 1996), VRP with Time Windows (VRPTW) (Berger and Barkaoui, 2004; Figliozzi, 2010), Stochastic VRP (SVRP) (Laporte et al., 1992; Dror et al., 1993), Split Delivery VRP (SDVRP) (Dror and Trudeau, 1989), VRP with a heterogeneous fleet of vehicles (HFVRP) (Prins, 2002), and Pickup and Deliveries VRP (PDVRP)

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(Dethloff, 2001). Several of these variants have also been generalized for handling multiple depots (Salhi and Sari, 1997; Polacek et al., 2004) and multiple echelons (Perboli et al., 2011; Soysal et al., 2015). Most studies consider distance minimization (Renaud et al., 1996; Berger and Barkaoui, 2004) and travel time minimization (Laporte et al., 1992; Li et al., 2010) for the objective function. Kara et al. (2007) minimized vehicle ton-miles and Bektas and Laporte (2011) minimized total cost instead of distance.

Recently, there has been a significant increase in the number of publications (Suzuki, 2011; Demir et al., 2012; Franceschetti et al., 2013; Qian and Eglese, 2016) on routing problems with fuel minimization as the objective. Initial studies with the objective of fuel minimization considered a simple linear function for fuel consumption based on distances; subsequent studies have considered load, speed, and recently, time-dependent speed. Palmer (2007) was the first to study the vehicle routing problem with the objective of minimizing CO_2 emissions. His study considered the effect of road topography, vehicle speeds, and congestion for CO_2 emission estimation. Unlike CO_2 emissions that are proportional to fuel consumption, NO_x emissions are not dependent on fuel consumed. The formulation by Carlos et al. (2014) considered NO_x emission and other fixed costs in addition to CO_2 emissions for a fixed fleet heterogeneous vehicle routing problem. Trucks spend a significant time idling while parked for deliveries. Suzuki (2011) incorporated idling fuel consumption during the waiting time for deliveries. The so-called Pollution Routing Problem (PRP) introduced by Bektas and Laporte (2011) was the first study to consider a fuel estimation function and used both load and fixed speed for fuel estimation. They have found that CO_2 cost is not as important as fuel and labor cost. They have also found that the total cost minimization led to routes with higher fuel consumption in order to bring down the driver cost.

Using a fuel estimation function with fixed speeds will result in significantly different fuel estimates compared to real world conditions and may not provide optimal solutions. To overcome this limitation, Demir et al. (2012) treated speed as a decision variable and came up with a speed optimization procedure which gives the optimal speed for minimal fuel consumption in each arc. However, implementing these optimized speeds in the field, particularly in city traffic, may be difficult because the traffic state restricts the controllable range of speed. Franceschetti et al. (2013, 2017) used time-dependent speeds instead of fixed speed throughout the day for the PRP. They have considered that a vehicle traveling between any two nodes can face the following three traffic conditions based on the start time of its journey: i) vehicle traveling entirely during congestion, ii) vehicle traveling partially during congestion and partially during free-flow speed, and iii) vehicle traveling completely at free-flow speed. Qian and Eglese (2016) followed a different approach by dividing the 24h period into 15-time slots and assuming that vehicles travel at a speed equal to the average speed in that time slot. Their study concluded that using distance based approach followed by speed optimization will perform marginally worse than the fuel minimization with simultaneous speed optimization case, but the latter takes significantly less time to solve. However, these authors are still considering constant speed during each time-slot. Turkensteen (2017) compared the accuracy of fuel consumption estimation and CO_2 emissions for the cases with fixed speed and continuously varying speed. His study concluded that using fixed speed consistently results in fuel consumption estimates that are less than half of the realistic driving conditions and hence not sufficiently accurate to be used in green vehicle routing problems.

While the importance of minimizing fuel consumed to obtain green routing strategies is well understood, it is surprising that none of these studies have considered acceleration as a factor influencing routing decisions. A possible reason for ignoring acceleration is perhaps the lack of data. However, Global Positioning System (GPS) data from probe vehicles have become widely available now. Trends in the traffic state based on the day of the week and the time of the day can be obtained from GPS data. This allows us to consider accurate speed profiles in addition to load in route planning.

We capture speed variations using driving cycles. A driving cycle is a speed-time profile of a representative vehicle that can be obtained by combining a series of micro-trips. A micro-trip is defined as the trip between the starts of two idling periods. Initial studies on the development of driving cycles started in 1970's and these studies can be classified based on how the candidate driving cycles are developed, and the set of assessment measures used for comparison. Most of the studies (Hung et al., 2007; Arun et al., 2017) in the literature have used a random selection of micro-trips for producing a candidate cycle and driving cycles are identified from these candidate cycles based on assessment parameters. A few studies (Liessner et al., 2016) have used the driving data clustering method, where micro-trips are first divided into different categories (or clusters) based on the "traffic conditions" (e.g., congested, free flow) and driving cycles are then developed using weighted samples from each cluster.

The main contribution of our study is the inclusion of load, speed, and acceleration in fuel consumption estimation using driving cycles for vehicle routing problems, and studying its effect on total fuel consumption estimation and route selection. The proposed methodology is straightforward since the driving cycles are developed using GPS data that is widely available. Using driving cycles allows the input for fuel consumption estimation to be partially pre-processed. Therefore, the proposed methodology does not worsen the run-time complexity of solving the VRP. We study the effect of using driving cycles for fuel consumption estimation in a series of experiments. First, the effect is evaluated on the traditional CVRP with homogeneous vehicles. The importance and magnitude of difference are likely to be best seen for the heterogeneous fleet case with multiple depots. We subsequently evaluate the impact on the multi-depot CVRP (MDCVRP) variant with both homogeneous and heterogeneous fleets. Extensive computational experiments were carried out on different variants of CVRP and MDCVRP to draw our conclusions.

The rest of the paper is organized as follows: in § 2 the driving cycle development procedure is discussed. In § 3 the fuel consumption estimation procedure is detailed. In § 4 a MILP formulation for the fuel minimization vehicle routing problem is presented, and computational results are discussed in § 5, followed by a summary and discussion in § 6.

2. Driving Cycle Development

There are two types of driving cycles that are developed - standard driving cycles and real world driving cycles. Standard driving cycles are used to estimate fuel efficiency and emission levels of vehicles. In this study we use data collected from the real world in order to develop driving cycles. The driving cycles used here are also referred to as real world driving cycles to distinguish them from standard driving cycles that are used for testing vehicles. Typically, standard driving cycles are used the world over to enforce emission control norms while real world driving cycles are used to test and estimate field performance.

2.1. Data Collection

Speed and time stamp data were collected from onboard GPS devices. GPS data were collected from two types of trucks (1 ton and 3.5 ton), each for 144 hours covering a distance of more than 450 km in the city of Chennai, India. The complete data set was separated into over 2000 micro-trips. Acceleration, deceleration, cruising, creeping and idling fractions are then computed (Arun et al., 2017).

2.2. Data Analysis

Parameters (refer to table 1) that define the driving characteristics are identified from the literature review (Amirjamshidi and Roorda, 2015; Ho et al., 2014; Kamble et al., 2009; Arun et al., 2017). Any driving cycle developed should ideally have driving characteristics similar to that observed in the real world data set. The driving characteristic parameters were calculated from the data collected for each truck (referred to as "population data" hereafter). These parameters serve as a *target* in the selection criteria of driving cycles.

2.3. Driving Cycle Construction

Candidate cycles are generated using an iterative process by combining random micro-trips till the desired distance is covered (Hung et al., 2007; Arun et al., 2017). Once a candidate cycle is developed, target parameters and relative error are calculated to identify the driving cycle. Relative error (Δ) is defined as the sum of percentage differences in target parameters for the population and a candidate cycle (refer equation (1)). The candidate cycle with less than 5% relative error is accepted as a driving cycle (Nesamani and Subramanian, 2011).

Table 1: Target parameters used in driving cycle development

Parameter	Description	1 ton truck	3.5 ton truck
Average speed (V)	Population average speed (kmph)	22.13	13.19
Average running speed (V_r)	Population average speed excluding idle time (kmph)	28.34	26.48
Average acceleration (a)	Population average acceleration (m/s^2)	0.5938	0.6024
Average deceleration (d)	Population average deceleration (m/s^2)	0.6537	0.6246
Percentage of time in acceleration mode (P_a)	Speed greater than 5 kmph and acceleration greater than 0.1 m/s^2	27.7209	21.3741
Percentage of time in deceleration mode (P_d)	Speed greater than 5 kmph and deceleration greater than 0.1 m/s^2	25.2052	20.6218
Percentage of time in idling mode (P_i)	Speed equals zero	35.9249	49.6392
Percentage of time in cruising mode (P_c)	Speed greater than 5 kmph and acceleration and deceleration should be less than 0.1 m/s^2	10.4654	8.1621
Percentage of time in creeping mode (P_{cre})	Speed less than 5 kmph and acceleration and deceleration should be less than 0.1 m/s^2	0.5556	0.1888
Root mean square acceleration (a_{rms})	Driver aggressiveness m/s^2	0.6595	0.6421

$$\Delta = \sum_{i=1}^{n} \frac{\left(\dfrac{p_i - P_i}{P_i}\right)}{n} \times 100 \tag{1}$$

Where,
P_i is target parameter i of population data,
p_i is target parameter i of a candidate cycle, and
n is the number of target parameters.
A software program that automates the above procedure of developing driving cycles for every edge in the network is developed. It is hard to find a driving cycle matching the exact length of the edge. Hence, any driving cycle with a distance that is up to 5% more than the edge distance is accepted and then truncated to the actual edge distance. All the driving cycles developed in our study are available online[1].

The procedure adopted here arbitrarily determines the driving cycles for each link. However, in practice, these driving cycles can be more realistically determined by using data from a similar road type to develop a driving cycle for an edge. With the availability of sufficient data, separate driving cycles for different times of day can also be developed.

3. Fuel Consumption Estimation

Several models exist for estimating fuel consumption. Popular models include the instantaneous fuel consumption model (Bowyer et al., 1985), the four-mode elemental fuel consumption model (Bowyer et al., 1985), the running speed fuel consumption model (Bowyer et al., 1985), the Comprehensive Modal Emission Model (CMEM) (Barth et al., 2004, 2005), and the COmputer Programme to calculate Emissions from Road Transportation (COPERT) model (Ntziachristos and Samaras, 2000). From the comparative analysis of these models by Demir et al. (2011), the four-mode elemental fuel consumption model and CMEM were found to be more accurate. However, these models require additional vehicle specific data and second-by-second speed data.

We use the CMEM for fuel consumption estimation because it takes into account most of the critical parameters such as speed, acceleration, load, and grade. Moreover, this model can be applied to heavy-duty diesel vehicles as well as smaller pickup trucks. CMEM consists of three modules, namely engine power module, engine speed module, and fuel rate module.
Engine Power (P) requirement is calculated using:

$$P = \frac{(Ma + Mg\sin\theta + MgC_r\cos\theta + 0.5C_d\rho Av^2)v}{1000\epsilon} + P_{acc} \tag{2}$$

[1]https://www.kaggle.com/surendra92/driving-cycle-data/

Engine speed (N) is interpolated between idle rpm and governing rpm using the speed of the vehicle and then Fuel Rate (FR) is calculated as follows:

$$FR = \frac{\varphi(kNV + P/\eta)}{U} \tag{3}$$

Description and values of the parameters used in above modules are shown in Table 2 (adopted from Demir et al. (2011)), and vehicle specific values of different trucks utilized in the test instances are provided in Table 3 (adopted from Demir et al. (2011), `http://ace.tatamotors.com`, and `http://light-trucks.tatamotors.com`).

Table 2: Description of parameters used in CMEM

Parameter	**Description**	**Value used**
v	Speed in m/s	
a	Acceleration in m/s^2	
N	Engine speed	
M	Gross vehicle weight in kg	
g	Gravitational constant m/s^2	9.81
θ	Road grade angle in degrees	0
ρ	Air density in kg/m^3	1.2041
A	Frontal surface area in m^2	See table 3
C_d	Coefficient of aerodynamic drag	See table 3
C_r	Coefficient of rolling resistance	See table 3
ϵ	Vehicle drive train efficiency	0.4
P_{acc}	Engine power demand associated with running losses of the engine	0
φ	Fuel-to-air mass ratio	0.0667
k	Engine friction factor	0.2
V	Engine displacement in liters	See table 3
η	Efficiency for diesel engines	0.45
U	Lower heating value for the fuel in MJ/kg	44 for diesel

Table 3: Vehicle specific parameters

Vehicle type	**A**	**Cd**	**Cr**	**V**	**Idle *rpm***	**Governing *rpm***
1 ton	2.81	0.8	0.045	2.1	600	2800
3.5 ton	3.341	0.9	0.07	5.83	540	2400

For ease of computing, equation (3) is simplified to a linear model as follows:

$$FR = \alpha + \beta M, \tag{4}$$

Where,

$\alpha = \dfrac{\varphi\left(kNV + \dfrac{0.5 C_d \rho A v^3}{1000\,\eta\,\epsilon}\right)}{U}$ is the weight independent part, and

$\beta M = \dfrac{\varphi(a + g\sin\theta + gC_r\cos\theta)v}{1000\,\epsilon\,\eta\,U} M$ is the weight dependent part.

Bektas and Laporte (2011) did not consider the first term (kNV) in the weight independent part for fuel consumption estimation because it is insignificant at higher speeds (>40 km/h). In cities, since speeds are typically < 40 km/h the first term needs to be considered. Equation (4) is used to calculate α and β for all the edges. Load on each edge that is obtained while solving the model is used in combination with the corresponding α and β to get the fuel consumption estimate for traveling on an edge.

We consider two models in this study: the driving cycle model and the average speed model. These two models differ on how speed is used in fuel consumption estimation. The first model uses speed from the driving cycle corresponding to the vehicle type used and the edge under consideration, whereas the latter uses the average speed of the driving cycle for the edge.

4. Model Description

Capacitated Vehicle Routing Problem (CVRP) is a family of problems with the objective of satisfying demands of a set of customers on minimum-cost vehicle routes that originate and terminate at a depot. One of the many extensions of CVRP is Multi-Depot Capacitated Vehicle Routing Problem (MDCVRP), where vehicles originate from and terminate at multiple depots. Here, we present the formulation of MDCVRP with a heterogeneous fleet since it is a generalized version and can handle both CVRP and MDCVRP. This problem is defined on a graph $G = (V, E)$ where $V = \{T, C\}$ is the set of vertices and $E = \{(i, j) : i, j \in V$ and $i \neq j\}$ is the set of edges. Let h be an index for vehicles, t be for depots, and i *or* j for customers. The following are the important parameters used in the model; α^h_{ij} is the constant and β^h_{ij} is the coefficient of weight in fuel consumption function while traversing the edge (i, j) using vehicle type h, γ^h_t is the number of type h vehicles available at the depot t, δ^h is the maximum number of type h vehicles that can be utilized, and ζ^h is the capacity for vehicle type h.

There are two sets of decision variables (x, Q) in the model. x^h_{ij} is a binary variable and is equal to 1 iff the edge between vertex i and vertex j is traversed by vehicle type h. Q^h_{ij} is a positive real number and is equal to the amount of load carried on the edge (i, j) by vehicle type h. The formulation is presented and explained below.

Notations	
$\mathbf{T} = \{1, 2, \ldots, t, \ldots\}$	Set of depots
$\mathbf{C} = \{1, 2, \ldots, c, \ldots\}$	Set of customers
$\mathbf{H} = \{1, 2, \ldots, h, \ldots\}$	Set of vehicle types available
γ^h_t	Number of vehicles of type h ($h \in \mathbf{H}$) available at depot t ($t \in \mathbf{T}$)
δ^h	Limit on the number of vehicles of type h ($h \in \mathbf{H}$) to be used
ζ^h	Capacity of vehicle type h ($h \in \mathbf{H}$)
α^h_{ij}	Constant in fuel consumption equation for edge ($i, j : i \, and \, j \in \mathbf{T} \cup \mathbf{C}$) and vehicle type h ($h \in \mathbf{H}$)
β^h_{ij}	coefficient of weight in fuel consumption equation for edge ($i, j : i \, and \, j \in \mathbf{T} \cup \mathbf{C}$) and vehicle type h ($h \in \mathbf{H}$)
x^{th}_{ij}	Binary variable equal to 1 if edge ($i, j : i \, and \, j \in \mathbf{T} \cup \mathbf{C}$) is used by vehicle h ($h \in \mathbf{H}$) starting from depot t ($t \in \mathbf{T}$)
Q^{th}_{ij}	Load carried by vehicle type h ($h \in \mathbf{H}$) through edge ($i, j : i \, and \, j \in \mathbf{T} \cup \mathbf{C}$) starting from depot t ($t \in \mathbf{T}$)
λ_{ij}	Edge distance between nodes i and j ($i \, and \, j \in \mathbf{T} \cup \mathbf{C}$)
ω_h	Curb weight of vehicle type h ($h \in \mathbf{H}$)
d_l	Demand of customer l ($l \in \mathbf{C}$)

Objective function:

$$min \sum_{t \in \mathbf{T}} \sum_{h \in \mathbf{H}} \sum_{\substack{i/j \in \mathbf{T} \cup \mathbf{C} \\ i \neq j}} ((\alpha^h_{ij} + \beta^h_{ij} \omega_h) x^{th}_{ij} + \beta^h_{ij} Q^{th}_{ij}) \tag{5}$$

Subject to constraints (6)-(15)

$$\sum_{j \in \mathbf{C}} x_{tj}^{th} \leq \gamma_t^h \ \ \forall\, t \in \mathbf{T}, h \in \mathbf{H} \tag{6}$$

$$\sum_{j \in \mathbf{C}} x_{tj}^{th} \leq \delta^h \ \ \forall\, t \in \mathbf{T}, h \in \mathbf{H} \tag{7}$$

$$\sum_{j \in \mathbf{C}} x_{pj}^{ph} = \sum_{j \in \mathbf{C}} x_{jp}^{ph} \ \ \forall\, p \in \mathbf{T}, h \in \mathbf{H} \tag{8}$$

$$\sum_{i \in \mathbf{C}} x_{ij}^{th} = \sum_{i \in \mathbf{C}} x_{ji}^{th} \ \ \forall\, j \in \mathbf{C} \cup \mathbf{T}, t \in \mathbf{T}, h \in \mathbf{H} \tag{9}$$

$$\sum_{t \in \mathbf{T}} \sum_{h \in \mathbf{H}} \sum_{\substack{i \in \mathbf{C} \cup \mathbf{T} \\ i \neq j}} Q_{ij}^{th} - \sum_{t \in \mathbf{T}} \sum_{h \in \mathbf{H}} \sum_{\substack{i \in \mathbf{C} \cup \mathbf{T} \\ i \neq j}} Q_{ji}^{th} = d_j, \ \ \forall\, j \in \mathbf{C} \tag{10}$$

$$\sum_{h \in \mathbf{H}} \sum_{t \in \mathbf{T}} \sum_{j \in \mathbf{C}} Q_{jp}^{th} = 0, \ \ \forall\, p \in \mathbf{T} \tag{11}$$

$$Q_{tj}^{th} \leq \zeta^h x_{tj}^{th} \ \ \forall\, j \in \mathbf{C}, t \in \mathbf{T}, h \in \mathbf{H} \tag{12}$$

$$\sum_{h \in \mathbf{H}} \sum_{t \in \mathbf{T}} \sum_{i \in \mathbf{T} \cup \mathbf{C}} x_{ij}^{th} = 1, \ \ \forall\, j \in \mathbf{C} \tag{13}$$

$$x_{ij}^{th} \in \{\ 0, 1\} \ \ \ \forall\, t \in \mathbf{T}, h \in \mathbf{H}, \{i \in \mathbf{C} \cup \mathbf{T}, j \in \mathbf{C} \cup \mathbf{T} \mid i \neq j\} \tag{14}$$

$$Q_{ij}^{th} \geq \mathbb{R}^+, \ \ \forall\, t \in \mathbf{T}, h \in \mathbf{H}, \{i \in \mathbf{C} \cup \mathbf{T}, j \in \mathbf{C} \cup \mathbf{T} \mid i \neq j\} \tag{15}$$

Objective function (5) minimizes total fuel consumption. Constraints (6) ensures that total routes using a specific vehicle type h starting from a depot do not exceed the maximum available vehicles at that depot. Constraints (7) limit the number of allowed vehicles for each vehicle type. Constraints (8) ensures that the number of vehicles entering and leaving every depot are equal. Constraints (9) and (10) ensure that there is only one route passing through each customer. Constraints (10) is for demand satisfaction at each customer node. Constraints (11) will make sure that a vehicle arriving at a depot is empty. Constraints (10) and (11) are also important for determining the load on each edge. Constraints (12) will not allow any vehicle to carry load beyond its capacity. Constraints (13) allow one customer to connect to exactly one depot. Constraints (14)-(15) specify the domains of the variables. For the distance minimization problem, the objective function (5) is changed to (16).

$$min \ \sum_{t \in \mathbf{T}} \sum_{h \in \mathbf{H}} \sum_{\substack{i,j \in \mathbf{T} \cup \mathbf{C} \\ i \neq j}} \lambda_{ij} x_{ij}^{th} \tag{16}$$

5. Computational Experiments and Results

Computational experiments were performed for the combinations shown in Table 4. CVRP with a heterogeneous fleet are not reported since the results for both homogeneous and heterogeneous fleets were found to be the same.

All tests were performed on a 2.2-GHz Xeon PC with 8 GB of RAM. The models were implemented in GAMS 23.9 and solved using CPLEX 12.1 solver. Multi-threading was used with usage up to 2 threads to reduce computation time, and all the instances were solved to optimality. A detailed explanation of these experiments is presented in the following sections.

Table 4: A matrix of computational experiments performed

Objective	CVRP	MDCVRP	
	Homogeneous	Homogeneous	Heterogeneous
Fuel minimization with driving cycle	✓	✓	✓
Fuel minimization with average speeds	✓	✓	✓
Distance minimization		✓	✓

5.1. Instance Sets

The instances from Christofides and Eilon (1969) [2] are modified [3] by us to evaluate the effect of driving cycle on the optimal routes in different scenarios. The major modifications are: i) the unitless coordinates are multiplied by 100 m to obtain meaningful values for fuel consumption, ii) a new vehicle type having a capacity twice that of the original is introduced, and iii) the maximum number of allowable vehicles for the new vehicle type is half of the default, since its capacity is double. The first modification alone is applied on all the instances, whereas the remaining two modifications are introduced in heterogeneous fleet formulations.

5.2. Effect of Driving Cycle

The above instance sets are solved with fuel minimization as the objective. Fuel consumption is computed for two cases: (i) considering average speed and (ii) using driving cycles. However, for a fair comparison, the fuel consumption is re-computed using driving cycles on the optimal routes obtained in case (i). This modified fuel consumption is compared with the fuel consumption obtained by directly optimizing using driving cycles.

Table 5 compares the optimal fuel consumption in driving cycle (DC) cases with modified fuel consumption from the average speed (AS) cases for CVRP. The second column shows the fuel consumption estimated on routes obtained while using driving cycles. Fuel consumption estimates using average speed are shown in column four and corresponding modified fuel consumption values are shown in the third column. The fifth column shows the percentage savings in fuel consumption considering driving cycle over average speeds. The last column shows percentage fuel consumption underestimate by using / considering average speeds over driving cycle. Using driving cycles resulted in an average savings of 7.44% of fuel compared to average speed for CVRP instances. Further, average speeds were underestimating fuel consumption by over 35%. In all cases considering driving cycles resulted in better solutions than average speeds. Run times for these instances are compared in Table 6, which clearly shows only minor differences exists in run times.

[2] Original instances are available at http://neo.lcc.uma.es/vrp/vrp-instances/capacitated-vrp-instances/
[3] Modified instances are available at http://www.vrp-rep.org/

Table 5: Comparison of fuel estimation (L) in driving cycle and average speed on CVRP instances

Instance	**Fuel consumption estimated using DC**		**Estimated fuel consumption using AS on AS routes (iii)**	**% savings** $\left(\frac{ii-i}{ii}\%\right)$	**% deviation** $\left(\frac{iii-ii}{ii}\%\right)$
	DC routes (i)	**AS routes (ii)**			
E22-D06	33.78	35.28	20.98	4.27	-40.53
E22-D08	39.04	44.33	25.40	11.92	-42.69
E22-D09	33.64	37.81	24.25	11.04	-35.87
E22-D10	34.09	38.21	26.47	10.80	-30.73
E22-D11	41.22	46.58	31.45	11.52	-32.48
E22-D12	35.75	38.34	22.71	6.75	-40.78
E22-D13	34.55	38.37	25.08	9.95	-34.64
E22-D14	30.43	38.05	23.85	20.04	-37.31
E22-D16	38.38	39.44	22.41	2.69	-43.17
E22-D17	42.52	43.31	27.98	1.83	-35.41
E22-D19	39.50	39.86	23.93	0.91	-39.97
E33-D01	50.20	53.64	36.07	6.41	-32.76
E33-D02	46.81	49.95	31.73	6.27	-36.48
E33-D03	60.65	62.77	42.72	3.38	-31.94
E33-D04	53.76	59.43	37.51	9.55	-36.89
E33-D07	51.63	53.15	34.68	2.86	-34.76
E33-D14	50.98	61.60	41.82	17.24	-32.10
E33-D16	50.67	58.31	35.63	13.10	-38.89
E33-D19	51.57	54.58	36.54	5.51	-33.05
E33-D24	51.19	52.61	36.27	2.71	-31.05
E33-D25	51.61	51.61	35.57	0.00	-31.07
E33-D28	50.99	53.13	34.94	4.02	-34.24
				7.40	**-35.76**

Table 6: Comparison of run times for driving cycle and average speed on CVRP instances

Instances	**Run time (in s)**		**Instances**	**Run time (in s)**	
	DC	**AS**		**DC**	**AS**
E22-D06	310	16	E33-D01	62	3511
E22-D08	46	18	E33-D02	890	1071
E22-D09	15	13	E33-D03	2740	9988
E22-D10	6	5	E33-D04	6806	1458
E22-D11	6	4	E33-D07	28013	6180
E22-D12	7	5	E33-D14	380	43
E22-D13	31	7	E33-D16	1574	2814
E22-D14	17	31	E33-D19	43	1523
E22-D16	9	15	E33-D24	3240	320
E22-D17	142	129	E33-D25	1830	6030
E22-D19	44	20	E33-D28	17743	16045
Average				**2907**	**2238.45**

In CVRP both heterogeneous and homogeneous fleets resulted in a similar solution for all the cases. To understand the effect of driving cycle on multi-depot and heterogeneous variants, experiments were run using MDCVRP with both homogeneous and heterogeneous fleets. Results for MDCVRP instances with homogeneous fleets are shown in Table 7. Similar to CVRP the results in MDCVRP also showed average savings of 8.19% in fuel and an over 34% underestimate by using average speeds compared to driving cycle.

Table 7: Comparison of fuel consumption (L) in driving cycle and average speed on MDCVRP instances with homogeneous fleets

Instance	**Fuel consumption estimated using DC**		**Estimated fuel consumption using AS on AS routes (*iii*)**	**% savings** $\left(\frac{ii-i}{ii}\%\right)$	**% deviation** $\left(\frac{iii-ii}{ii}\%\right)$
	DC routes (*i*)	**AS routes (*ii*)**			
E22-D06D17	29.81	33.42	22.41	10.79	-32.94
E22-D08D14	36.59	36.59	24.86	0.00	-32.04
E22-D09D19	34.96	35.75	22.59	2.20	-36.80
E22-D10D14	32.96	34.38	23.43	4.15	-31.85
E22-D11D12	35.15	41.99	28.37	16.30	-32.45
E22-D12D16	36.19	36.25	21.83	0.15	-39.78
E22-D13D14	29.77	34.43	22.58	13.55	-34.40
E22-D13D16	35.11	38.17	24.74	8.00	-35.16
E22-D13D17	38.03	39.63	27.89	4.04	-29.63
E22-D14D19	33.68	37.08	23.64	9.17	-36.23
E22-D17D19	33.82	38.67	23.46	12.55	-39.33
E22-D19D21	37.93	44.56	28.80	14.88	-35.37
E33-D01D09	46.45	51.54	34.44	9.87	-33.17
E33-D02D13	43.16	46.36	28.17	6.90	-39.22
E33-D03D17	48.78	49.20	32.14	0.84	-34.68
E33-D04D05	48.62	50.28	33.74	3.31	-32.89
E33-D07D25	42.30	50.69	34.39	16.55	-32.15
E33-D14D22	50.28	60.47	41.86	16.85	-30.78
E33-D16D22	42.09	52.09	32.48	19.19	-37.64
E33-D16D24	49.24	50.66	34.17	2.81	-32.55
E33-D19D26	45.90	53.71	36.46	14.54	-32.12
E33-D22D26	44.97	46.23	30.59	2.79	-33.86
E33-D24D28	47.19	48.95	31.64	3.59	-35.35
E33-D25D28	50.56	52.51	35.06	3.72	-33.23
Average				**8.20**	**-34.32**

Considering average speeds in fuel consumption estimates not only leads to increase in fuel consumption but also in total distance traveled. Table 8 compares the total distance traveled between the driving cycle model and average speed model. Results show that there are average savings of 15.81% when driving cycles are considered.

Table 8: Comparison of distance traveled (km) in MDCVRP with homogeneous fleets

Instance	**Distance Traveled (in km)**		**Savings**	**Instance**	**Distance Traveled (in km)**		**Savings**
	DC	**AS**			**DC**	**AS**	
E22-D06D17	388.92	451.67	13.89	E33-D01D09	564.69	681.59	17.15
E22-D08D14	384.83	428.67	10.23	E33-D02D13	585.84	680.17	13.87
E22-D09D19	348.73	418.18	16.61	E33-D03D17	532.97	668.69	20.3
E22-D10D14	426.18	429.75	0.83	E33-D04D05	281.27	646.07	56.46
E22-D11D12	412.27	544.43	24.27	E33-D07D25	493.86	595.07	17.01
E22-D12D16	443.23	468.15	5.32	E33-D14D22	537.86	734.33	26.75
E22-D13D14	439.20	484.15	9.28	E33-D16D22	594.70	776.58	23.42
E22-D13D16	471.42	541.24	12.90	E33-D16D24	653.55	653.55	0.00
E22-D13D17	384.37	461.60	16.73	E33-D19D26	564.61	682.57	17.28
E22-D14D19	418.89	546.68	23.37	E33-D22D26	578.06	603.87	4.27
E22-D17D19	540.18	596.47	9.43	E33-D24D28	597.89	679.83	12.05
E22-D19D21	533.97	623.77	14.39	E33-D25D28	598.21	692.98	13.68
Average							**15.81**

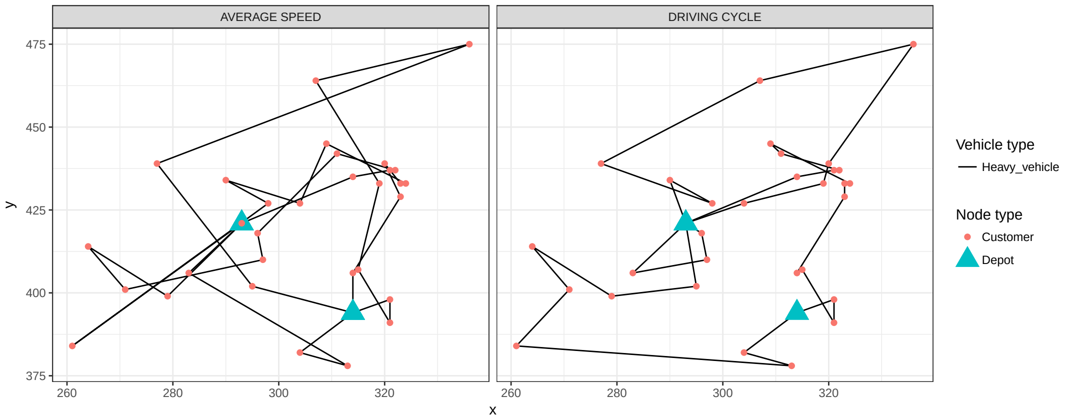

Figure 1: Optimal routes for the instance E33-D14D22

Figure 1 shows the optimal routes obtained with average speed and driving cycle for the instance E33-D14D22. From the figure and above tables it is clear that inaccurate fuel estimates lead to routes that not only require more fuel but often longer travel distances.

As anticipated, MDCVRP with heterogeneous fleet (refer Table 9) resulted in higher average fuel savings (12.43%) compared to homogeneous case. However, the underestimate by average speeds was found to be similar (33.89%) compared to MDCVRP with a homogeneous fleet and CVRP.

Table 9: Comparison of fuel consumption (L) in driving cycle and average speed on MDCVRP instances with heterogeneous fleets

Instance	Fuel consumption estimated using DC		Estimated fuel consumption using AS on AS routes (*iii*)	% savings $\left(\frac{ii-i}{ii}\%\right)$	% deviation $\left(\frac{iii-ii}{ii}\%\right)$
	DC routes (*i*)	AS routes (*ii*)			
E22-D06D17	26.27	32.71	22.96	19.70	-29.79
E22-D08D14	28.83	30.39	19.39	5.13	-36.19
E22-D09D19	27.97	34.93	22.89	19.93	-34.48
E22-D10D14	25.70	30.29	20.13	15.17	-33.53
E22-D11D12	33.77	40.78	27.78	17.18	-31.87
E22-D12D16	27.09	27.29	17.06	0.74	-37.49
E22-D13D14	26.58	27.99	17.85	5.04	-36.24
E22-D13D16	21.91	31.12	19.77	29.60	-36.48
E22-D13D17	32.46	35.69	25.90	9.05	-27.42
E22-D14D19	24.36	32.63	20.45	25.35	-37.32
E22-D17D19	24.80	24.80	15.48	0.00	-37.58
E22-D19D21	31.82	46.63	30.26	31.75	-35.10
E33-D01D09	47.75	51.54	34.44	7.34	-33.17
E33-D02D13	44.59	50.59	32.21	11.85	-36.32
E33-D03D17	45.66	50.31	33.62	9.24	-33.16
E33-D04D05	48.62	50.28	33.74	3.32	-32.90
E33-D07D25	41.99	48.63	32.73	13.65	-32.68
E33-D14D22	49.63	60.30	41.58	17.70	-31.04
E33-D16D22	42.09	50.29	31.84	16.30	-36.68
E33-D16D24	49.24	50.66	34.17	2.81	-32.56
E33-D19D26	46.94	53.71	36.46	12.61	-32.13
E33-D22D26	44.35	51.47	34.62	13.82	-32.72
E33-D24D28	47.19	50.97	34.01	7.43	-33.29
E33-D25D28	50.56	52.51	35.06	3.72	-33.23
Average				**12.43**	**-33.89**

Table 10 contains the results of distance minimization case for MDCVRP instances in different scenarios. The second and third columns show the total distance traveled during fuel minimization with driving cycle and average speeds respectively. The fourth column shows the total distance traveled with the distance minimization objective. The last two columns in this table represent the percentage savings in distance while using driving cycle compared to average speed case and driving cycle compared to distance minimization. There are three important observations in this table: (i) the distance minimization objective resulted in the least distance traveled, (ii) average speeds always resulted in suboptimal solutions, and (iii) total distance traveled considering driving cycles is less by 13.72% on an average compared to cases considering average speed. On longer edges, speed variations are more probable which may lead to greater fuel consumption. This issue is neglected in the average speed case that leads to higher underestimation of fuel consumption on these edges and, hence, suboptimal routes.

Interestingly, these results indicate that use of driving cycle in fuel consumption estimation caused a greater reduction of distance in homogeneous fleet than in heterogeneous fleet instances. This is surprising especially since the fuel savings were greater for the heterogeneous case. The contradiction in fuel and distance savings may be attributed to the difference in the underestimates by average speed model based on vehicle type. These differences might have led to more vehicles being used and hence lead to higher empty return trips in the homogeneous case than in the heterogeneous case.

Table 10: Comparison of distance traveled (km) in MDCVRP instances with heterogeneous fleets

Instance	**Fuel Minimization**		**Distance**	**% savings**	**% deviation**
	DC (i)	**AS (ii)**	**Minimization (iii)**	$\left(\frac{ii-i}{ii}\%\right)$	$\left(\frac{iii-i}{i}\%\right)$
E22-D06D17	388.92	451.67	270.22	13.89	-30.52
E22-D08D14	384.83	428.67	270.22	10.23	-29.78
E22-D09D19	348.73	418.19	270.22	16.61	-22.51
E22-D10D14	426.18	429.75	270.22	0.83	-36.59
E22-D11D12	412.28	544.43	268.87	24.27	-34.78
E22-D12D16	443.23	468.15	273.36	5.32	-38.33
E22-D13D14	439.20	484.15	277.96	9.28	-36.71
E22-D13D16	471.42	541.24	277.96	12.90	-41.04
E22-D13D17	384.37	461.60	273.36	16.73	-28.88
E22-D14D19	418.89	546.68	276.15	23.37	-34.08
E22-D17D19	540.19	596.47	289.29	9.44	-46.45
E22-D19D21	533.97	623.77	297.18	14.40	-44.35
E33-D01D09	564.69	681.59	378.59	17.15	-32.96
E33-D02D13	585.84	680.17	378.59	13.87	-35.38
E33-D03D17	532.97	668.69	378.59	20.30	-28.97
E33-D04D05	604.58	646.07	378.88	6.42	-37.33
E33-D07D25	493.86	595.07	378.59	17.01	-23.34
E33-D14D22	537.86	734.33	392.48	26.75	-27.03
E33-D16D22	594.70	776.58	390.90	23.42	-34.27
E33-D16D24	653.55	652.69	392.08	-0.13	-40.01
E33-D19D26	564.61	682.57	390.90	17.28	-30.77
E33-D22D26	578.06	603.87	392.08	4.27	-32.17
E33-D24D28	597.89	679.83	392.08	12.05	-34.42
E33-D25D28	598.21	692.98	392.08	13.68	-34.46
Average				**13.72**	**-33.96**

6. Summary and Discussion

As cities the world over look to tackle their air quality issues, a concerted effort from all stakeholders is required. Freight operators have a significant and direct role to play in this effort. To begin with routing decisions of freight operators can easily be reframed so as to minimize environmental impact. In this paper, we proposed a methodology that estimates fuel consumption more accurately using driving cycles. The proposed methodology does not add to the complexity of the Vehicle Routing Problem (VRP) and yet provides more accurate results. The improved accuracy is a result of considering the effect of acceleration in fuel consumption estimation.

The methodology is evaluated for the following problems: Capacitated VRP with homogeneous fleet, and Multi-Depot CVRP with homogeneous and heterogeneous fleets. Fuel consumption was estimated using CMEM for two cases - with and without acceleration - referred to as driving cycle case and average speed case. All the CVRP and MDCVRP instances were solved to optimality using the CPLEX solver.

The inclusion of acceleration in fuel consumption estimation resulted in routes that are on average 8-12% more fuel efficient and 13-15% shorter compared to using average speeds case. The driving cycle case has shorter routes compared to the average speed case in all the instances tested. On longer edges , speed variations are more probable which may lead to greater fuel consumption. Additionally, the fuel consumption during idling in traffic is captured by the driving cycle case. These issues are neglected in the average speed case that leads to inaccurate fuel consumption estimation on these edges and, hence, suboptimal routes. However, these results are based on the assumption that all the edges have similar driving characteristics. In real networks, driving cycles may vary by road type and hence further research is required to generalize these results.

The effect of acceleration will vary by vehicle type as well; this leads to completely different routes in the case of heterogeneous fleet. Our study concentrated on smaller networks with 22 and 33 nodes. We expect the savings in fuel consumed to be higher for larger instances. However, larger instances may require heuristic solution methodologies since CPLEX and other analytical techniques may not solve to optimality in a reasonable timeframe. Finally, the study is based on driving cycles developed from data collected in the city of Chennai. It is important to replicate the results using data from other cities in the world to generalize the results obtained here.

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