URBAN VEHICLE ENERGY CONSUMPTION FOR POLICY EVALUATION: IMPACT OF ELECTRIC VEHICLES

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ABSTRACT

Novel technologies such as electric vehicles will have a fundamental impact on the performance of a network and it is important that planners have a tool to accurately assess policies aimed at reducing vehicle fuel consumption and emissions. This work presents a novel framework to estimate city-wide vehicle environmental effects that integrates a dynamic traffic assignment model with a novel application of a vehicle energy consumption model. All vehicle drive technologies can be incorporated into the energy model framework. Initial results demonstrate how energy consumption differs for internal combustion engine, electric, and hybrid electric vehicles.

Keywords: Energy issues, sustainability assessment, electric vehicles, dynamic traffic assignment, applications of DTA

Subject area: (Please put a "X" as appropriate, you may choose more than one)

	a)	Transportation Infrastructure and Built Environment
X	b)	Sustainability Issues in Transportation
	c)	Transportation Surveys
	d)	Travel Behavior Modeling
	e)	Technology, Transportation and Telecommunications
	f)	Logistics and Supply Chain Management
X	g)	Transport Dynamics
	h)	Others

Submission for HKSTS Outstanding Student Paper Award (You are a postgraduate student and the sole author of the paper): (Please put a "X" as appropriate)

	Yes	X	No

1. INTRODUCTION

As the impact of climate change grows increasingly apparent, it is vital that governments create policies targeting the sources of harmful emissions in order to mitigate the effects caused by human activity. Of interest to transport planners are management strategies affecting vehicular traffic, particularly on the scale of more than just a small area. Despite being the subject of much attention in the literature, producing accurate and reliable estimations of vehicle energy consumption and emissions, and then the corresponding evaluation of a policy, remains a challenging and timely topic.

This work expands a traffic modelling and vehicle energy estimation tool to account for the impact of electric vehicles (EVs). For reasons such as their potential to reduce negative environmental impact from the transport sector, EVs are a popular topic in the research community. Additionally, EVs serve as a source of mobile energy consumption that introduces a closer tie between the road network and the electric power system. Ultimately, electric energy providers will need to predict time dependent EV energy demands, which are the result of mobile driving patterns. In order to aid the integration between the transport and electric power systems, novel models that capture vehicle driving patterns, EV energy use, and spatiotemporal charging will be necessary to make accurate and effective evaluations of policies targeting environmental goals.

The current paper expands on the model proposed by Levin et al (2014a), which uses dynamic traffic assignment (DTA) to estimate vehicle energy consumption based on speed, acceleration, and road grade. In this work, the model is extended to include more realistic vehicle trajectories and electric vehicles, which consume energy in a different way from traditional vehicles, particularly due to their ability to recapture energy that is lost to friction brakes in traditional vehicles. Vehicle energy consumption remains the topic of focus in this paper, which is also a proxy for many sources of vehicle emissions.

For the case of large scale networks, DTA is an appropriate modelling tool because changes in the urban network will inevitably affect users' behavior, which cannot be captured using alternative approaches such as microsimulation or historic data. If this reactive decision-making is not accounted for, model outputs may overestimate environmental reductions in fuel and emissions that result from policy implementations, leading to lower effectiveness and possibly suboptimal policy selection. Additionally, if the changes in energy consumption due to novel technologies are not properly accounted for, predicted policy performance may not be realized.

The contribution of this work is as follows:

- We integrate an advanced traffic modelling tool (i.e., simulation based dynamic traffic assignment) with a detailed vehicle energy consumption and emissions estimation approach;
- We introduce methods to incorporate multiple vehicle technologies, i.e., traditional internal combustion engine vehicles and electric vehicles;
- Based on initial empirical analysis, we investigate how network performance metrics will differ due the presence of alternate technologies such as EVs.

2. BACKGROUND

The energy consumption and emissions of vehicles is an important consideration for transport policy makers. However, vehicle modelling for environmental purposes is not straightforward. There are two key components to vehicle fuel and emissions modelling: sensitivity to traffic characteristics in regards to 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). Due to the cross-disciplinary nature of this problem, environmental impact assessments of urban vehicle traffic are rarely comprehensive in both of the two key components.

In terms of the micro-interactions of vehicle specific factors that determine vehicle performance, vehicle modelling approaches based on a dynamic simulation approach produce very detailed estimations of vehicle fuel consumption and emissions (He et al, 2012). However, this approach uses a drive cycle to capture vehicle movements and is computationally prohibitive to scale up to many vehicles in a network. Alternatively, transport planners utilize static models that include only changes in vehicle speed (Aziz & Ukkusuri, 2012), which may not account for the impact of more complex factors such as vehicle acceleration or route choice.

One of the important questions for policy-makers is how aggregations will impact model predictions and policy assessments. Int Panis et al (2011) show the different predictions of speed reduction policy evaluations that can result from different tools (i.e., macroscopic vs microscopic emissions modelling), which creates uncertainties for policy makers. Furthermore, based on results from a microscopic emissions model, they conclude that reducing the speed limit in urban areas has a small impact on the vehicle emissions, which may be a counter-intuitive result.

From a transport modelling perspective, traffic microsimulation is a popular tool to use for vehicle energy consumption and emissions estimation because of its sensitivity to fine-grained traffic characteristics and second-by-second vehicle output. These approaches are usually based on vehicle power equations or statistical methods that generate speed-acceleration look up tables (Ahn et al, 2002). Some examples of traffic microsimulation used for policy analysis include speed limit reduction and traffic signal coordination (Int Panis et al, 2006; Madireddy et al, 2011), traffic calming measures (Ahn et al, 2009), and ITS evaluation. Another potential policy to reduce overall vehicle energy consumption and emissions is to choose eco-routing strategies, where the drivers choose shortest energy cost paths instead of shortest travel time. Ahn and Rakha (2013) provide a case study of eco-routing based on the INTEGRATION microsimulation framework and show that reduction in fuel consumption along the lines of 3-6% are possible. They observe that the reduction in fuel consumption is related to a reduction in travel distance and an additional travel time of about 5%.

While traffic microsimulation is useful, it is computationally expensive to scale up to large networks. Dynamic traffic assignment (DTA) presents a popular alterative. However, DTA is not as popular of a tool for environmental policy assessment, potentially due to the many challenges faced when integrating the two models (Wagner et al, 2007). Some examples include Hao et al (2010), who use an activity based travel demand model integrated with a dynamic traffic assignment routing approach to estimate vehicle urban vehicle emissions and Levin et al (2014a), who investigate the impact of road grade on city vehicle energy consumption predictions.

Electric vehicles remain a timely topic as availability and popularity with drivers continues to increase. Some works have begun combining traditional transport planning methods with electric vehicles for environmental impact assessment (Gardner et al, 2013a; Gardner et al, 2013b; He et al, 2014). However, these models are not time-dependent, and therefore unable to capture important interactions of acceleration and regenerative braking on EV energy consumption. Additionally, these approaches cannot help electric energy providers completely predict time-dependent EV charging behavior. One example can be seen in Bhavsar et al (2014), who use a microsimulation approach to compare routing strategies of different vehicle types, including EVs. The energy consumption was based on a dynamic simulation approach. While Bhavsar et al present a model that is highly detailed for EV energy consumption, it is not easily scalable to large urban networks. This work seeks to fill this gap by proposing a detailed energy consumption model based on a dynamic framework that is appropriate to apply to large networks.

3. MODELLING APPROACH

This section presents a flexible framework for integrating a vehicle energy consumption model with a dynamic traffic assignment approach. The framework is outlined in Figure 1, which begins by employing a DTA model to determine time-dependent vehicle trajectories. Section 3.1 further discusses the DTA platform. Next, the environmental model is used to calculate vehicle energy consumption and emissions. Vehicle energy consumption is the subject of focus in this work, and Section 3.2 describes the energy consumption model in more detail. Finally, Section 3.3 discusses the integration and system performance metrics for the proposed modelling approach.

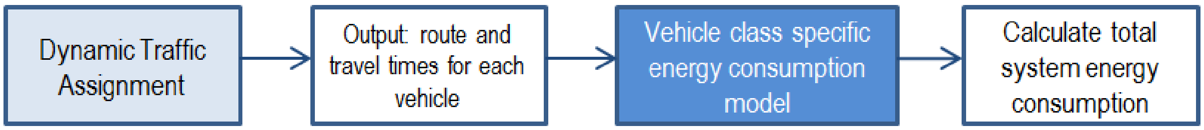

FIGURE 1 Outline of integrated modelling approach in this work

3.1 Dynamic traffic assignment model

DTA is a mesoscopic network modelling problem that estimates vehicle flow patterns for a specified period of time based on a forecasted travel demand. The routing approach in DTA is based on the dynamic user equilibrium (DUE) principle, where travel time on all used paths between an origin-destination-departure time (ODT) tuple is equal. A DTA module is an iterative procedure that determines which route vehicles from each ODT pair will choose, where travel costs are time-dependent and influenced by the route choices and network conditions created by other vehicles. This work employs the VISTA platform, which is well-established in the literature (Ziliaskopoulos et al, 2000, Levin et al, 2014b; Levin et al, 2014c).

DTA is a powerful tool that is useful for regional transport planning policy purposes. One of the primary advantages of DTA is that it can be used to evaluate the impact of changes in the network, such as infrastructure development, tolls, or availability of information. This work is interested in using a large-scale DTA model to examine both system wide and corridor specific impacts from an environmental perspective, primarily through vehicle energy consumption. While traffic microsimulation is sometimes seen as an alternative to DTA, the primary purpose of each model remains distinct. In terms of large-scale modelling, DTA has less intensive data and computational requirements than traffic microsimulation. While a separate approach may be to employ DTA to find vehicle route choices and then a microsimulation tool to predict the fine-grained behavior of vehicles, it is noted that avoiding the labor intensive microsimulation module would be a desirable outcome for planners and is worthy of investigation.

3.2 Vehicle energy consumption model

Highly accurate estimation of vehicle energy consumption generally requires input data in two areas: a vehicle's mobility pattern and vehicle-specific parameters. A third important consideration is the time frame in which energy consumption is calculated. This section discusses the three considerations in the context of the current work.

This work utilizes a parametric analytical expression approach to calculating vehicle energy consumption (PAMVEC) (Simpson, 2005). The PAMVEC 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). However, the original PAMVEC model was based on the use of standardized drive cycles (a profile of vehicle speed over a time period, intended to capture realistic driving behaviors). The novel application in this work applies a modified PAMVEC model to a "drive cycle" that is essentially created using a DTA vehicle trajectory. The advantages of this approach lie in its straightforward implementation, flexibility, and transparency.

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 the vehicle experiences during a certain time period, while the characteristic acceleration quantifies the rate at which the vehicle's speed changes. This application treats each link as an individual drive cycle where the vehicle experiences an average velocity, velocity ratio, and characteristic acceleration.

Figure 2 summarizes how energy consumption is calculated for internal combustion engine vehicles (ICVs) in this work. This work uses a DTA model to find a vehicle's route and link travel times, which then provide an average link speed (based on the time the vehicle entered and exited each link). The cell transmission model on each link is then used to find the characteristic acceleration and velocity ratio for each link. Energy is equal to the power consumed multiplied by the time period, which is the travel time of vehicle i on link a. These steps are not specific to a vehicle class.

However, the total power consumption for a vehicle depends on the vehicle's powertrain architecture, which differs between vehicle technologies. For an ICV, total power consumption is the combination of power consumed by a vehicle's engine and the power consumed due to engine loss, a function of engine's efficiency. The engine power is a combination of wheel power, brake power, drive loss (due to the specific vehicle powertrain) and accessory power. The wheel power is calculated based on the road load equations, available in any introduction to transport textbook. For ICVs, some amount of power is lost to the vehicle's friction brakes and inefficiencies in the powertrain.

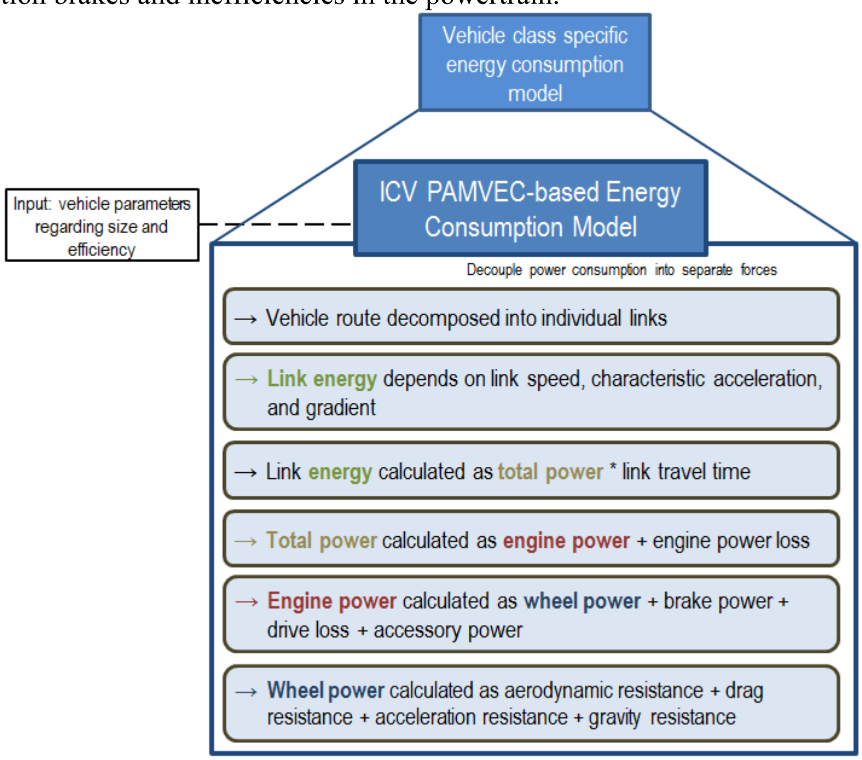

FIGURE 2 Summary of how energy consumption is calculated for ICVs

There are a number of inputs necessary for the detailed calculation of vehicle energy consumption. This work employs the representative vehicle approach, where one set of parameters is used to describe an "average" vehicle. The necessary inputs include: the frontal area of the vehicle, the aerodynamic drag coefficient, the rolling resistance coefficient, the rotational inertia factor, the engine efficiency factor, the transmission efficiency factor, and the accessory power. In order to maintain consistency with the original

PAMVEC (for the purposes of comparison), this approach utilizes the same set of vehicle parameters (Simpson, 2005).

In addition to conventional ICVs, this work is also interested in capturing the impact of alternative technology vehicles on network-wide energy consumption. Another benefit of the PAMVEC-based approach is that the original model proposed methods to represent alternate technology vehicles, including series hybrid electric vehicles (SHEV), parallel hybrid electric vehicles (PHEV), and battery electric vehicles (BEVs), also known as all-electric vehicles (such as the Nissan Leaf). The three vehicles types differ in the structure of their drive train, and hybrid implies multiple power sources (i.e., engine and battery).

Electric vehicles consume energy in a fundamentally different way from conventional ICVs due to their drive train architecture. For a BEV, a common drive train consists of an electric battery that powers a motor and a single-speed transmission. Another fundamental difference lies in the braking system. Regenerative braking, a form of braking that allows the recapture of energy instead of losing the energy to conventional friction braking, extends the range of EVs and may have an important impact on spatiotemporal predictions of EV energy consumption.

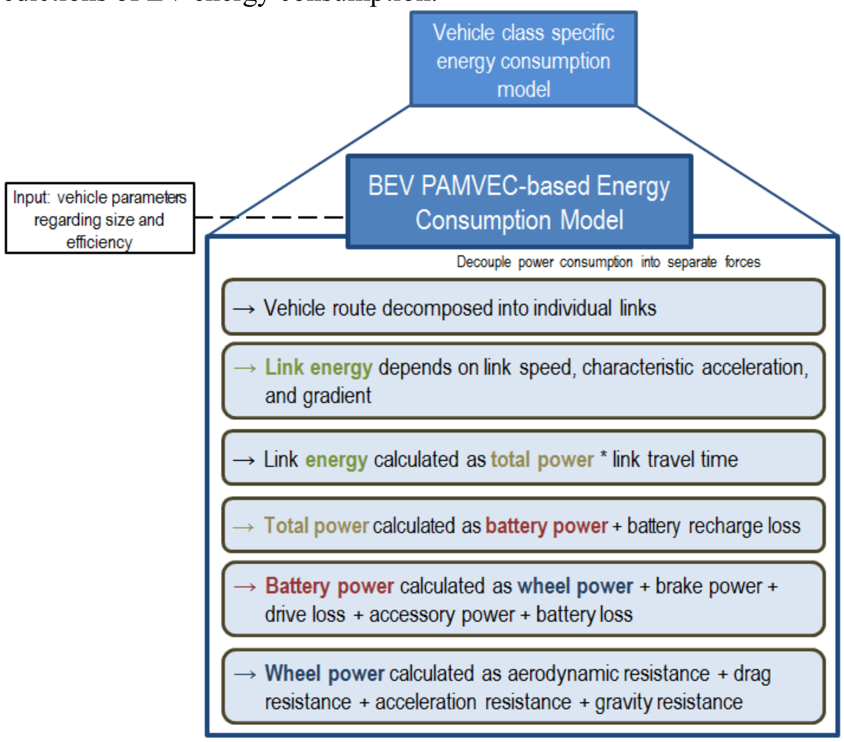

FIGURE 3 Summary of how energy consumption is calculated for BEVs

The energy consumption calculation for BEVs is summarized in Figure 3. This work calculates EV energy consumption using an adapted approach based on the PAMVEC model. For EVs, total power consumed is the combination of the power consumed by the battery and the power lost to recharging inefficiencies. The battery power is calculated as the combination of wheel power, brake power, drive loss, battery loss, and accessory power. The representative vehicle input parameters include: the frontal area of the vehicle, the aerodynamic drag coefficient, the rolling resistance coefficient, the rotational inertia factor, the transmission efficiency factor, the battery efficiency factor, the recharger efficiency, the motor efficiency factor, the braking regeneration coefficient, and the accessory power. The reader is referred to the original PAMVEC (Simpson, 2007) for more details.

4. DEMONSTRATION OF RESULTS

This section presents results for dynamic environmental assessment tool described in Section 3. Results are presented on two test networks: Sioux Falls and Downtown Austin. The Sioux Falls network has 24 zones, 76 links, and 42227 trips. Sioux Falls does not include road grade data. Downtown Austin has 171 zones, 546 intersections, 1247 links, 62836 trips, and an average absolute value link grade of 0.95 degrees.

The modelling approach presented in this work examines the impact of alternative technologies, primarily EVs. However, estimating the location of EVs in the network is a significantly more challenging data requirement and out of the scope of this work. Therefore, the ratio of ICV, BEV, SHEV, and PHEV vehicles in the network were input by percentage and then randomly selected in the network. In order to isolate the model behavior of the different vehicle types, we first make the unrealistic assumption of 100% of each vehicle type. Note that the model as presented features energy consumption calculations for multiple vehicle classes but the traffic assignment to determine route choice is not multiclass because vehicle type does not affect route choice. However, energy consumption estimation will still reveal important observation for policy-makers who may wish to encourage the use of EVs in the network.

Table 1 summarizes the system level results for each of the four vehicle types for the Sioux Falls and Downtown Austin networks. The estimation of network efficiency, the MPGe (miles per gallon equivalent) is very similar for the vehicle types in each network. As expected, BEVs consume significantly less energy than ICVs.

TABLE 1 Summary of system results for each vehicle type on the test networks

Vehicle Type	Sioux Falls Network		DT Austin Network	
	Total Energy (kWh)	MPGe	Total Energy (kWh)	MPGe
ICV	208,226	19.98	719,663	20.74
BEV	48,450	85.88	172,502	86.54
PHEV	124,893	33.32	451,976	33.03
SHEV	127,818	32.55	482,788	30.92

Finally, Figure 4 examines the frequency distributions for BEVs and ICVs on the Downtown Austin network. The horizontal axis in Figure 4 represents the estimated MPG of each vehicle and the vertical axis indicates how many vehicles were estimated to be in that MPG range. As expected, BEVs are more efficient, but there is a wide range due to the differing distance and conditions each vehicle experiences. Policies that only account for the average conditions may neglect important consequences for vehicles that are on the tails of the distribution.

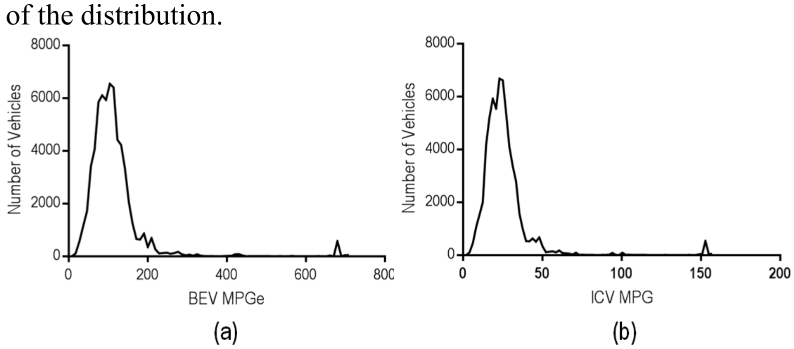

FIGURE 4 Vehicle MPGe distribution for (a) BEVs and (b) ICVs on the DT Austin network

5. CONCLUSION AND FURTHER RESEARCH

As the environmental impact of urban traffic becomes a more important issue, planners need tools to effectively and accurately assessment the impact of policy issues on a regional scale. This work integrates a dynamic traffic assignment model to capture the impact of route choice and a novel application of a vehicle energy consumption model that accounts for multiple vehicle classes. Initial results compared the impact of electric vehicle technology compared to conventional internal combustion engine vehicles on city energy consumption estimation. This work proposes a flexible, scalable framework, and can be expanded in a number of directions. The next step is to incorporate realistic EV travel demand predictions and to provide some means to verify model predictions.

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