ON ESTIMATING VEHICLE ENERGY CONSUMPTION USING DYNAMIC TRAFFIC ASSIGNMENT VEHICLE TRAJECTORIES

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Abstract

Due to increased emphasis on the importance of measuring the environmental impact from transport vehicles, there is a growing interest in calculating vehicle energy consumption and emissions on a city-wide scale. However accurate vehicle energy and emissions estimations require detailed vehicle behaviour on a timescale generally more disaggregate than obtained from dynamic traffic assignment simulations. This work discusses the challenges faced when deriving vehicle trajectories from DTA output and then proposes two methods to integrate DTA and energy consumption models. These approaches were compared on a small network and future work in verifying the analysis was discussed.

1. INTRODUCTION

With the growing concern of environmental sustainability issues in transportation, planners need to accurately assess the impact of infrastructure design and ITS technologies on vehicle fuel consumption and emissions. Such challenges present an ideal application for dynamic traffic assignment models. However, accurate modelling of vehicle fuel consumption and emissions requires detailed data of second-to-second vehicle dynamics, specifically speed profiles using a time discretization of one second or less. General approaches to DTA provide first order output of vehicle position at time periods of larger discretization. However, aggregating fuel and emissions models to the time intervals commonly associated with DTA or using simple aggregate measures may fail to capture important speed-changing characteristics that have an impact on fuel consumption and emissions. On the other hand, sampling from DTA output at smaller intervals may predict unrealistic accelerations and decelerations.

While newer techniques in DTA may output vehicle position at smaller time intervals, it is also worthwhile to investigate methods of integrating current approaches to DTA with energy consumption and emissions modelling through the generation of continuous vehicle speed profiles based on trajectories, from which all characteristics of vehicle motion can be derived. Thus, this work is motivated by the need to use DTA to evaluate the environmental impact of transport planning projects, a subproblem of which is to produce accurate vehicle position trajectories from which to calculate speed profiles. However, constructing vehicle trajectories from common DTA output such as the cell transmission model is not a trivial problem, as will be further discussed.

Therefore we propose two methods of integrating DTA with vehicle energy consumption models. The first uses discrete cell based approximations, while the second is a link-based method that uses parametric expressions for vehicle energy consumption that take advantage of alternative vehicle motion characteristics in order to indirectly represent acceleration. This contrast will allow us to highlight the issue of possibly unrealistic accelerations by comparing the results from the two methods.

This article is organized as follows. Section 2 recaps some literature and discusses similar problems faced in other transportation applications, such as constructing vehicle trajectories from loop detector data. Section 3 examines some of the issues that arise due to the discretization of CTM. Section 4 explains the methodology. Section 5 implements and compares the two methods, while Section 6 concludes this article with a discussion of future research directions.

2. BACKGROUND

Accurate vehicle fuel and emissions modelling includes two key components: sensitivity to traffic characteristics and vehicle movement (e.g., road geometry, traffic control type, demand volumes, driver behaviour, acceleration, deceleration, other vehicle characteristics), and sensitivity to the correct vehicle parameters (fuel consumption rate, acceleration, deceleration, mass, engine efficiency, etc). Software packages such as ADVISOR emphasize the latter (i.e., vehicle engine characteristics) and produce detailed predictions of vehicle performance (Markel et al., 2002). However, they are reliant on artificial driving cycles to provide vehicle movement and computationally prohibitive to integrate with DTA.

Other traditional approaches used aggregate estimations of traffic characteristics and often assumed that vehicle fuel consumption is a polynomial function of speed (Rilett & Benedek, 1994; Hickman et al, 1999; Sharma & Mishra, 2013). However, traditional static approaches cannot capture the effects of acceleration and braking, which depending on traffic conditions has been estimated to represent about 30% of vehicle fuel consumption and emissions (Evans et al, 1976). Thus, a dynamic traffic model is theoretically better suited for accurate energy and emissions calculations.

Previous environmental impact analyses using DTA have utilized aggregate link characteristics (i.e., average link speed) to calculate fuel and emissions (Aziz & Ukkusuri, 2012) or fuel consumption evaluation only at the time intervals of simulation (Zegeye et al, 2010). Other approaches use traffic microsimulation tools to generate the second-to-second vehicle trajectory for accurate fuel consumption assessment (Ahn et al, 2002; Rakha & Ahn, 2004). While microsimulation approaches may be appropriate for certain projects, computational complexity would make it unsuitable for large-scale applications.

The usefulness of vehicle position trajectories is well recognized in many transportation applications. In particular, this applies to the problem of deriving vehicle trajectories to estimate vehicle states and to make travel time estimations based on data from loop detectors or other imaging technology. These data sources often contain inconsistencies due to measurement techniques, and thus accurate speed and acceleration profiles cannot be found without adjusting the data.

Methods of obtaining vehicle trajectories range from simpler piecewise constant speed and piecewise linear speed based approaches using loop detector data (Van Lint & Van der Zijpp, 2003), to more sophisticated smoothing and filtering methods that are appropriate for datasets of high fidelity (Thiemann et al, 2008; Toledo et al, 2007; Punz et al, 2011; Wang et al, 2011).

Of particular interest is Toledo et al, who propose a local regression technique, an appropriate method given strongly nonlinear form of trajectory data, and Wang et al, who use an adaptive smoothing method on data from dual loop detectors to estimate traffic states in order to evaluate the environmental impact of dynamic traffic management schemes. Toledo et al (2007) show that with appropriately selected window size and polynomial order, consistent positions, speeds, and accelerations can be found from the vehicle trajectory data. However, this approach faces the issues of noisy and inaccurate data, and due to the large window size necessary for higher level polynomial approximations, may not be appropriate for datasets widely displaced in time (such as the output from DTA).

While the issue of constructing vehicle trajectories from detector data and constructing the trajectory from the output of DTA are similar on the surface, they ultimately face quite a different set of challenges. As is detailed in Section 3, DTA output faces significant issues due to discretization errors, and in order to maintain consistency, these must be overcome before more sophisticated filtering approaches can be applied. Additionally, the approaches described above appeared to handle a less diverse set of road architectures (mostly freeway corridors with some congestion), as opposed to DTA approaches which must handle vehicle behaviours across a city network.

3. POTENTIAL ERRORS IN VEHICLE TRAJECTORIES FROM CELL TRANSMISSION MODEL

Energy consumption models typically require obtaining vehicle trajectories from the model, specifically speed and acceleration data at small timesteps. For microsimulation models, speed and acceleration are usually determined by car following and lane changing models, making such trajectories a simple output. However, since microsimulation is computationally intractable for large city networks, obtaining these trajectories from dynamic traffic assignment (DTA) models is valuable for analyses on larger networks. DTA models are built on more aggregate traffic flow behavior which does not easily lend itself to the detailed vehicle trajectories expected by energy consumption models. This section discusses some potential inaccuracies in methods for obtaining vehicle trajectories from the commonly used cell transmission model (CTM) (Daganzo, 1994; 1995). Although the discussion is specific to CTM, it should highlight some of the challenges in obtaining accurate vehicle trajectory information from other DTA models as well.

3.1 AVERAGE CELL SPEED

In CTM, links are divided into segments called *cells* such that a vehicle traveling at free flow speed can traverse one cell per timestep Δt. At any time during a vehicle's travel through the network the vehicle is located in a cell. Therefore, it is convenient to determine the average speed in cell *i* as

$$\bar{v}_i = \frac{L_i}{k_i \Delta t} \tag{E1}$$

where L_i is the length, $\bar{v}_i$ is the average speed, and k_i is the number of timesteps spent in the cell. This is consistent with CTM, but the challenge with this, and other first-order (speed-based) models arises when considering acceleration, a major factor in the engine power output. A simple approach is to choose

$$\bar{a}_i = \frac{\bar{v}_{i+1} - \bar{v}_i}{k_i \Delta t} \tag{E2}$$

where $\bar{a}_i$ is average acceleration in cell i, and $i + 1$ denotes the succeeding cell, as in Zegeye et al. (2010). Since speed changes between cells are instantaneous, an example which violates the engine power of most vehicles is easy to concoct: Suppose the free flow speed is 88ft/s and the timestep is $\Delta t = 3$sec. Due to reaching an intersection, the vehicle traverses cell i in $k_i = 1$ timestep but slows in cell $i + 1$, spending $k_i = 10$ timesteps waiting for a traffic light. The resulting predicted deceleration of -26.4ft/s^2 is well beyond the braking capabilities of most passenger vehicles.

Additionally, the approach of using the above $\bar{v}_i$ and $\bar{a}_i$ to determine power required during the $k_i \Delta t$ time spent in cell i is inconsistent with the reported trajectory. CTM reports that the vehicle traveled L_i in $k_i \Delta t$; for $\bar{a}_i \neq 0$, the trajectory expressed by an initial speed of $\bar{v}_i$ with an acceleration of $\bar{a}_i$ indicates a displacement of

$$\bar{v}_i k_i \Delta t + \frac{1}{2}\bar{a}_i (k_i \Delta t)^2 = L_i + \frac{1}{2}\bar{a}_i (k_i \Delta t)^2 \quad \text{(E3)}$$

In the previous example, the trajectory would predict a distance traveled of 145.2ft, which is 55% of the cell length.

3.2 CHOOSING ACCELERATION BASED ON DISPLACEMENT AND TIME

Since CTM and most DTA models provide trajectories in the form of position and time, we next discuss determining a valid constant acceleration value consistent with both displacement and time. This involves solving the equation

$$L_i = v_0 k_i \Delta t + \frac{1}{2}\tilde{a}_i (k_i \Delta t)^2 \quad \text{(E4)}$$

for $\tilde{a}_i$, where v_0 is the velocity upon entering the cell. Unfortunately, this cannot be done on a single cell basis by taking $v_0 = \bar{v}_{i-1} + a_i k_{i-1} \Delta t$. This is demonstrated by solving for $\tilde{a}_{i+1}$ in the above example. Assume zero acceleration required in cell i due to maintaining the same speed as in cell $i-1$. Then

$$\tilde{a}_{i+1} = 2\frac{L_i - \bar{v}_i k_{i+1} \Delta t}{(k_{i+1} \Delta t)^2} = -5.28\text{ft/s}^2 \quad \text{(E5)}$$

While within the limits of vehicle braking, decelerating at -5.28ft/s^2 for the 30 seconds spent in cell $i+1$ results in the implausible final speed of -70.4ft/s, describing a vehicle that entered the intersection and backed out.

3.3 OTHER CHALLENGES

Finally, there are a number of important traffic flow characteristics that are easily lost to approaches that include averaging and smoothing. In particular, the acceleration and deceleration of vehicles due to congestion and due to intersections will have an important impact on energy consumption in addition to being constrained by driver behaviour. Given that DTA does not include any consideration with real data, it will be particularly challenging to incorporate the wide range of driving behavior observed in traffic networks. Treiber et al (2008) found about an 80% increase in fuel consumption due to congestion (although about a fourfold increase in travel time) using the NGSIM datasets, but it would be interesting to know the impact on an entire city network.

4. ENERGY MODEL

Vehicle energy consumption and emissions estimation is an important application of a DTA model. However, DTA output is not easily integrated with accurate energy and fuel models, as discussion in Section 3. Therefore this work proposes two methods to calculating energy consumption. Both approaches are based on road vehicle performance expressions that detail tractive effort and resistance, the well-established road load equations (Simpson, 2005). Energy consumption is a function of a vehicle's speed, acceleration, and road grade throughout the network. However, the two methods treat the acceleration component of energy consumption in a different manner.

First we'll discuss the power model, and then detail the differences between the two methods. For internal combustion engine vehicles (ICEVs), power regeneration is not available, so the total power required by the wheels to overcome resistance P_{wheels} is

$$P_{\text{wheels}} = \max\left(0, P_{\text{aero}} + P_{\text{roll}} + P_{\text{accel}} + P_{\text{grade}}\right) \tag{E6}$$

where P_{aero}, P_{roll}, $P_{\text{acceleration}}$, and P_{grade} are the power requirements to overcome aerodynamic resistance, rolling resistance, gravitational resistance, and gravitational potential energy, respectively. These are found using the well-known road load equation, and functions of vehicle speed, acceleration and road grade. In addition to the power requirements, a vehicle consumes energy due to loss from inherent inefficiencies in the powertrain and losses due to braking. Transmission and engine loss are included in this approach. Transmission energy loss depends on the transmission efficiency, η_{trans}.

$$P_{\text{drive loss}} = \frac{1-\eta_{\text{trans}}}{\eta_{\text{trans}}}\left(P_{\text{wheel}} + m_{\text{total}}k_{\text{m}}av\right) \tag{E7}$$

The above power requirements, as well as accessory power for non-driving usage, is the demand on the engine:

$$P_{\text{engine}} = P_{\text{wheel}} + P_{\text{drive loss}} + P_{\text{accessory}} \tag{E8}$$

However, a vehicle also loses energy due to the engine efficiency η_{engine}. This power loss may be calculated as:

$$P_{\text{engine loss}} = \frac{1-\eta_{\text{engine}}}{\eta_{\text{engine}}}P_{\text{engine}} \tag{E9}$$

Total power usage by the ICEV is a sum of engine output and engine loss:

$$P_{\text{ICEV}} = P_{\text{engine}} + P_{\text{engine loss}} \tag{E10}$$

The two methods in this work differ in their treatment of vehicle speed and acceleration.

4.1 METHOD 1

The first method introduced, referred to as Method 1, utilizes a parametric analytical expression approach to calculating vehicle energy consumption (PAMVEC) (Simpson, 2005). This approach is founded on the core assumption that tractable and intractable power flow to a vehicle's engine can be uncoupled and separated. Based on this assumption, Simpson derives a set of expressions incorporating the road load equations that perform well during testing (<15% errors).

Simpson's method is essentially a lumped parameter approach meant to be used to compare the performance of different vehicles using drive cycles. Instead of using acceleration, this approach uses the following three parameters to characterize a driving pattern: average velocity, velocity ratio (root mean cubed velocity divided by average velocity), and the characteristic acceleration. The velocity ratio describes the range of speeds, while the characteristic acceleration quantifies the rate at which the vehicle's speed changes. The original work was intended to be used with artificial driving cycles to describe the speed profile of a vehicle over its complete journey.

However, Method 1 applies the three parameters (average velocity, velocity ratio, characteristic acceleration) to each link, thus providing information about the speed range and variation within a link without directly calculating an acceleration. This makes Method 1 well-suited to being integrated with DTA model.

Finally, this approach can be used to account for different vehicle technologies (Simpson, 2005), which could be beneficial to include in a DTA energy consumption estimation.

4.2 METHOD 2

Method 2, a cell based discrete approximation approach, uses average speed $\bar{v}$ from each cell defined by equation (E1), and determines acceleration $\bar{a}$ from the change in speed between cells as in equation (E2), as used by Zageye et al. (2010). As previously discussed, although this method is consistent with CTM speed output, the accelerations are not consistent with the trajectory. Nevertheless, since this method has been considered by previous work, we include it here for comparison, because even though it is prone to errors, it would be useful to be able to measure the impact of those errors. To make the analysis meaningful, we use the PAMVEC vehicle specific power equations but on a second-by-second basis, with P_{roll}, P_{accel}, and P_{grade} as a function of $\bar{v}$ and $\bar{a}$.

4.3 METHOD 3

Method 3 is based on an average link speed. This is the method that is typically used in practice and is included here as a basis for comparison. The energy consumption regression model was based on data from the Environmental Protection Agency's MOVES 2010a (Motor Vehicle Emissions Simulator) software package (Gardner et al, 2013). The regression model to calculate total energy consumption E in the network as a function of the speed s on link (i, j) is presented in E11.

$$E(s_{ij}) = \sum_{(i,j)\in A} 14.58 s_{ij}^{-0.6253} \qquad \text{(E11)}$$

4.4 REPRESENTATIVE VEHICLE APPROACH

Due to the wide range of characteristics in a typical city vehicle population, most aggregate modelling approaches choose a "characteristic vehicle" to represent all vehicles in a network. Methods 1 and 2 use the characteristic vehicle approach in order to support the purposes of demonstration. Therefore, parameters for the Holden VY Commodore sedan (Simpson, 2005) were used to calculate energy consumption of all vehicles, which can be found in Table 1.

TABLE 1 Holden VY Commodore sedan parameters used in this model.

A	frontal area	2.5m^2
C_D	aerodynamic drag coefficient	0.32
C_RR	rolling resistance coefficient	0.01
g	gravitational acceleration	9.81m/s^2
m_total	vehicle mass	1640kg
ρ	density of air	$1.2\ \text{kg/m}^3$
η_engine	Engine efficiency	0.17
η_trans	Transmission efficiency	0.90
$P_\text{accessory}$	Accessory power	1 kW
k_m	Rotational inertia factor	1.1

5. COMPARISON OF RESULTS

In this section, we examine the results from the three methods of energy calculation integrated with DTA on the three networks of varying size and demand. First we explore the implications for individual vehicles, then for the aggregate network, and finally the implications for DTA.

5.1 RESULTS FOR INDIVIDUAL VEHICLES

First we examine the impact of the alternative methods on a single representative vehicle trajectory using the Sioux Falls network. The Sioux Falls network is composed of 24 nodes and 76 links. All nodes are origins and destinations and this work used an inflated demand of 43253 vehicles. Figure 2 shows the energy consumption rate (power) profile in the solid line and the position profile in the dashed line for Method 1, which was link-based parametric modelling approach. The sharp bends in the vehicle position profile represent instantaneous speed changes that result in unrealistic accelerations. However, we can also observe from Figure 2 that the effect of intersection behaviour does not appear to be as clearly represented using this approach. This is due to the fact that the method was based on link average values.

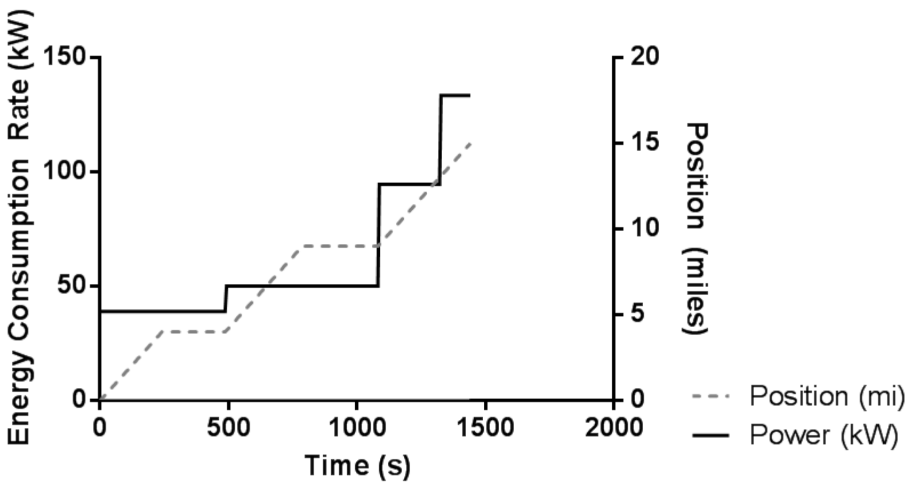

Figure 2. Energy consumption rate profile for a representative vehicle trajectory using Method 1

Figure 3 shows the power profile and the position profile for the same representative vehicle except where the power consumption is calculated using Method 2, the cell based approximation approach. The vehicle position trajectory is the same in both Figure 2 and 3. As expected, Method 2 appears to capture stopping behaviour at intersections more directly. Method 2 predicts sharp jumps in the energy consumption rate due to the instantaneous change in speed output by the CTM model. This leads to unrealistic accelerations; however it is unclear whether the high value for acceleration will overestimate energy consumption or underestimate due to the fact that the speed change takes place over a shorter period of time.

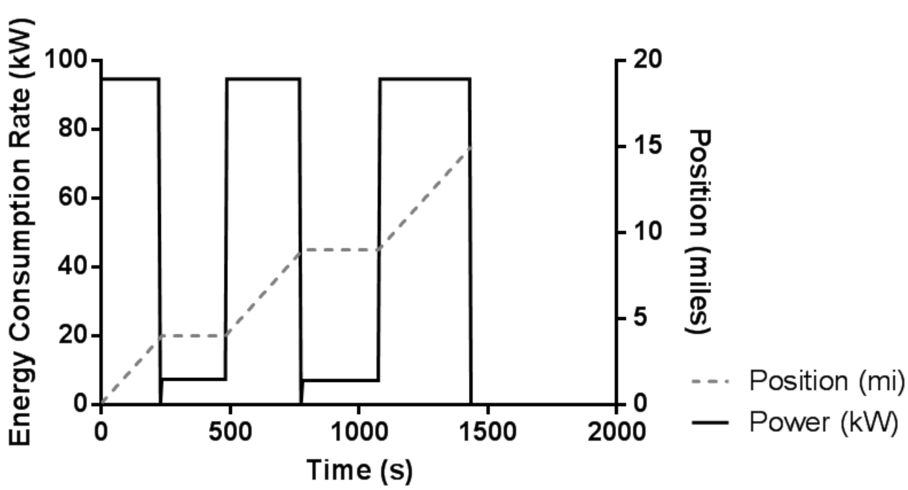

Figure 3. Energy consumption rate profile for a representative vehicle trajectory using Method 2

Next, we also compare the difference between Method 1 and Method 2 on individual vehicles. Figure 4 shows a frequency distribution for the individual results of the change in energy consumption, found as:

$$\Delta E_i = 1 - \frac{E_i^1}{E_i^2} \tag{E12}$$

Where E_i is the energy consumption of vehicle i, and E^1 and $E^2$are the energy consumption calculations from Method 1 and Method 2 respectively. The numbers labelled on the horizontal axis represent the midpoint of the frequency "bin", with all vehicles whose ΔE results were within $\pm 1\%$ of the listed number being included in the count. Figure

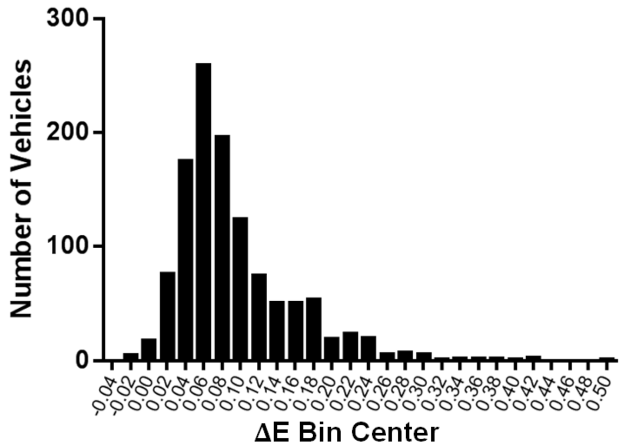

Figure 3. Comparison of the energy consumption results for individual vehicles

5.2 City Network Results

The aggregate results for the Sioux Falls, downtown Austin, and Memphis networks are shown in Table 2. Table 2 reveals disparate results and a glimpse into the complex problem at hand. A single method did not make either the largest or the smallest prediction for all three networks (although M2 was between the other two in all three cases). There is little apparent consistency and no immediately obvious pattern revealed by the predictions from the three methods. Therefore more testing would be appropriate before drawing further conclusions.

Table 2. Results for the energy consumption estimation on the three networks

Network	Demand (vehicles)	Distance travelled (miles)	Method 1		Method 2		Method 3	
			Aggregate (kWh)	Per vehicle (MPG)	Aggregate (kWh)	Per vehicle (MPG)	Aggregate (kWh)	Per vehicle (MPG)
Sioux Falls	28,848	261,996	448,217	21.3	418,796	22.8	332,396	28.72
DT Austin	31,418	56,531	66,819	30.83	78,150	26.36	87,855	23.45
Memphis	73,906	73,192	106,367	25.07	111,199	23.99	119,210	22.37

5.3 Implications for DTA

Finally, we are also interested in knowing the impact of different energy estimation approaches in terms of how they can be used to rank and evaluate infrastructure design projects. A true network design problem is beyond the scope of this paper, but we instead look at how the three methods of estimating energy change due to change in the network. The scenario we examine is when all links in the Sioux Falls network are affected in the same way, possibly due to a weather event. The capacity on all links is either decreased or increased by 25%, and then we compare how the energy estimation changes. All links were selected in order to show a noticeable impact at the network level; changes to individual links may be expected to have a greater impact on effected routes, but less impact on the total. Table 3 shows the results and the percentage change of the energy prediction compared to the base case (with expected capacities) for each of the three methods. Table 4 shows the results when the demand has been inflated by 50%.

Table 3. Results under an average demand on the Sioux Falls network

Capacity	**Travel time**	**M1**	**M2**	**M3**
-25%	35%	4.8%	3.8%	6.2%
25%	-42%	-3.2%	-3.8%	-11.7%

Table 4. Results under an inflated demand (+50%) on the Sioux Falls network

Capacity	**Travel time**	**M1**	**M2**	**M3**
-25%	72%	17.6%	14.2%	18.7%
25%	-50%	-8.5%	-7.2%	-15.9%

The most noticeable implication from Tables 3 and 4 regards how much more sensitive travel time is to changes in the network than energy consumption. While travel time saw significant changes in the four different scenarios, the impact on all three methods of energy consumption was more muted. This result confirms the findings of Treiber et al (2008), who saw an increase in emissions of about 80% due to congestion, but that travel time had increased fourfold.

The results shown here reflect the implementation of two methods of accounting for complicated acceleration behaviour that is output by DTA. However, as discussed, both methods may be prone to errors in different ways. Method 1 uses the cubic root mean velocity and the characteristic acceleration to create short "driving cycles" for a vehicle on each link. This method is well suited to DTA due to the fact that it doesn't require an explicit vehicle acceleration, although it may overestimate power consumption due to the discretization errors and the corresponding higher speed estimations. Method 2 makes unrealistic acceleration assumptions, but the acceleration takes place over a short time period. Further investigation is needed to judge the extent to which these approaches make accurate estimations.

6. CONCLUSION AND FUTURE DIRECTIONS

Environmental impact evaluations are an ideal application for DTA models and increasingly important as the impact of global climate change becomes more evident. However, accurate vehicle energy consumption and emissions estimations require finer grained details of vehicle motion than is generally output from DTA models.

The issue of deriving vehicle position trajectories from DTA output is not trivial and prone to significant discretization errors. Therefore this work compared two methods of integrating energy consumption calculations based on vehicle specific power requirements with a DTA model. Method 1 used average velocity, velocity ratio, and characteristic acceleration on each link as a proxy for directly calculating vehicle acceleration, and then created short "drive cycles" for each link to capture the variation in vehicle motion. Method 2 was cell based and directly calculated vehicle speed and acceleration based on cell decomposition and the speed difference between cells. However, this method can result in unrealistic accelerations. While a cell-based approach may result in unrealistic accelerations, the link-based approach may not account for stopping behaviour due to congestion and intersections.

While there are a number of challenges to be overcome, the issue of constructing vehicle trajectories from DTA output is critical for accurate environmental evaluations using DTA. In the future, more sophisticated curve-fitting techniques will be explored. Additionally, we will examine driving behaviour in stopping conditions from the context of traffic flow theory and its impact on vehicle trajectories in more detail. In addition, more work in validation will be important. In particular, it will be worthwhile to compare the results from an energy and emissions model integrated with DTA to that from a large-scale microsimulation.

ACKNOWLEDGEMENTS

This research was in part made possible by the generous support of NICTA. NICTA is funded by the Australian Government as represented by the Department of Broadband, Communications and the Digital Economy and the Australian Research Council through the ICT Centre of Excellence program.

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