EcoMark: Evaluating Models of Vehicular Environmental Impact

Chenjuan Guo Yu Ma Bin Yang Christian S. Jensen Manohar Kaul
Department of Computer Science, Aarhus University, Denmark
{cguo, yu, byang, csj, mkaul}@cs.au.dk

ABSTRACT

The reduction of greenhouse gas (GHG) emissions from transportation is essential for achieving politically agreed upon emissions reduction targets that aim to combat global climate change. So-called eco-routing and eco-driving are able to substantially reduce GHG emissions caused by vehicular transportation. To enable these, it is necessary to be able to reliably quantify the emissions of vehicles as they travel in a spatial network. Thus, a number of models have been proposed that aim to quantify the emissions of a vehicle based on GPS data from the vehicle and a 3D model of the spatial network the vehicle travels in. We develop an evaluation framework, called EcoMark, for such environmental impact models. In addition, we survey all eleven state-of-the-art impact models known to us. To gain insight into the capabilities of the models and to understand the effectiveness of the EcoMark, we apply the framework to all models.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Design, Experimentation, Measurement

Keywords

3D Spatial Network, Evaluation, Trajectories, Vehicular Environmental Impact

1. INTRODUCTION

Reduction in the greenhouse gas (GHG) emissions is crucial for combating global warming that has increasingly adverse effects on life on Earth. The European Union (EU) aims to reduce GHG emissions by 30% by 2020 [11], and the group of Eight (G8) plans a 50% reduction by 2050 [4]. Australia aims at a more ambitious target: an 80% reduction by 2050 [3]. China targets a 17% reduction over 2010 levels by 2015 [2].

The transportation sector is the second largest in terms of GHG emissions, trailing only the energy sector. In the EU, emissions from transportation account for nearly a quarter of the total GHG emissions [7]. Further, road transport generates more than two-thirds of transport-related GHG emissions and accounts for about one-fifth of the EU total emissions of carbon dioxide (CO_2), the major greenhouse gas [8]. Therefore, reduction targets such as the above pose great challenges to the transportation sector in general and to vehicular transportation in particular.

In addition to improved design of vehicles and engines, eco-driving [18, 19] and eco-routing [33, 45] are simple yet effective approaches, which can achieve approximately 8–20% reduction in fuel consumption and GHG emissions from road transportation. Eco-driving targets eco-friendly driver behavior, e.g., accelerating moderately, maintaining an even driving speed, and avoiding frequent starts and stops, etc. Eco-routing recommends routes that aim to minimize fuel consumption and GHG emissions.

An important first step in reducing environmental impact is to be able to measure the impact. Thus, scientists in research areas such as energy engineering, civil engineering, and environmental science have proposed a range of models that aim to measure fuel consumption and GHG emissions [23, 26, 42]. These models consider a wide range of factors, e.g., vehicle speed and acceleration, different physical features of vehicles, and geometric information on the spatial network in which the driving occurs.

While nearly a dozen impact models exist, no comprehensive comparison of these models exists. Moreover, the utility of the models for eco-driving and eco-routing is also not well understood. This paper represents the first attempt at addressing these deficiencies by developing an evaluation framework, called EcoMark, for evaluating and comparing impact models using GPS trajectories and a 3D spatial network.

The use of GPS trajectories and a 3D spatial network bring the following benefits: (i) Many vehicles are equipped with GPS, and GPS data is plentiful and easy to collect. Thus, GPS data sets offer very good coverage of spatial networks, which enables Ecomark-based comparison of models to occur in a broader range of settings than in previous evaluations, where only limited selections of routes were considered [15, 41]. (ii) GPS trajectories are capable of providing the dynamic, travel-related information required by the models, e.g., velocities and accelerations of vehicles, and of reflecting the traffic conditions in a spatial network. (iii) A 3D spatial network captures both the lengths and the grades (degree of incline or decline) of road segments, which are factors that affect fuel usage and GHG emissions. Although several models take grades into account [21, 30, 45], only Tavares et al. [45] report on empirical studies with a 3D spatial network to measure the influence of grades on fuel consumption and GHG emissions.

To the best of our knowledge, this paper proposal of EcoMark and its subsequent application of EcoMark represents the first com-

ACM SIGSPATIAL GIS '12, November 6-9, 2012. Redondo Beach, CA, USA

prehensive study of the environmental impact of road transportation using GPS trajectories and a 3D spatial network.

The paper makes three contributions. First, a sophisticated evaluation framework is proposed that encompasses a 3D spatial network model. Second, a categorization and comparison of all eleven known models that can estimate fuel usage and GHG emissions is conducted. Third, comprehensive experimental studies are conducted on a half-year collection of GPS data from vehicles traveling in North Jutland, Denmark. Interesting findings obtained from the evaluation framework are discussed.

The remainder of this paper is organized as follows. Section 2 gives a comprehensive review of the state-of-the-art techniques for estimating fuel consumption and GHG emissions. Section 3 presents the EcoMark framework and also covers the modeling of a 3D spatial network. Section 4 categories the 11 models into instantaneous models and aggregated models and discusses them in detail. Section 5 reports on the application of EcoMark to the impact models. Conclusions are drawn in Section 6.

2. RELATED WORK

The fuel consumed by a vehicle is influenced by multiple factors [16,20,22], such as *vehicle technology* (e.g., vehicle model and size, engine power, and type of fuel), *vehicle status* (e.g., mileage, age, and engine status), *vehicle operating conditions* (e.g., vehicle velocity and acceleration, power demands, and engine speed), *driving behavior* (e.g., aggressive driving), *air conditions* (e.g., atmospheric pressure, air humidity, and wind effects), *road conditions* (e.g., road grade and surface roughness), and *traffic conditions* (e.g., vehicle-to-vehicle and vehicle-to-control interactions). In general, different models consider different selections of these factors to compute fuel usage and GHG emissions.

Models for estimating fuel consumption or GHG emissions have been developed over the past thirty years and can be classified macroscopic and microscopic scale models [31]. Macroscopic models [17, 25–27] account for the total fuel consumed during an extended time period (e.g., a day, a week, or a year) when traveling in an extended region (e.g., a city or a state) [22].

Macroscopic models are suitable for applications where coarse estimation of environmental impact is desired. However, macroscopic models are unable to accurately estimate the environmental impact of a particular road segment traveled by an individual vehicle or of a particular driving operation (e.g., braking hard), which are of interest in eco-routing and eco-driving.

In contrast, microscopic models estimate the instantaneous fuel consumption or GHG emissions of individual vehicles at given time points (usually at seconds) using instantaneous velocities and accelerations. Some models utilize additional information, including vehicle status, vehicle operating conditions, and road conditions.

Microscopic models are further classified into three categories [22]. *Emission map models* [29] provide lookups in velocity-acceleration matrices and return corresponding emission values. *Regression-based models* [23,30,42] employ mathematical functions of second-by-second velocities and accelerations of a vehicle to predict instantaneous fuel consumption or GHG emissions. They do not consider physical features of vehicles. *Load-based models* [28, 35, 37, 40, 43] are the most comprehensive microscopic models, and they consider a wide range of parameters, such as second-by-second velocities and accelerations, grades of road segments, air conditions, engine maximum power, gear ratio, and engine power demands.

Microscopic models are often employed to evaluate the environmental impact of individual road segments on a spatial network and particular driving operations. The comprehensive load-based models generally offer the best estimates of fuel consumption. However, the required parameters are difficult to obtain for individual vehicles in a scalable manner. In contrast, regression-based models are fairly easy to apply because their input, e.g., instantaneous velocities and accelerations, can be obtained directly from GPS trajectories. EcoMark aims to evaluate the environmental impact of travel using models that do not require vehicle-specific factors. The details of the qualifying models are covered in Section 4.

Rakha et al. conduct a comparison [15, 41] of a regression-based model, VT-Micro [16, 42], a load-based model, CMEM [43], and a macroscopic model, MOBILE6 [26]. The study finds that VT-Micro estimates fuel consumption more accurately than do the other two models. The study uses GPS data as input and considers the fuel consumption of a vehicle when it travels on highway routes and on arterial routes, respectively. The estimates obtained from VT-Micro and CMEM follow the same trend and indicate that choosing arterial routes generate less emissions than when choosing highway routes, whereas estimates obtained from MOBILE6 suggest the opposite.

To the best of our knowledge, EcoMark is the first work that performs a comprehensive comparison and analysis of fuel consumption models using GPS vehicle tracking data and a 3D spatial network, and with an emphasis on how the models considered can be utilized for eco-routing and eco-driving.

3. ECOMARK DESIGN

Following an overview of EcoMark, we cover the modeling and construction of a 3D model of a transportation network and describe the trajectories that are used in EcoMark.

3.1 EcoMark Overview

EcoMark is designed to evaluate state-of-the-art models of vehicular environmental impact in terms of fuel consumption and GHG emissions. It aims to provide an understanding of the utility of the impact models in relation to eco-driving and eco-routing and to offer insight into aspects such as which models can be used for identifying relationships between environmental impact and driver behavior, thus enabling eco-driving, and which models are suitable for assigning weights to road segments that capture environmental impact, thus enabling eco-routing.

Figure 1 depicts an overview of EcoMark. Three types of raw data are used in EcoMark: a set of GPS observations, a 2D spatial network, and a laser scan point cloud [10]. A map matching module takes as input the set of GPS observations and the 2D spatial network. It outputs a set of map matched trajectories. A 3D spatial network generation module creates a 3D spatial network from the 2D spatial network and the laser scan point cloud. The trajectories and the 3D spatial network are fed into EcoMark as input data.

Unless stated otherwise, we use 2D to denote the latitude-longitude plane ((x, y) plane) and 3D to denote the latitude-longitude-altitude space ((x, y, z) space).

Road grades are generally difficult to obtain because the major maps available, e.g., OpenStreetMap [6], Google Maps [5], and Bing Maps [1], are 2D and lack grades of road segments. Thus, although some models [21, 30] take grades into account, this parameter has generally been set to zero in practice due to the unavailability of segment grade information.

In EcoMark, we use a 3D spatial network that provides grade information for all road segments. This network is constructed by using a laser scan point cloud for lifting a 2D spatial network. The use of laser point data yields a model with much higher accuracy than what can be obtained when using Shuttle Radar Topography Mission (SRTM) data [9], which has been used in the past. This is because the SRTM data contains only one altitude value for each

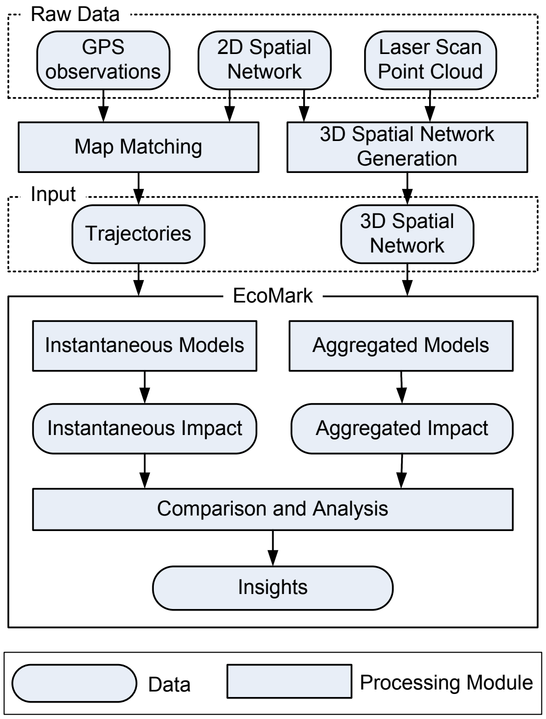


Figure 1: An Overview of EcoMark

$30m \times 30m$ region, whereas the laser data we use contains one altitude value for each $1m \times 1m$ region. The generation of the 3D spatial network is covered in Section 3.4.

In principle, the models supported in EcoMark take as input traffic and road information that can be obtained from GPS trajectories and a 3D spatial network, but do not require vehicle-specific factors. The supported models are categorized into *instantaneous models* and *aggregated models*. The instantaneous models take as input instantaneous (i.e., second-by-second) velocities and accelerations and output instantaneous fuel usage or GHG emissions. In contrast, the aggregated models take as input average velocities and output aggregated fuel usage or GHG emissions. The aggregated models can be applied at different aggregation levels, e.g., at the level of road segments or at the level of trajectories.

We use EcoMark to perform the following comparisons and analyses: (1) comparison and analysis of instantaneous models; (2) comparison and analysis of aggregated models; (3) aggregation of the instantaneous results, and comparison of them with the results obtained from the aggregated models; (4) comparison of the (instantaneous and aggregated) results with and without the use of road grades. Finally, meaningful conclusions, in terms of eco-driving and eco-routing, are drawn based on the sophisticated comparisons and analyses.

3.2 Trajectories

Since vehicle tracking using GPS is widespread and growing, GPS based vehicle tracking data is increasingly available and is thus an attractive source of vehicle movement data [14]. Thus, it is used in EcoMark.

A **trajectory**, denoted as $\mathcal{T}$=(p_1, p_2, ..., p_X), is a sequence of GPS observations, where a GPS observation p_i specifies the location (typically 2D with latitude and longitude coordinates) and velocity of a vehicle at a particular time point. It is clear that instantaneous velocities are available from GPS trajectories, and instantaneous accelerations can be derived based on consecutive GPS observations.

Given a spatial network G, a map matching algorithm [38] is able to associate each observation in a trajectory with a specific location on an edge in $G.\mathbb{E}$. The map matching algorithm also enhances the accuracy of GPS trajectories by correcting inaccurate observations and filtering noisy observations.

An alternative to using GPS is to use roadside technologies, e.g., Bluetooth sensors and loop detectors, for the capture of vehicle velocities. However, only Bluetooth sensors may be able to link individual observations to specific vehicles, and the observations are much less frequent than what can be achieved with GPS. Thus, such velocities are less attractive for the estimation of the environmental impact of a vehicle.

3.3 Modeling a 3D Spatial Network

A spatial network captures both topological and geometric aspects of a transportation network in a certain region. In EcoMark, a **3D spatial network** is defined as a directed, weighted graph G = $(\mathbb{V}, \mathbb{E}, F, H)$, where $\mathbb{V}$ and $\mathbb{E}$ is the vertex set and edge set, respectively; and F and H are functions that record the geometric information of vertices and edges, i.e., record the embedding of vertices and edges into geographical space.

A vertex $v_i \in \mathbb{V}$ indicates a road intersection or an end of a road. $\mathbb{E}$ is the edge set, and an edge $e_k \in \mathbb{E} \subseteq \mathbb{V} \times \mathbb{V}$ is defined as a pair of vertices and represents a directed road segment connecting the two constituent vertices. For example, edge e_k=(v_i, v_j) represents a road segment that enables travel from source vertex v_i to target vertex v_j.

Function $F : \mathbb{V} \rightarrow \mathbb{R} \times \mathbb{R} \times \mathbb{R}$ takes as input a vertex and returns a 3D point. Function $H : \mathbb{E} \times \mathbb{R} \rightarrow \mathbb{R}$ takes as input an edge and a value x, where x indicates the distance along the edge from the source vertex to a point on the edge. The function outputs the grade of the point on the edge. In EcoMark, positive grades indicate uphill directions and negative grades indicate downhill directions.

Assume that v_1 and v_2 are the vertices of a road segment in a 3D spatial network, and A is the grade inflection point on the road segment. Figure 2 shows the altitude-longitude projection of the road segment.

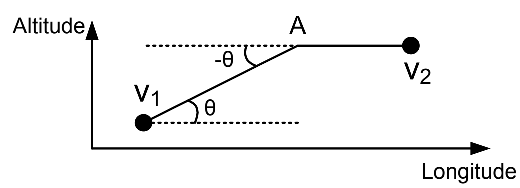


Figure 2: Altitude-longitude Projection of a Road Segment

For edge (v_1, v_2), the grade of the sub-edge from v_1 to A is θ, and the grade of the sub-edge from A to v_2 is 0. Thus, $H((v_1, v_2), x) = \theta$ if $0 \leqslant x \leqslant |v_1, A|_{3D}$, where $|\cdot|_{3D}$ indicates the 3D Euclidean distance between two 3D points; $H((v_1, v_2), x) = 0$ if $|v_1, A|_{3D} \leqslant x \leqslant |v_1, A|_{3D} + |A, v_2|_{3D}$. Similarly, for edge ($v_2$, v_1), $H((v_2, v_1), x) = 0$ if $0 \leqslant x \leqslant |v_2, A|_{3D}$; $H((v_2, v_1), x) = -\theta$ if $|v_2, A|_{3D} \leqslant x \leqslant |v_2, A|_{3D} + |A, v_1|_{3D}$.

3.4 Realizing a 3D Spatial Network

The 3D spatial network generation module augments a 2D spatial network with appropriate altitude information extracted from a laser scan point cloud, which contains a set of 3D points reflecting the surface of a certain region. An approximated surface of the region becomes available by transforming these 3D points into a TIN

(Triangular Irregular Network) [39] surface. The altitude information of a 2D spatial network becomes available by projecting the 2D spatial network to the TIN surface, thus generating its corresponding 3D spatial network.

Specifically, we consider the region of North Jutland, Denmark in EcoMark. We obtain a 2D spatial network of North Jutland from OpenStreetMap, and we employ a laser scan point cloud that covers North Jutland to generate a 3D spatial network of North Jutland. The detail of realizing the 3D spatial network is beyond the scope of EcoMark.

If GPS observations encompass altitude information, road grades can also be derived from GPS trajectories. However, GPS observations can be inaccurate, rendering derived grades less accurate than grades obtained using a laser scan point cloud.

4. MODEL ANALYSIS

EcoMark covers eleven state-of-the-art models that estimate vehicular environmental impact. These models are categorized into *instantaneous models* and *aggregated models* as defined in Section 3.1, and are described in Sections 4.1 and 4.2, respectively.

All the models share the property that their input can be derived from GPS trajectories, e.g., velocities and accelerations, or can be obtained from a 3D spatial network, e.g., road grades. Values are not specified for some parameters below due to space limitations, but can be obtained from the original papers. To ease the following discussion, important notation is introduced in Table 1.

Notation	Description	Unit
v_t	instantaneous velocity at time point t	m/s or km/h
a_t	instantaneous acceleration at time point t	m/s^2 or $km/h/s$
θ_t	road grade at time point t	degree or %
f_t	instantaneous environmental impact at time point t	g/s or mL/s
$\bar{f}$	environmental impact per unit distance	g/km or mL/km

Table 1: Notation

4.1 Instantaneous Models

4.1.1 EMIT

The EMIssions from Traffic (**EMIT**) model [23] was proposed by Cappiello et al. and aimed to require simple input while still considering physical features of vehicles. EMIT assumes that (1) the road grade is 0; (2) the engine power required for accessories, e.g., air conditioning, is 0; (3) no history effects, e.g., cold-start, are present; and (4) only hot-stabilized conditions are considered. It takes as input instantaneous velocity v_t (m/s) and acceleration a_t (m/s^2) and predicts the fuel consumption rate f_t (g/s) at time point t.

$$f_t = \begin{cases} \alpha + \beta \cdot v_t + \gamma \cdot v_t^2 + \delta \cdot v_t^3 + \zeta \cdot a_t \cdot v_t & \text{if } P_{tract} > 0 \\ \alpha' & \text{if } P_{tract} \leqslant 0 \end{cases}$$

where α, β, γ, δ, ζ and α' are model-specific parameters [23], and P_{tract} is calculated according to the following equation.

$$P_{tract} = A \cdot v_t + B \cdot v_t^2 + C \cdot v_t^3 + M \cdot a_t \cdot v_t + M \cdot g \cdot \sin\theta_t \cdot v_t,$$

where A, B, C and M are parameters related to physical vehicle features, $g = 9.81$ is the gravitational constant, and θ_t is the road grade and is always set to 0 [23].

4.1.2 VT-Micro

VT-Micro, by Rakha et al. [16, 42], is a regression model that uses only instantaneous velocities and accelerations without considering the physical features of vehicles. VT-Micro makes the following assumptions: (1) the model is developed for light-duty vehicles and trucks; (2) the model only estimates fuel consumption and vehicle emissions for hot-stabilized conditions and does not consider the effect of vehicle start.

The model takes as input the instantaneous velocity v_t (km/h) and acceleration a_t ($km/(h \cdot s)$), and it estimates fuel consumption or emission rate f_t (mL/s or g/s) at time point t as follows.

$$f_t = \begin{cases} \exp(\sum_{i=0}^{3}\sum_{j=0}^{3}(K_{i,j} \cdot v_t^i \cdot a_t^j)) & \text{if } a_t \geqslant 0 \\ \exp(\sum_{i=0}^{3}\sum_{j=0}^{3}(L_{i,j} \cdot v_t^i \cdot a_t^j)) & \text{if } a_t < 0 \end{cases}$$

where $K_{i,j}$ and $L_{i,j}$ are model coefficients for accelerating ($a_t \geqslant 0$) and decelerating ($a_t < 0$) conditions, respectively.

4.1.3 MEF

MEF, by Lei et al. [34], is a regression-based model based on VT-Micro [42] and POLY [46]. It employs not only current velocity and acceleration, but also historical accelerations, to estimate emissions and fuel consumption.

At time point t, MEF takes as input the current velocity v_t and the current acceleration a_t, and also the historical (up to 9 seconds before t) accelerations, i.e., $a_{t-i}, i = 1, ..., 9$. The instantaneous fuel consumption or emissions rate f_t (g/s) at time point t is calculated as follows.

$$f_t = \begin{cases} \exp(\sum_{i=0}^{3}\sum_{j=0}^{3}(\lambda_{i,j} \times v_t^i \times \bar{a}_t^j)) & \text{if } \bar{a}_t \geqslant 0 \\ \exp(\sum_{i=0}^{3}\sum_{j=0}^{3}(\gamma_{i,j} \times v_t^i \times \bar{a}_t^j)) & \text{if } \bar{a}_t < 0 \end{cases}$$

where $\lambda_{i,j}$ and $\gamma_{i,j}$ are model coefficients and $\bar{a}_t$ is the composite acceleration given as $\bar{a}_t = \alpha \cdot a_t + (1-\alpha) \cdot \sum_{i=1}^{9} \frac{a_{t-i}}{9}$, where α is set to 0.5.

4.1.4 SP

Vehicle **Specific Power** (SP) is due to Jiménez-Palacios [30]. Instead of designing a model for estimating emission rates or fuel consumption directly, Jiménez-Palacios defines SP as the instantaneous power per unit mass of a vehicle. Jiménez-Palacios argues that SP is directly related to the vehicle engine load and thus to emission rates and fuel consumption. Thus, the model is claimed to be more reliable than the models solely based on velocities and accelerations.

At time point t, SP takes as input vehicle velocity v_t (m/s) and acceleration a_t (m/s^2) as well as road grade θ_t (%) and the headwind into a vehicle v_w (m/s). The SP value at time point t, denoted as SP_t, is defined as follows.

$$SP_t = v_t \cdot (1.1 \cdot a_t + 9.81 \cdot \theta_t + 0.132) + 0.000302 \cdot (v_t + v_w)^2 \cdot v_t$$

4.1.5 Joumard

Joumard et al. [32] carried out a study to identify the most important parameters that influence fuel consumption and emissions rates and that thus can be used to assess the design of traffic management systems on their impact on traffic pollution. The model, denoted as **Joumard**, assumes that: (1) travel occurs in urban conditions, and

(2) the engine is hot. Joumard takes as input instantaneous velocity v_t (m/s) and acceleration a_t (m/s^2), and it computes the instantaneous fuel f_t as follows.

$$f_t = v_t + v_t \cdot a_t,$$

and Joumard et al. do not specify the unit of f_t.

4.1.6 SIDRA-Inst

SIDRA, by Bowyer et al. [21], is a framework that includes four fuel consumption estimation models. SIDRA has been developed into commercial products[1]. The four models are designed in an increasing order of aggregation and integrate vehicle energy features (e.g., vehicle mass and drag force). The four interrelated models follow the same modeling framework, where a more aggregated model is derived from a more detailed model. Specifically, the SIDRA framework includes an instantaneous model, a four-mode element (i.e., acceleration, cruise, deceleration and idle) model, a running speed model, and an average travel speed model, denoted as SIDRA-Inst, SIDRA-4Mode, SIDRA-Running, and SIDRA-Avg, respectively.

SIDRA-Inst, the least aggregated model, takes as input instantaneous vehicle speed v_t (m/s) and acceleration a_t (m/s^2) and road grade θ_t (%) at time point t, and it computes the instantaneous fuel consumption f_t (mL/s) as follows.

$$f_t = \begin{cases} 0.444 + 0.09 \cdot R_t \cdot v_t + [0.05 \cdot 4a_t^2 \cdot v_t]_{a_t>0} & R_t > 0 \\ 0.444 & R_t \leqslant 0 \end{cases}$$

where $R_t = 0.333 + 0.00108 \cdot v_t^2 + 1.2 \cdot a_t + 0.1177 \cdot \theta_t$ is the total tractive force required to drive the vehicle.

4.2 Aggregated Models

4.2.1 Song

Song et al. [44] offer a model that aims to capture the effects of dynamic traffic conditions on fuel consumption and to evaluate the effects of different operational strategies in a transportation network. The model, denoted as **Song**, is built on SP, but omits the road grade used in SP. Given a route e, Song takes as input all instantaneous vehicle velocities (m/s) and accelerations (m/s^2) recorded on e and computes a relative fuel consumption indicator I_e for a light duty vehicle that traverses e. This is done as follows.

$$I_e = \frac{\beta \cdot \sum_{t=1}^{T} \tau_t + T}{\gamma \cdot \frac{\sum_{t=1}^{T} v_t}{\varepsilon}},$$

where T is the total travel time (s) on route e; β γ and ε are coefficients [44]; and τ_t is a surrogate variable of vehicle specific power at time point t, which equals SP'_t if $SP'_t > 0$, and equals 0 if $SP'_t \leqslant 0$, where $SP'_t = v_t \cdot (1.1 \cdot a_t + 0.132) + 0.000302 \cdot v_t^3$.

4.2.2 Tavares

Tavares et al. [45] propose a route optimization method for minimizing the vehicle fuel consumption that is needed for the collection and transportation of municipal solid waste on Santiago Island.

The cost function, denoted as **Tavares**, is derived from COPERT [36] and is designed for estimating fuel consumption of heavy duty diesel vehicles. It takes into account the average velocity $\bar{v}$ (km/h) on a road segment, the percentage of vehicle load LP, and the road grade θ (%). It computes the fuel consumption per unit distance $\bar{f}$ (g/km) as follows.

$$\bar{f} = FCS \cdot LCF \cdot GrCF,$$

where FCS=1068.4 $\cdot$ $\bar{v}^{-0.4905}$ indicates the basic fuel consumption; LCF= $1 + 0.36 \cdot \frac{(LP-50)}{100}$ indicates the additional influence of vehicle weight; and $GrCF$=0.41$\cdot e^{0.18 \cdot \theta}$ indicates the additional influence of road grades.

4.2.3 SIDRA-4Mode

SIDRA-4Mode [21] is a four-mode elemental model for estimating fuel consumption when a vehicle drives on a road segment, making repeated stops and starts. The driving can be modeled as a cruise-deceleration-idle-acceleration-cruise (CDIAC) cycle. In particular, the overall fuel consumption F_s (mL) is calculated by $F_s = F_{c1} + F_d + F_i + F_a + F_{c2}$, where F_{c1} (mL) and F_{c2} (mL) are the fuel consumptions when a vehicle cruises at speed v_1 with distance x_1 and at speed v_2 with distance x_2, respectively; F_d (mL), F_i (mL), and F_a (mL) are the fuel consumption when the vehicle is decelerating, idle, and accelerating, respectively.

Due to the space limitation, only the function for cruise, i.e., F_c, is covered here. Readers may refer to the original report [21] for the details of F_d, F_i, and F_a.

Cruising occurs when traveling between consecutive accelerations or decelerations. The function F_c takes as input the average cruising speed v_c (km/h) (allowing small fluctuations), the cruising distance x_c (km), and the road grade θ (%), and it computes the cruising fuel consumption F_c (mL) as $F_c = \bar{f}_c \cdot x_c$, where the cruising fuel consumption per unit distance $\bar{f}_c$ (mL/km) is defined as follows.

$$\begin{aligned} \bar{f}_c &= \tfrac{1600}{v_c} + 30 + 0.0075 \cdot v_c^2 + 108 \cdot k_{E1} \cdot E_{k+} \\ &\quad + 171.2 \cdot E_{k+}^2 + 10.6 \cdot k_G \cdot \theta, \end{aligned}$$

where E_{k+} is the marginal fuel consumption due to speed fluctuations and k_{E1} and k_G are calibration parameters [21].

4.2.4 SIDRA-Running

SIDRA-Running [21] is a more aggregated model derived from SIDRA-4Mode. The overall fuel consumption of a trip made by a vehicle includes the fuel consumed during the period of running and the fuel used when the vehicle is stopped briefly. The model requires as input x_s (km), the total travel distance; t_s (s), the total travel time; θ (%), the road grade; v_i (km/h) and v_f (km/h), the initial and final velocity during each positive acceleration, with the constraint that $v_i < v_f$; and t_i (s), the total idle (stopped) time.

In cases where v_i, v_f, and t_i are unknown, they can be estimated using given functions, or they can be replaced by other parameters [21].

The fuel consumption of the running mode F_s (mL) is estimated as $F_s = F_i + \bar{f}_r \cdot x_s$, where $F_i = 0.444 \cdot t_i$ is the fuel consumption during idle periods and $\bar{f}_r$ (mL/km) indicates the average fuel consumption per unit distance excluding idle periods, which is computed as follows.

$$\begin{aligned} \bar{f}_r &= \tfrac{1600}{v_r} + 30 + 0.0075 \cdot v_r^2 + 108 \cdot k_{E1} \cdot E_{k+} \\ &\quad + 54 \cdot k_{E2} \cdot E_{K+}^2 + 10.6 \cdot k_G \cdot \theta, \end{aligned}$$

where $v_r = \frac{3600 \cdot x_s}{(t_s - t_i)}$ is the average running speed (km/h) and k_{E1}, k_{E2}, and k_G are calibration parameters [21].

4.2.5 SIDRA-Avg

SIDRA-Avg, the average travel speed fuel consumption model, is the simplest and most aggregated model in the SIDRA framework, where only the average travel speed is required [21]. SIDRA-Avg takes as input the total travel distance x_s (km) and the total travel time t_s (s) including the time when stopped.

[1] http://www.sidrasolutions.com/

	Models	Input			Physical Features	Absolute Value	Vehicle Type	Model Year	Data Source
		Velocity	Acceleration	Grade					
Instantaneous	EMIT [23]	✓	✓	×	✓	✓	Light	2002	U.S.
	VT-Micro [16,42]	✓	✓	×	×	✓	Light	2004	U.S.
	SP [30]	✓	✓	✓	✓	×	Unknown	1999	U.S.
	MEF [34]	✓	✓	×	×	✓	Light	2010	China
	Joumard [32]	✓	✓	×	×	×	Passenger	1995	EU
	SIDRA-Inst [21]	✓	✓	✓	✓	✓	Light, Heavy	1985	Australia
Aggregated	Song [44]	✓	✓	×	✓	×	Light	2009	China
	Tavares [45]	✓	×	✓	×	✓	Heavy	2009	Cape Verde
	SIDRA-4Mode [21]	✓	×	✓	✓	✓	Light, Heavy	1985	Australia
	SIDRA-Running [21]	✓	×	✓	✓	✓	Light, Heavy	1985	Australia
	SIDRA-Avg [21]	✓	×	×	✓	✓	Light, Heavy	1985	Australia

Table 2: A Summary of Models for Estimating Vehicular Environmental Impact

It is suggested that the model can only be used in urban road networks and that the average travel speed should be below 50 km/h. When the average speed exceeds 50 km/h, SIDRA-Running should be used instead [21]. The fuel consumption per unit distance $\bar{f}_a$ (mL/km) is defined as follows.

$$\bar{f}_a = \frac{1600}{v_s} + 73.8,$$

where $v_s = \frac{3600 \cdot x_s}{t_s}$ is the average travel speed (km/h).

4.3 Summary

In the summary of models in Table 2, ✓ (×) indicates that a model considers (does not consider) a feature.

The *inputs* required by the models are obtainable from GPS trajectories (e.g., velocities and accelerations) or from a 3D spatial network model (e.g., grades), and therefore all models can be applied straightforwardly in most road transportation networks. Table 2 shows that instantaneous models require both velocities and accelerations as input, while most aggregated models take only velocities as input. The road grade is an optional input parameter in the instantaneous as well as the aggregated models. Studies exist that indicate the benefits of considering road grades in the models [45].

Some models, specifically EMIT, SP, Song, and the SIDRA family, explicitly combine physical vehicle features (indicated by the *Physical Features* column in the table) in the fuel consumption computation, whereas the remaining models, namely VT-Micro, MEF, Joumard, and Tavares, do not consider such features. No correlation exists between the type of model, i.e., instantaneous or aggregated model, and the use of physical features.

Most models predict an absolute impact value with units (indicated by the *Absolute Value* column. The units of the absolute impact values reported by instantaneous models are typically volume unit per time unit (e.g., mL/s) or mass unit per time unit (e.g., mg/s). For the aggregated models, volume (or mass) unit per distance unit, e.g., mL/km or g/km, are reported. In contrast to the majority of models, SP and Song provide merely a relative indicator of fuel consumption. Although Joumard is able to predict an "absolute" value, its unit is unclear in the description of the model [32]. Therefore, we regard the value as a relative indicator.

All the models have prerequisites on vehicle types, as listed in the *Vehicle Type* column. The models are also developed during different years and in different regions (as listed in the *Model Year* and *Data Source* columns). Therefore, the gathered traffic information and the measured fuel consumption that were used to calibrate the models may also be different. This may to some extent explain the use of different parameters in the models.

5. EMPIRICAL STUDIES

We conduct comprehensive empirical studies to compare and analyze the 11 models, in order to obtain insight into the properties of the different categories of models and how to apply the models to eco-driving and eco-routing.

5.1 Setup

The two main input data sources of EcoMark are GPS trajectories and a 3D spatial network, as described in Section 3.1. We use GPS data collected from 150 vehicles traveling in North Jutland, Denmark, during January to June 2007. The GPS data covers a variety of traffic conditions, e.g., peak and off-peak hour traffic, highway traffic and arterial road traffic. The sampling frequency is 1 Hz, which makes application to the instantaneous models easy.

We apply an existing map matching tool [38] along with a 2D spatial network of North Jutland, Denmark obtained from OpenStreetMap to the GPS data, from which we get a set of $52,084$ trajectories, denoted as $\mathbb{T}$.

The statistics of the trajectories are provided in Table 3 that lists the number of trajectories belonging to different categories. In the table, *roadseg* indicates the number of road segments traversed by a trajectory; *avgvel* indicates the average velocity of a trajectory; and *duration* indicates the total travel time of a trajectory. The units of the average velocity and the duration are km/h and minute(s), respectively. The corresponding 3D spatial network of North Jutland, Denmark is obtained as described in Section 3.4.

# total	52,084	# *roadseg* ⩽100	47,333
# *avgvel* ⩽ 50	37,018	# *roadseg* >100	4,751
# 50 < *avgvel* ⩽ 100	14,701	# *duration* < 30	44,544
# *avgvel* > 100	365	# *duration* ⩾ 30	7,461

Table 3: Statistics of Trajectories in $\mathbb{T}$

5.2 Evaluating Instantaneous Models

Experiments are conducted to evaluate whether the instantaneous models show consistent estimation of environmental impact given the same trajectories. To quantify the consistency between two models m and n, vector based cosine similarity is applied, as defined in Equation 1.

$$consistency(m,n) = \frac{1}{|\mathbb{T}|} \cdot \sum_{\mathcal{T} \in \mathbb{T}} \cos(\mathcal{L}_{\mathcal{T}}^{(m)}, \mathcal{L}_{\mathcal{T}}^{(n)}) \qquad (1)$$

where $\mathcal{L}_{\mathcal{T}}^{(m)}$ is a vector that contains the impact values of trajectory $\mathcal{T}$ computed by model m and function $\cos(\cdot,\cdot)$ computes the cosine similarity between two vectors.

The similarity between each two instantaneous models is shown in Table 4. As can be observed, EMIT, SP, Joumard, and SIDRA-Inst show comparatively similar behavior with similarities above 83%. In contrast, VT-Micro and MEF exhibit dissimilarity with the other models.

	VT-Micro	SP	MEF	Joumard	SIDRA-Inst
EMIT	69.6%	84.5%	19.7%	89.2%	93.5%
VT-Micro	1	50.2%	26.0%	71.5%	62.7%
SP	-	1	0.58%	86.4%	85.1%
MEF	-	-	1	12.2%	13.7%
Joumard	-	-	-	1	83.3%

Table 4: Consistencies Between Instantaneous Models

As an example, a trajectory $\mathcal{T}_1$, with $2,375$ GPS observations, is chosen to compare the behaviors of the instantaneous models. Figure 3(a) and (b) shows the instantaneous environmental impact from the 70th to the 100th seconds as computed by the models; Figure 3(c) and (d) shows the instantaneous velocities and accelerations during the same period. Figure 3 also indicates that the instantaneous environmental impact estimated by most models, except MEF, are highly correlated with accelerations.

Experiments are also conducted on the environmental impact caused by different driving behaviors, which in turn are indicated by different instantaneous velocities and accelerations. Four trajectories with distinct driving behaviors are chosen, as shown in Table 5, whose velocities and accelerations are also plotted in Figure 4(c) and (d). The accelerations of $\mathcal{T}_5$, whose values are around zero, are omitted to increase the readability of Figure 4(d).

	High Velocity	Low Velocity
Aggressive Acceleration	$\mathcal{T}_3$	$\mathcal{T}_4$
Moderate Acceleration	$\mathcal{T}_5$	$\mathcal{T}_6$

Table 5: Trajectories with Different Driving Behaviors

EMIT shows high consistency with most instantaneous models (see Table 4) and thus is utilized to demonstrate the environmental impact of the four trajectories. As shown in Figure 4(a) and (b), the results indicate that: (1) environmental impact of moderate accelerations ($\mathcal{T}_5$ and $\mathcal{T}_6$) is much less than the impact of aggressive accelerations ($\mathcal{T}_3$ and $\mathcal{T}_4$); (2) driving with high velocities and aggressive accelerations yields higher environmental impact than when driving with low velocities and aggressive accelerations. For example, although the variations in the accelerations of $\mathcal{T}_4$ is greater than those of $\mathcal{T}_3$, $\mathcal{T}_4$ generally has a lower environmental impact than does $\mathcal{T}_3$.

5.3 Evaluating Aggregated Models

Aggregated models are used to estimate environmental impact per unit length on road segments traversed by trajectories. A similar consistency comparison is conducted to gain insight into the similarity of each pair of aggregated models by applying Equation 1. As shown in Table 6, all models show similar estimation trends with similarities higher than 80%. Having similarities of at least 96.9%, Tavares, SIDRA-Running, and SIDRA-Avg are highly consistent with each other.

	Tavares	SIDRA-4Mode	SIDRA-Running	SIDRA-Avg
Song	86.4%	81.4%	88.3%	88.8%
Tavares	1	90.8%	96.9%	97.3%
SIDRA-4Mode	-	1	88.6%	88.4%
SIDRA-Running	-	-	1	99.7%

Table 6: Consistencies of Aggregated Models

Trajectory $\mathcal{T}_2$, which covers 114 road segments, is utilized as an example to show the behaviors of the aggregated models. The aggregated impact estimated by the aggregated models between the 50th to the 100th road segments is reported in Figure 5. In general, all the aggregated models behave similarly: the average velocity on a segment is inversely proportional to the environmental impact per unit length.

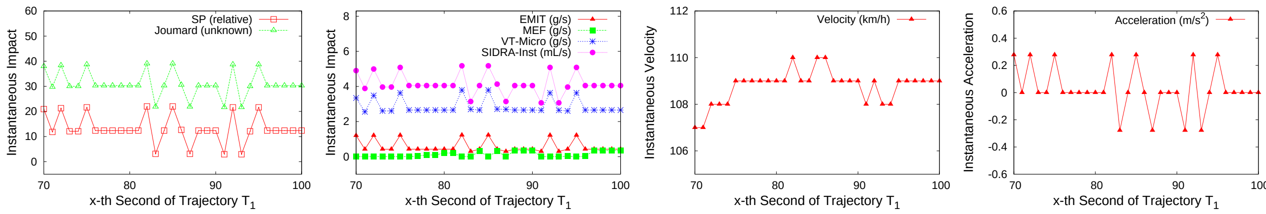
For example, the velocities on the 75th and 78th segments (see the two dips in Figure 5(d)) are lower than on other segments traversed by $\mathcal{T}_2$, and thus the the corresponding environmental impact per unit length on the two segments is higher. As it takes longer to traverse a unit length with a lower velocity, a higher environmental impact per unit length results.

Existing routing algorithms [12, 13] can be employed to enable eco-routing if the edge weights reflect the environmental impact of traversing the edges (i.e., road segments). Based on the findings reported in Figure 5 and Table 6, we argue that the aggregated models are appropriate for assigning eco-weights (i.e., environmental impact related weights) to road segments in order to enable eco-routing. We suggest the use of SIDRA-Running because the minimum input required, the total length and total travel time (or average velocity) of segments, are fairly easy to obtain.

Although the impact estimated by Song and SIDRA-4mode are more sensitive to changes in velocity than for the other aggregated models (see Figure 5), these two models require instantaneous travel information during computation. Therefore, they are not easy to use in scenarios where only average velocities are known. SIDRA-Avg and Tavares are not recommended because the former cannot be used when velocities are above 50km/h [21] and the latter is intended for heavy vehicles.

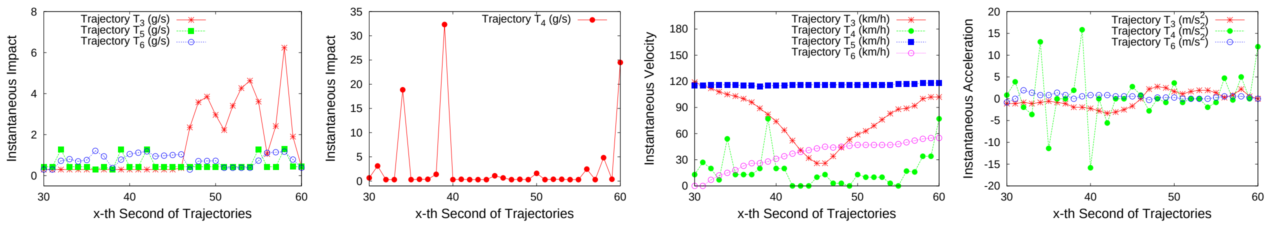
Given a road segment, the impact estimated by SIDRA-Running is closely related to the average velocity. Thus, it is useful to determine whether different trajectories on the same road segment have similar average velocity. Thus, we study the 222 road segments that are frequently traversed by $\mathbb{T}$. The absolute deviations of the average velocities on these road segments are reported in Figure 8(a). We find that on 86 segments, the absolute deviations of the average velocities are smaller than 2km/h, as seen in the first bar. Only on 3 segments are the absolute deviations of average velocities high, i.e., between 14km/h and 16km/h, as seen in the $8th$ bar. Figure 8(a) indicates that the average velocities on most road segments are similar, which renders it is possible to derive a single, meaningful eco-weight for each of such road segment.

The average velocities on some road segments vary significantly over time. In some cases, this is due to rush-hour congestion. We plot the absolute deviation during different periods of a particular



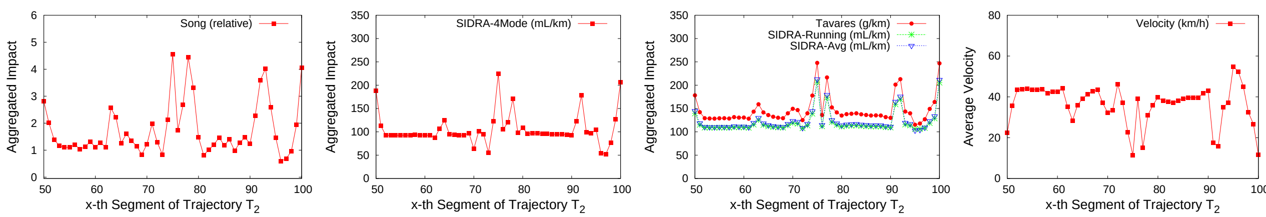
(a) With relative values (b) With absolute values (c) Instantaneous Velocities (d) Instantaneous Accelerations

Figure 3: Comparison of Instantaneous Models on Trajectory $\mathcal{T}_1$



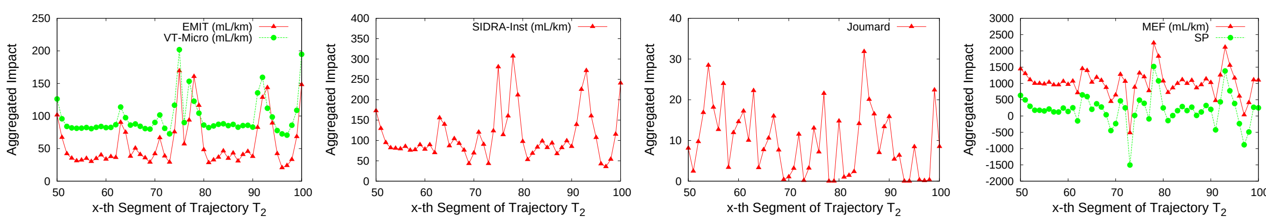
(a) EMIT on $\mathcal{T}_3$, $\mathcal{T}_5$ and $\mathcal{T}_6$ (b) EMIT on $\mathcal{T}_4$ (c) Instantaneous Velocities (d) Instantaneous Accelerations

Figure 4: Environmental Impact Versus Driving Behavior



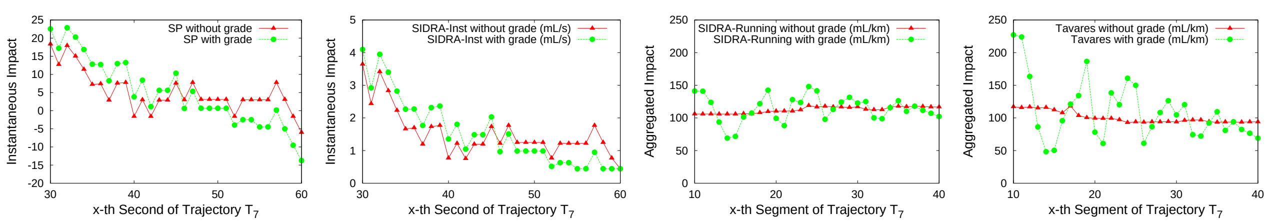
(a) Song (b) SIDRA-4Mode (c) Three Models (d) Average Velocity

Figure 5: Comparison of Aggregated Models on Trajectory $\mathcal{T}_2$



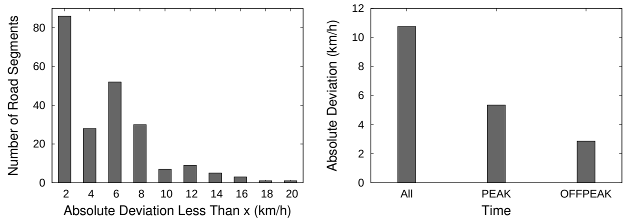
(a) EMIT and VT-Micro (b) SIDRA-Inst (c) Joumard (d) SP and MEF

Figure 6: Aggregation of Instantaneous Models on Trajectory $\mathcal{T}_2$



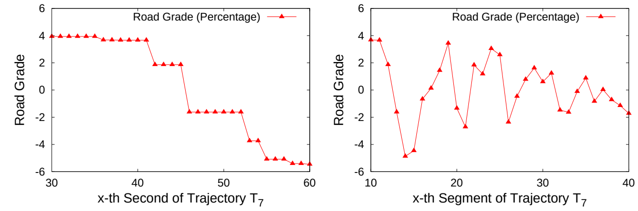
(a) SP (b) SIDRA-Inst (c) SIDRA-4Mode (d) Tavares

Figure 7: Effect of Road Grades on Trajectory $\mathcal{T}_7$



(a) Absolute Deviations (b) Temporal Variations

Figure 8: Aggregated Models and Eco-Weights



(a) For Instantaneous Models (b) For Aggregated Models

Figure 9: Road Grades

road segment in Figure 8(b). Although the average velocities are quite different during the entire day (see the bar for *All*), the average velocities are similar during peak and off-peak periods (bars *PEAK* and *OFFPEAK*). Thus, time dependent eco-weights are suggested for such road segments, e.g., different eco-weights should be used for different periods.

For road segments where drivers behave significantly different, i.e., with large average velocity deviations and without clear peak and off-peak periods, ranges are suggested to be used as eco-weights. Alternatively, driver specific eco-weights should be considered.

5.4 Aggregation of Instantaneous Models Versus Aggregated Models

The aggregated environmental impact on a road segment can also be obtained by aggregating the instantaneous impact that is estimated by an instantaneous model on the road segment. In the following experiment, the aggregation is computed by summing the instantaneous impacts on the segment and dividing the sum by the length of the segment.

Trajectory $\mathcal{T}_2$ is utilized to demonstrate the degree of consistency of the aggregated impact estimated by aggregating instantaneous impact and the aggregated impact estimated directly by the aggregated models.

As shown in Figure 6, the aggregations of VT-Micro, EMIT, and SIDRA-Inst behave similarly to the aggregated models. In particular, VT-Micro shows the most consistent results. In contrast, the aggregations of Joumard, SP, and MEF do not behave consistently with the aggregated models and do not show relationships with average velocities (see Figure 5(d)).

The experiment suggests that some instantaneous models are not suitable for aggregation in order to estimate the aggregated environmental impact and thus should not be used for assigning eco-weights to road segments. However, VT-Micro, EMIT, and SIDRA-Inst demonstrate the ability to provide reasonable aggregated environmental impact.

5.5 Effect of Road Grades

Experiments are carried out to evaluate the influence of varying road grades on environmental impact. A hilly route, traversed by Trajectory $\mathcal{T}_7$, where the road segments have both positive and negative grades is, therefore, chosen—see Figure 9.

Figure 7(a) and (b) plots the instantaneous impact estimated by SP and SIDRA-Inst with and without considering grades. The results demonstrate that positive (negative) road grades cause higher (lower) the environmental impact compared to the impact without considering grades.

Two aggregated models, SIDRA-4Mode and Tavares, are chosen to demonstrate the effect of road grades on the aggregated impact. As shown in Figure 7(c) and (d), the aggregated impact estimated by both models is higher for segments with positive grade than for segments with negative grade. Tavares is more sensitive to road grades. The difference between the impact with and without grades as estimated by Tavares is greater than for SIDRA-4Mode.

5.6 Empirical Findings

Instantaneous Models and Eco-driving: Instantaneous models estimate instantaneous environmental impact, e.g., second by second fuel usage, from instantaneous velocities and accelerations. Since instantaneous velocities and accelerations reflect driving behaviors, instantaneous models can be used to measure the environmental impact of different such behaviors. Instantaneous models, along with classical data mining methods, can be used to classify good and bad driving behaviors in terms of environmental impact, which in turn may suggest good driving behaviors to drivers. Thus, instantaneous models are appropriate for eco-driving applications.

Aggregated Models and Eco-routing: Aggregated models estimate environmental impact per unit length using average velocities or starting and ending velocities. Such impact can be utilized for assigning eco-weights to road segments, thus enabling eco-routing.

From this point of view, the aggregated models offer a foundation for eco-routing. In addition, instantaneous impact on a road segment predicted by an instantaneous model, e.g., VT-Micro, can be aggregated and then used as the eco-weight of the road segment.

We suggest employing SIDRA-Running to compute eco-weights for road segments because the least input required by this model can be obtained from GPS trajectories. We also suggest that a single eco-weight per road segment suffices in some cases, while time dependent weights or a range of weights should be considered in other cases, as presented in Section 5.3.

Importance of 3D Spatial Networks: Road grades substantially affect the environmental impact predicted by both instantaneous and aggregated models. Therefore, the use of 3D spatial networks benefits both eco-driving and eco-routing.

6. CONCLUSIONS

We develop EcoMark that evaluates models of vehicular environmental impact. Eleven state-of-the-art impact models are categorized into instantaneous models and aggregated models. The models are compared and analyzed based on a substantial collection of 1 Hz GPS trajectories and a 3D spatial network. The empirical study suggests that the instantaneous models are appropriate for eco-driving, while the aggregated models are helpful for eco-routing. The use of a 3D spatial network that records road grades benefits both eco-driving and eco-routing.

In future work, it is relevant to study how well the models predict actual environmental impact. Such a study is possible if vehicular CAN bus data that records the actual GHG emissions and fuel usage along with corresponding GPS observations are available.

Acknowledgments

This work was supported by the Reduction project that is funded by the European Commission as FP7-ICT-2011-7 STREP project number 288254.

7. REFERENCES

[1] Bing maps. http://www.bing.com/maps/.
[2] Energy and climate goals of china's 12th five-year plan. http://tinyurl.com/73mntqg.
[3] Fact sheet: Australia's emissions reduction targets. http://tinyurl.com/7vpzufx.
[4] G8 plans 50% reduction in greenhouse gases. http://tinyurl.com/68hn2a.
[5] Google maps. http://maps.google.com/.
[6] OpenStreetMap. http://www.openstreetmap.org/.
[7] Reducing emissions from transport. http://tinyurl.com/7ex6am3.
[8] Road transport: Reducing co2 emissions from light-duty vehicles. http://tinyurl.com/6gtlzzz.
[9] Shuttle radar topography mission. http://www2.jpl.nasa.gov/srtm/.
[10] Usgs center for lidar information coordination and knowledge. http://lidar.cr.usgs.gov/.
[11] What is the eu doing on climate change? http://tinyurl.com/75qex2g.
[12] J. Yuan, Y. Zheng, C. Zhang, W. Xie, X. Xie, G. Sun, and Y. Huang. T-drive: driving directions based on taxi trajectories. In *GIS*, pages 99–108. ACM, 2010.
[13] D. Luxen and C. Vetter. Real-time routing with openstreetmap data. In *GIS*, pages 513–516. ACM, 2011.
[14] D. Pfoser, S. Brakatsoulas, P. Brosch, M. Umlauft, N. Tryfona, and G. Tsironis. Dynamic travel time provision for road networks. In *GIS*, page 68. ACM, 2008.
[15] K. Ahn and H. Rakha. The effects of route choice decisions on vehicle energy consumption and emissions. *Transportation Research Part D: Transport and Environment*, 13(3):151–167, 2008.
[16] K. Ahn, H. Rakha, A. Trani, and M. Van Aerde. Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels. *Journal of Transportation Engineering*, 128(2):182–190, 2002.
[17] ARB. *EMFAC2007 version 2.30: Calculating emission inventories for vehicles in California*. U.S. the California Air Resources Board (ARB), 2007.
[18] J. Barkenbus. Eco-driving: An overlooked climate change initiative. *Energy Policy*, 38(2):762–769, 2010.
[19] M. Barth and K. Boriboonsomsin. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment*, 14(6):400–410, 2009.
[20] P. Boulter, I. McCrae, and T. Barlow. A review of instantaneous emission models for road vehicles. *Transport Research Laboratory, Published Project Report 267, Final*, 2007.
[21] D. Bowyer, R. Akçelik, D. Biggs, and A. R. R. Board. Guide to Fuel Consumption Analyses for Urban Traffic Management. Technical report, Australian Road Research Board, 1985.
[22] A. Cappiello. Modeling traffic flow emissions. Master's thesis, Massachusetts Institute of Technology, 2002.
[23] A. Cappiello, I. Chabini, E. K. Nam, A. Lue, and M. A. Zeid. A statistical model of vehicle emissions and fuel consumption. In *The IEEE 5th International Conference on Intelligent Transportation Systems*, pages 801–809. IEEE, 2002.
[24] E. Dijkstra. A note on two problems in connexion with graphs. *Numerische mathematik*, 1(1):269–271, 1959.
[25] EEA. *Copert 4 User Manual (version 5), Computer Programme to Calculate Emissions from Road Transport*. European Environment Agency, 2007.
[26] EPA. *User's Guide to MOBILE6, Mobile Source Emission Factor Model*. U.S. EPA National Vehicle and Fuel Emissions Laboratory, 2001.
[27] EPA. *Technical Guidance on the Use of MOVES2010 for Emission Inventory Preparation in State Implementation Plans and Transportation Conformity*. U.S. EPA National Vehicle and Fuel Emissions Laboratory, 2010.
[28] S. Hausberger, M. Rexeis, M. Zallinger, and R. Luz. Emission factors from the model phem for the hbefa version 3, 2009.
[29] J. Hickman, D. Hassel, R. Joumard, Z. Samaras, and S. Sorenson. Methodology for calculating transport emissions and energy consumption. *TRL Report SE/491/98: Deliverable for EU project MEET*, 1999.
[30] J. L. Jiménez-Palacios. *Understanding and Quantifying Motor Vehicle Emissions with Vehicle Specific Power and TILDAS Remote Sensing*. PhD thesis, Massachusetts Institute of Technology, 1998.
[31] R. Joumard et al. Methods of estimation of atmospheric emissions from transport: European scientist network and scientific state-of-the-art. *INRETS report LTE*, 9901, 1999.
[32] R. Joumard, P. Jost, J. Hickman, and D. Hassel. Hot passenger car emissions modelling as a function of instantaneous speed and acceleration. *Science of the Total Environment*, 169:167–174, 1995.
[33] T. Kono, T. Fushiki, K. Asada, and K. Nakano. Fuel consumption analysis and prediction model for "eco" route search. In *15th World Congress on Intelligent Transport Systems and ITS America's 2008 Annual Meeting*, 2008.
[34] W. Lei, H. Chen, and L. Lu. Microscopic Emission and Fuel Consumption Modeling for Light-duty Vehicles Using Portable Emission Measurement System Data. In *World Academy of Science, Engineering and Technology*, pages 918–925, 2010.
[35] E. K. Nam and R. Giannelli. Fuel consumption modeling of conventional and advanced technology vehicles in the Physical Emission Rate Estimator (PERE). Technical report, U.S. Environmental Protection Agency, 2005.
[36] L. Ntziachristos, Z. Samaras, and E. E. Agency. *COPERT III Computer programme to calculate emissions from road transport: methodology and emission factors (version 2.1)*. European Environment Agency, 2000.
[37] L. Pelkmans, P. Debal, T. Hood, G. Hauser, and M.-R. Delgado. Development of a simulation tool to calculate fuel consumption and emissions of vehicles operating in dynamic conditions. *SAE*, 2004.
[38] F. Pereira, H. Costa, and N. Pereira. An off-line map-matching algorithm for incomplete map databases. *European Transport Research Review*, 1(3):107–124, 2009.
[39] T. Peucker, R. Fowler, J. Little, and D. Mark. The triangulated irregular network. In *Amer. Soc. Photogrammetry Proc. Digital Terrain Models Symposium*, volume 516, page 532, 1978.
[40] H. Rakha, K. Ahn, K. Moran, B. Saerens, and E. Van den Bulck. Virginia tech comprehensive power-based fuel consumption model: Model development and testing. *Transportation Research Part D: Transport and Environment*, pages 492–503, 2011.
[41] H. Rakha, K. Ahn, and A. Trani. Comparison of MOBILE5a, MOBILE6, VT-MICRO, and CMEM models for estimating hot-stabilized light-duty gasoline vehicle emissions. *Canadian Journal of Civil Engineering*, 30(6):1010–1021, 2003.
[42] H. Rakha, K. Ahn, and A. Trani. Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions. *Transportation Research Part D: Transport and Environment*, 9(1):49–74, 2004.
[43] G. Scora and M. Barth. Comprehensive Modal Emission Model (CMEM), Version 3.01 UserŠs Guide. *University of California Riverside Center for Environmental Research and Technology*, 2006.
[44] G. Song, L. Yu, and Z. Wang. Aggregate Fuel Consumption Model of Light-Duty Vehicles for Evaluating Effectiveness of Traffic Management Strategies on Fuels. *Journal of Transportation Engineering*, 135:611–618, 2009.
[45] G. Tavares, Z. Zsigraiova, V. Semiao, and M. Carvalho. Optimisation of MSW collection routes for minimum fuel consumption using 3D GIS modelling. *Waste Management*, 29(3):1176–1185, 2009.
[46] H. Teng, L. Yu, and Y. Qi. Statistical Microscale Emission Models Incorporating Acceleration and Deceleration. In *81st Transportation Research Board Annual Meeting*, 2002.