INTEGRATION Framework for Modeling Eco-routing Strategies: Logic and Preliminary Results

Hesham A. Rakha (Corresponding author)
Charles E. Via, Jr. Department of Civil and Environmental Engineering
3500 Transportation Research Plaza, Blacksburg, VA 24061
Phone: (540) 231-1505 Fax: (540) 231-1555
hrakha@vt.edu

Kyoungho Ahn
Center for Sustainable Mobility, Virginia Tech Transportation Institute
3500 Transportation Research Plaza, Blacksburg, VA 24061
Phone: (540) 231-1509 Fax: (540) 231-1555
kahn@vt.edu

Kevin Moran
Advanced Driver Assistance Systems, NAVTEQ Corporation
425 West Randolph Street, Chicago, IL 60606
Phone: (312) 894-7601 Fax: (312) 894-8441
kevin.moran@navteq.com

ABSTRACT
The paper presents the INTEGRATION microscopic traffic assignment and simulation framework for modeling eco-routing strategies. Two eco-routing algorithms are developed: one based on vehicle sub-populations (ECO-Subpopulation Feedback Assignment or ECO-SFA) and another based on individual agents (ECO-Agent Feedback Assignment or ECO-AFA). Both approaches initially assign vehicles based on fuel consumption levels for travel at the facility free-flow speed. Subsequently, fuel consumption estimates are refined based on experiences of other vehicles within the same class. The proposed framework is intended to evaluate the network-wide impacts of eco-routing strategies. This stochastic, multi-class, dynamic traffic assignment framework was demonstrated to work for two scenarios. Savings in fuel consumption levels in the range of 15 percent were observed and potential implementation challenges were identified.

INTRODUCTION

Motorists typically choose routes that minimize their travel cost (e.g., travel time). Therefore, drivers typically select longer routes if they produce travel cost savings. The commonly used User Equilibrium (UE) and System Optimum (SO) traffic assignment algorithms utilize minimum travel time or the marginal travel time, respectively as a generalized cost to assign traffic flows over a network. However given that UE and SO assignments are estimated based on travel time, the fuel consumption and emissions of UE and SO conditions may not produce optimum energy and emission levels.

Several researchers have attempted to enhance traffic assignment methods using environmental cost functions. For example, Tzeng and Chen [1] developed a multi-objective traffic assignment method using nonlinear programming techniques and produced various solutions that minimize CO emissions. By utilizing eigenvector weighting with pair-wise comparison, the researchers estimated compromised solutions for the flow patterns. They applied the case study to metropolitan Taipei to evaluate the developed traffic assignment model. The approach assumed fixed link-specific CO emissions and the total emissions were computed by summing up across all vehicles on a link [1].

Rilett and Benedek (1994) and Benedek and Rilett (1998) investigated an equitable traffic assignment with environmental cost functions. They emphasized the impacts of CO emissions when UE and SO traffic assignments were applied to a sample network, a simple network of Ottawa, Canada and a calibrated network of Edmonton, Canada. The studies utilized a simple macroscopic CO emission model used in the TRANSYT 7F software. The emission model utilized the average speed and the link length as input variables. The researchers showed that the traffic flows of the SO-CO (the traffic flows that have the minimum total CO emissions) condition were roughly equivalent to the flows of the UE and SO conditions within a small error range [2, 3].

Sugawara and Niemeier (2002) developed an emission-optimized traffic assignment model that used average speed CO emission factors developed by the California Air Resources Board (CARB). The sample network case study concluded that emission-optimized trip assignments can reduce system-level vehicle emissions moderately when compared to time-dependent UE and SO solutions. The research also found that an emission-optimized assignment is most effective when the network is under low to moderately congested conditions, saving up to 30% of total CO emissions; when the network is highly congested, the emission reduction is diminished to 8%. The authors explain that under emission-optimized conditions, less traffic volume is assigned to the freeway because emission levels are very high at freeway free-flow speeds [4].

Nagurney and her colleagues developed a multi-class and multi-criteria traffic network equilibrium model with an environmental criterion and claimed that a desired environmental quality standard can be achieved by the proposed model through a particular weighting method. In the study, a fixed amount of CO emission rate per traveler per link was utilized to estimate the total CO emissions [5-7].

An earlier study by Ahn and Rakha [8] investigated the impacts of route choice decisions on vehicle energy consumption and emission rates for different vehicle types using microscopic and macroscopic emission estimation tools. The results demonstrated that the faster highway route choice is not always the best route from an environmental and energy consumption perspective. Specifically, the study found that significant improvements to energy and air quality could be achieved when motorists utilized a slower arterial route although they incurred additional travel time. The study also demonstrated that macroscopic emission estimation tools (e.g. MOBILE6) could produce erroneous conclusions given that they ignore transient vehicle behavior along a route. The findings suggest that an emission- and energy-optimized traffic assignment can significantly improve emissions over the standard User Equilibrium (UE) and System Optimum (SO) assignment formulations. Finally the study demonstrated that a small portion of the entire trip involved high engine-load conditions that produced significant increases in total emissions; demonstrating that by minimizing high-emitting driving behavior, air quality could be improved significantly.

The objective of this paper is to develop an eco-routing framework that can be used to evaluate the network-wide impacts (travel time, fuel consumption, and vehicle emissions) of different levels of market penetration of eco-routing vehicles. The framework is also capable of testing the framework under different levels of fuel consumption estimate accuracies.

In terms of the paper layout initially the INTEGRATION modeling framework is described given that it is used to develop the proposed eco-routing testbed. Subsequently, the proposed algorithms for modeling eco-routing strategies are presented. The framework is then tested and validated on a sample small network. Implementation challenges are then discussed followed by the conclusions of the paper.

INTEGRATION MODELING FRAMEWORK

The INTEGRATION software is an agent-based microscopic traffic assignment and simulation software [9-12], conceived as an integrated simulation and traffic assignment model and performs traffic simulations by tracking the movement of individual vehicles every 1/10th of a second. This allows detailed analyses of lane-changing movements and shock wave propagations. It also permits considerable flexibility in representing spatial and temporal variations in traffic conditions. In addition to estimating stops and delays [13-15], the model can also estimate the fuel consumed by individual vehicles, as well as the emissions [16-19]. The model also estimates the expected number of vehicle crashes using a time-based crash prediction model [20]. The INTEGRATION model has not only been validated against standard traffic flow theory [14, 15, 21, 22], but also has been utilized for the evaluation of real-life applications [23-25]. The types of analyses that can be performed with these built-in models extend far beyond the capabilities of EPA's MOBILE6 model [26, 27].

Traffic Assignment

Within the INTEGRATION software, the selection of the next link to be taken by a vehicle is determined by the model's internal routing logic [28-31]. There exist many different variations to the model's basic assignment technique. Some of these techniques are static and deterministic, while others are stochastic and dynamic. However, regardless of the particular technique that is utilized to determine these routings, the selection of the next link that a vehicle should take is done using a vehicle-specific array that lists for the vehicle the entire sequence of links from its origin to its destination. Upon the completion of any link, a vehicle simply queries this array to determine which link it should utilize next to reach its ultimate destination in the most efficient manner. When travel across this next link is in turn completed, the selection process is then repeated until a link whose downstream node is the vehicle's ultimate trip destination is reached. Within the INTEGRATION software five different vehicle classes are specified and each vehicle class can have its unique routing logic.

The INTEGRATION simulation model currently provides for eight basic traffic assignment/routing options:

1. Time-Dependent Method of Successive Averages (MSA)
2. Time-Dependent Sub-Population Feedback Assignment (SFA)
3. Time-Dependent Agent Feedback Assignment (AFA)
4. Time-Dependent Dynamic Traffic Assignment (DTA)
5. Time-Dependent Frank-Wolf Algorithm (FWA)
6. Time-Dependent External Routing 1 – File 8 (ER1)
7. Time-Dependent External Routing 2 – File 9 (ER2)
8. Distance Based Routing

Traffic Modeling

Once the routes of travel are selected, the INTEGRATION model updates the vehicle longitudinal and lateral location (lane choice) every deci-second. The longitudinal motion of a vehicle is based on a user-specified steady-state speed-spacing relationship and the speed differential between the subject vehicle and the vehicle immediately ahead of it. In order to ensure realistic vehicle accelerations, the model uses a vehicle dynamics model that estimates the maximum vehicle acceleration level. Specifically, the model utilizes a variable power vehicle dynamics model to estimate the vehicle's tractive force that implicitly accounts for gear-shifting on vehicle acceleration. The model computes the vehicle's tractive effort ($F_n(t)$), aerodynamic, rolling, and grade-resistance forces, as described in detail in the literature [32, 33].

The car-following model is formulated as:

$$u_n(t+\triangle t) = \min\left\{\begin{array}{l} u_n(t) + a_n(t)\triangle t, \\ \dfrac{-c_1 + c_3 u_f + \tilde{s}_n(t+\triangle t) - \sqrt{A}}{2c_3}, \\ \sqrt{u_{n-1}(t+\triangle t)^2 + d_{max}\left(\tilde{s}_n(t+\triangle t) - \dfrac{1}{k_j}\right)} \end{array}\right\} \tag{1}$$

Where $A = [c_1 - c_3 u_f - \tilde{s}_n(t+\triangle t)]^2 - 4c_3[\tilde{s}_n(t+\triangle t)u_f - c_1 u_f - c_2]$

The model constants are computed as

$$c_1 = \frac{u_f}{k_j u_c^2}\left(2u_c - u_f\right); \quad c_2 = \frac{u_f}{k_j u_c^2}\left(u_f - u_c\right)^2; \quad c_3 = \frac{1}{q_c} - \frac{u_f}{k_j u_c^2};$$

and the vehicle spacing is computed as:

$$\tilde{s}_n(t+\Delta t) = x_{n-1}(t) - x_n(t) + \left\lfloor u_{n-1}(t+\Delta t) - u_n(t) \right\rfloor \Delta t + 0.5 a_{n-1}(t+\Delta t)\Delta t^2$$

Here $u_n(t+\Delta t)$ is the speed of the following vehicle (vehicle n) at time $t+\Delta t$; $a_n(t)$ is the acceleration of the subject vehicle (vehicle n); u_f is the roadway mean free-flow speed; u_c is the roadway mean speed-at-capacity; q_c is the roadway mean capacity; k_j is the roadway mean jam density; $x_n(t)$ is the position of the subject vehicle at time t; and $x_{n-1}(t)$ is the position of the lead vehicle at time t; d_{max} is the maximum acceptable deceleration level the driver is willing to exert (m/s^2). This model ensures that the vehicle acceleration does not exceed the vehicle dynamics maximum acceleration level.

The lane selection and lane-changing logic was described and validated against field data in an earlier publication [34]. A later study [35] demonstrated the validity of the INTEGRATION software for estimating the capacity of weaving sections by comparing the software to field-observed weaving section capacities.

Estimation of Vehicle Fuel Consumption and Emission Levels

The INTEGRATION model computes a number of measures of effectiveness (MOEs), including the average speed; vehicle delay; person delay; fuel consumed; vehicle emissions of carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), oxides of nitrogen (NO_x), and particulate matter (PM) in the case of diesel engines; and the vehicle crash risk and severity.

The computation of deci-second speeds permits the steady-state fuel consumption rate for each vehicle to be computed each second on the basis of its current instantaneous speed and acceleration level [16-19, 27, 36]. The VT-Micro model was developed as a statistical model from experimentation with numerous polynomial combinations of speed and acceleration levels to construct a dual-regime model as described in Equation (2), where $L_{i,j}$ are model regression coefficients at speed exponent i and acceleration exponent j, $M_{i,j}$ are model regression coefficients at speed exponent i and acceleration exponent j, v is the instantaneous vehicle speed in kilometers per hour (km/h), and a is the instantaneous vehicle acceleration (km/h/s). These fuel consumption and emission models were developed using data that were collected on a chassis dynamometer at the Oak Ridge National Labs (ORNL), data gathered by the Environmental Protection Agency (EPA), and data gathered using an on-board emission measurement device (OBD). These data included fuel consumption and emission rate measurements (CO, HC, and NO_x) as a function of the vehicle's instantaneous speed and acceleration levels. The VT-Micro fuel consumption and emission rates were found to be highly accurate compared to the ORNL data, with coefficients of determination ranging from 0.92 to 0.99. A more detailed description of the model derivation is provided in the literature [17].

$$F(t) = \begin{cases} \exp\left(\sum_{i=1}^{3} \sum_{j=1}^{3} L_{i,j} v^i a^j \right) & \text{for } a \geq 0 \\ \exp\left(\sum_{i=1}^{3} \sum_{j=1}^{3} M_{i,j} v^i a^j \right) & \text{for } a < 0 \end{cases} \tag{2}$$

From a general point of view, the use of instantaneous speed and acceleration data for the estimation of energy and emission impacts of traffic improvement projects provide a major advantage over state-of-practice methods that estimate vehicle fuel consumption and emissions based exclusively on the average speed and number of vehicle-miles traveled by vehicles on a given transportation link.

PROPOSED ECO-ROUTING LOGIC

Two eco-routing algorithms were added to the INTEGRATION routing logic. These algorithms correspond to routing methods 9 and 10. Routing method 9 is very similar to routing method 2 while routing method 10 is similar to 3 except that the objective function is to minimize a vehicle's fuel consumption level as opposed to its travel time. The two new routings are described in detail in this section.

Model Initialization

Initially, when the network is empty routes are selected by computing the vehicle fuel consumption level for each link based on travel at the facility's free-flow speed considering the grade on the link. The fuel consumption rate for a cruising speed equal to the free-flow speed and a grade of G can be computed as

$$F(t) = \exp\left(\sum_{i=1}^{3} \sum_{j=1}^{3} L_{i,j} v_f^i \left(gG \right)^j \right) \tag{3}$$

Here $F(t)$ is the fuel consumption rate (l/s); g is the gravitational acceleration (9.8067 m/s^2) and G is the roadway grade (dimensionless).

The total fuel consumed on the link can then be estimated as

$$F_l = 3600 \times F(t) \times \frac{d_l}{\left(v_f \right)_l} \quad \forall\, l \tag{4}$$

Here F_l is the total fuel consumed on link l (liters); d_l is the length of link l (km); and $(v_f)_l$ is the free-flow speed on link l (km/h).

Model Updating

Following the initial vehicle routing, vehicles record their fuel consumption experiences prior to exiting a link. A moving fuel consumption estimate for each link in the network is created as

$$F_{l,c}^{\prime t} = \alpha F_{l,c}^{t} + \left(1 - \alpha \right) F_{l,c}^{\prime t - \Delta t} \tag{5}$$

Here $F_{l,c}^{\prime t}$ is the smoothed fuel consumption estimate for vehicle class c on link l at instant t; α is a user specified smoothing constant in the interval [0,1]; $F^{t}_{l,c}$ is the observed fuel consumption estimate for vehicle class c on link l at instant t; and $F'^{t-\Delta t}_{l,c}$ is the smoothed fuel consumption estimate for vehicle class c on link l at instant t-Δt.

Errors in the fuel consumption estimates can also be introduced using a white noise error function as

$$F''^{t}_{l,c} = F'^{t}_{l,c} + w_c \quad (6)$$

Where $F''^{t}_{l,c}$ is the final fuel consumption level of vehicle class c on link l at instant t and w_c is a user-specified white noise error in the fuel consumption estimates. This error term is either normally or log-normally distributed with a mean of zero and a user specified coefficient of variation (ratio of standard deviation to mean fuel consumption measurement). The introduction of random errors allows for the modeling of stochastic user equilibrium where different sub-populations or drivers have different minimum paths.

ECO-Sub-population Feedback Assignment

Routing Mechanism 9 involves the application of an ECO-SFA mechanism, however in this case the minimum path is based on the fuel consumption experiences of other drivers within the same class. Specifically, all drivers within a specific class are divided into five sub populations each consisting of 20% of all drivers within the class. The paths for each of these sub populations are then updated every t seconds during the simulation based on real-time measurements of the link fuel consumption levels for that specific vehicle class. As was the case with routing mechanism 2, the value of t is a user-specified value. Furthermore, the minimum path updates of each vehicle sub population are staggered in time, in order to avoid having all vehicle sub populations update their paths at the same time. This results in 20% of the driver paths being updated every t/5 s.

ECO-Agent Feedback Assignment

Routing mechanism 10 involves the application of the above feedback mechanism to individual drivers, rather than sub populations. It is referred to as an ECO-AFA. The main difference is that, while the paths under method 9 were always shared by at least 20% of the drivers, within method 10 all paths are customized to each individual driver and may therefore be unique relative to any other drivers. Given that paths can be computed for individuals, rather than sub populations, the path calculations are triggered based on a vehicle's departure rather than some average time interval as in method 9 (ECO-SFA). In other words, when paths are calculated for sub-populations in method 9, paths are recomputed for an entire sub-population at specified intervals in anticipation of their subsequent use when vehicles belonging to that sub-population actually depart. This means that paths may often be several seconds, if not minutes old, when a specific vehicle actually departs. In contrast, for method 10, the path for a specific vehicle is computed at the time of departure of that vehicle from its origin and from each link. This implies that the paths are computed based on the most recent information that is available at that time. It should also be noted that the selection of the next link that a vehicle should take is done using a vehicle-specific array that lists for that vehicle the entire sequence of links from its origin to its destination. Upon the completion of any link, a vehicle simply submits its experiences fuel consumption on the link and then queries this array to determine which link it should utilize next to reach its ultimate destination in the most efficient manner. When travel across this next link is in turn completed, the updating and selection process is then repeated until a link whose downstream node is the vehicle's ultimate trip destination is reached. Again as was mentioned earlier, the vehicle only uses the experiences of other vehicles in the same class to update the fuel consumption estimates on a link. This allows for a multi-class, stochastic, dynamic, ECO-routing user equilibrium. The routing is multi-class because vehicles are only affected by experiences of other vehicles in the same class. The routing is dynamic because the vehicle can change its route while en-route as traffic conditions change.

MODEL TESTING ON A SIMPLE NETWORK

The eco-routing algorithm was tested on a sample network composed of two alternative routes for travel from zone 1 to zone 2 (squared nodes), as illustrated in Figure 1. The first route involved travel along an arterial route (path 1→3→5→2), while the second path involved travel along a combination of arterial and freeway travel (path 1→3→4→5→2). Links 1, 2, and 5 were arterials with a free-flow speed of 77 km/h while links 3 and 4 were freeway links with a free-flow speed of 100 km/h. The speed-at-capacity on the arterial and freeway facilities were set approximately equal to the free-flow speed (76 and 99 km/h, respectively) in order to ensure that the average speed did not vary as a function of the level of congestion on the roadway. All links were 0.5 km long except for link 2, which was 1.0 km long, in order to ensure that both paths were of equal length (2 km). All vehicles would travel on the arterial route to node 3 and then would have two equal distance choices: a slower arterial route (link 2) or a faster freeway route (links 3 and 4). The two routes then meet at node 5 and vehicles travel the remainder of the trip along the arterial facility (link 5).

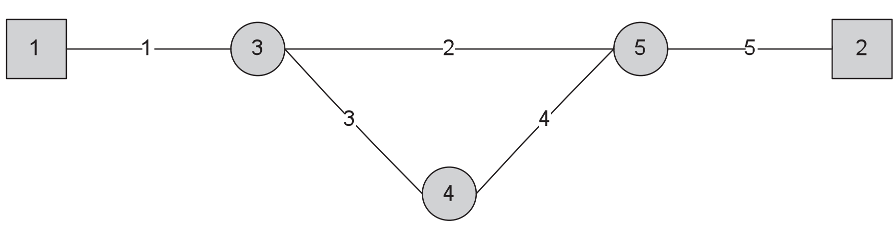

Figure 1. Sample Network Configuration

The optimum fuel consumption rate can be derived by taking the derivative of Equation (2) with respect to speed and setting it equal to zero as demonstrated in Equation (7). If the grades on the roadways are zero Equation (7) is simplified as demonstrated in Equation (8). The speed that produces the minimum vehicle fuel consumption (optimum speed) for the average ORNL vehicle is 76.6 km/h.

$$\left(L_{1,0}+L_{1,1}a+L_{1,2}a^2+L_{1,3}a^3\right)v_{opt}+2\left(L_{2,0}+L_{2,1}a+L_{2,2}a^2+L_{2,3}a^3\right)v_{opt}^2 + 3\left(L_{3,0}+L_{3,1}a+L_{3,2}a^2+L_{3,3}a^3\right)v_{opt}^3=1 \tag{7}$$

$$L_{1,0}v_{opt}+2L_{2,0}v_{opt}^2+3L_{3,0}v_{opt}^3-1=0 \tag{8}$$

The variation in vehicle fuel consumption levels for the ORNL composite vehicle to travel along a 1-km section of roadway as a function of the vehicle cruise speed is illustrated in Figure 2. The figure demonstrates that the shape of the function is a bowl shape with the minimum fuel consumption rate of 0.0777 L/km occurring at a cruise speed of 76.65 km/h. The fuel consumption rate relative to the minimum rate is 1.07 for a cruise speed of 100 km/h (i.e. travel at 100 km/h results in a 7 percent increase in the fuel consumption rate), as demonstrated in Figure 2(b) and Table 1.

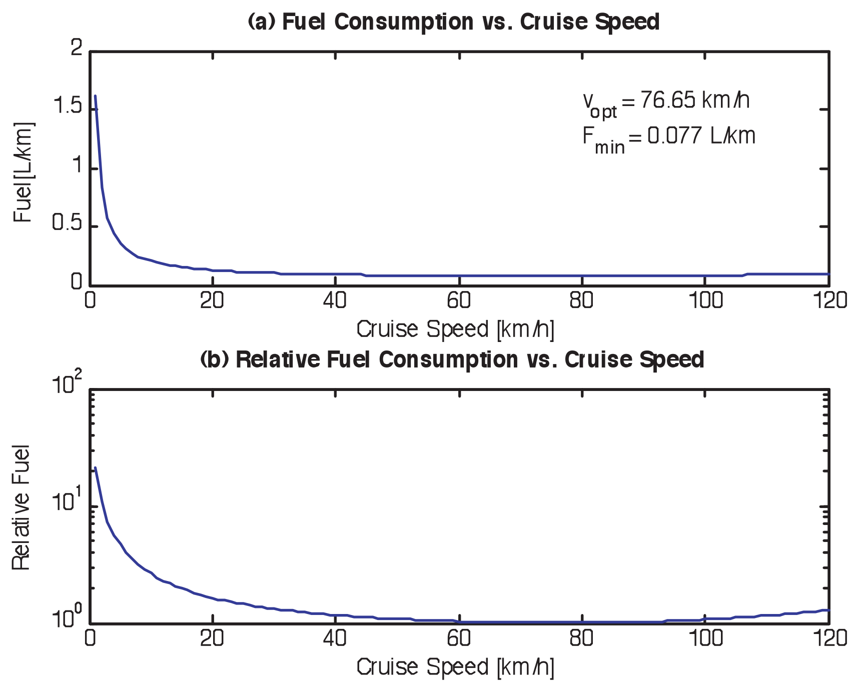

Figure 2. Variation in Fuel Consumption as a Function of Cruise Speed (a) Fuel Consumption; (b) Fuel Consumption Relative to Optimum Fuel Consumption

Table 1. Variation in Relative Fuel Consumption as a Function of Cruise Speed

v (km/h)	F/F_{min}	v (km/h)	F/F_{min}	v (km/h)	F/F_{min}	v (km/h)	F/F_{min}
70	1.005	80	1.001	90	1.021	100	1.070
71	1.004	81	1.002	91	1.025	101	1.077
72	1.002	82	1.003	92	1.029	102	1.084
73	1.001	83	1.005	93	1.033	103	1.092
74	1.001	84	1.006	94	1.037	104	1.099
75	1.000	85	1.008	95	1.042	105	1.108
76	1.000	86	1.010	96	1.047	106	1.117
77	1.000	87	1.013	97	1.052	107	1.126
78	1.000	88	1.015	98	1.058	108	1.136
79	1.001	89	1.018	99	1.064	109	1.146

Consequently, from a travel time perspective it would be more efficient to travel along the freeway roadway while from a fuel economy perspective it would be more efficient to travel along the arterial.

A total demand of 1200 veh/h traveling from zone 1 to 2 was loaded onto the network for the first 1200 seconds. The simulation was continued until all vehicles cleared the network. This resulted in a total of 400 vehicles being simulated, as summarized in Table 2.

Each of the scenarios constitutes four runs: Scenario 1 includes runs 3 through 6 while Scenario 2 includes runs 7 through 10. The runs reflect four routing strategies, as follows:

a. Runs 3 and 7 model the proposed time-dependent sub-population feedback eco-routing logic (ECO-SFA or routing method 9);
b. Runs 4 and 8 model the time-dependent sub-population feedback user equilibrium logic (SFA or routing method 2);
c. Runs 5 and 9 model the proposed time-dependent agent-based feedback eco-routing logic (ECO-AFA or routing method 10); and
d. Runs 6 and 10 model the time-dependent agent-based feedback assignment (AFA or routing method 3).

Scenario 1: Arterial with Freeway Diversion (Run 3 – 6)

In scenario 1 links 1 and 5 were arterial links and would be typical of driver's commute where one typically starts on lower facility roadways and then has the option to travel on a freeway or continue travel on the lower facility roadway. Both options then entail traveling on the lower facility roadway to reach their destination.

Table 2. Summary Results for Scenarios 1 and 2

Measure	Run 3	Run 4	Run 5	Run 6	Run 7	Run 8	Run 9	Run 10
Total Demand	400	400	400	400	400	400	400	400
Total Travel Distance (veh-km)	799	798	799	798	798	798	799	798
Tptal Vehicle Stop	30	97	0	97	93	0	95	0
Total Travel Time (veh-s)	36862	33401	37321	33401	32832	28680	33440	28680
Total Stopped Delay (veh-s)	0	0	0	0	0	0	0	0
Total Decel/Accel Delay (veh-s)	166	435	1	435	442	0	432	0
Total Fuel Consumption (veh-L)	65	76	62	76	76	66	77	66
Total HC Emission (veh-g)	101	312	47	312	295	58	312	58
Total CO Emission (veh-g)	2267	8414	729	8414	7769	1037	8422	1037
Total NOx Emission (veh-g)	147	219	129	219	226	227	221	227
Total CO2 Emission (veh-g)	148412	165014	143207	165014	166546	153194	166854	153194
Avg. Distance (km)	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
Avg. Stop	0.07	0.24	0.00	0.24	0.23	0.00	0.24	0.00
Avg. Travel Times (s)	92.16	83.50	93.30	83.50	82.08	71.70	83.60	71.70
Avg. Stopped Delay (veh-s)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Avg. Decel/Accel Delay (veh-s)	0.42	1.09	0.00	1.09	1.11	0.00	1.08	0.00
Avg. Fuel Consumption (L)	0.16	0.19	0.15	0.19	0.19	0.17	0.19	0.17
Avg. HC Emissions (g)	0.25	0.78	0.12	0.78	0.74	0.14	0.78	0.14
Avg. CO Emissions (g)	5.67	21.03	1.82	21.03	19.42	2.59	21.05	2.59
Avg. Nox Emissions (g)	0.37	0.55	0.32	0.55	0.57	0.57	0.55	0.57
Avg. CO2 Emissions (g)	371.03	412.53	358.02	412.53	416.37	382.98	417.14	382.98

As demonstrated in the results of Table 2 that routing methods 2 and 3 (runs 4 and 6) result in all vehicles taking the freeway route in order to minimize the driver travel times. This route, however results in an average fuel consumption of 0.19 L/veh.

Alternatively, when vehicles are routed using the routing mechanism 9 (run 3) one of the sub-populations uses route 2 (freeway route) for the initial update horizon (first 300 s), as illustrated in Figure 3. The majority of vehicles use route 1 (arterial route) and all vehicles use route 1 after vehicle feedback is received. Figure 3(a) shows the initial oscillations in experienced travel times depending on the route of choice. In the case travel along links 1 and 5 is 48 s while travel along the parallel freeway section is 36 s (travel along links 3 and 4) and travel along the parallel arterial is 46.8 s (link 2). The total travel time along the arterial/freeway route (route 2: links 1, 3, 4, and 5) is 82.8 s while travel along the arterial route is 93.5 s (route 1: links 1, 2, and 5), as illustrated in Figure 3(b). As demonstrated in Figure 3(c) travel along route 2 results in a higher fuel consumption level compared to route 1. It should be noted that some vehicles that travel along route 1 experience higher fuel consumption levels because of the congestion that forms upstream of the diverge point at node 3. This routing mechanism reduces the vehicle fuel consumption level from 0.19 (run 4) to 0.16 L (run 3) for the entire trip (see Table 2), which corresponds to a 15 percent reduction in the average fuel consumption level. This saving in fuel consumption comes at an increase of 10 percent in travel time (92.6 versus 83.5 s).

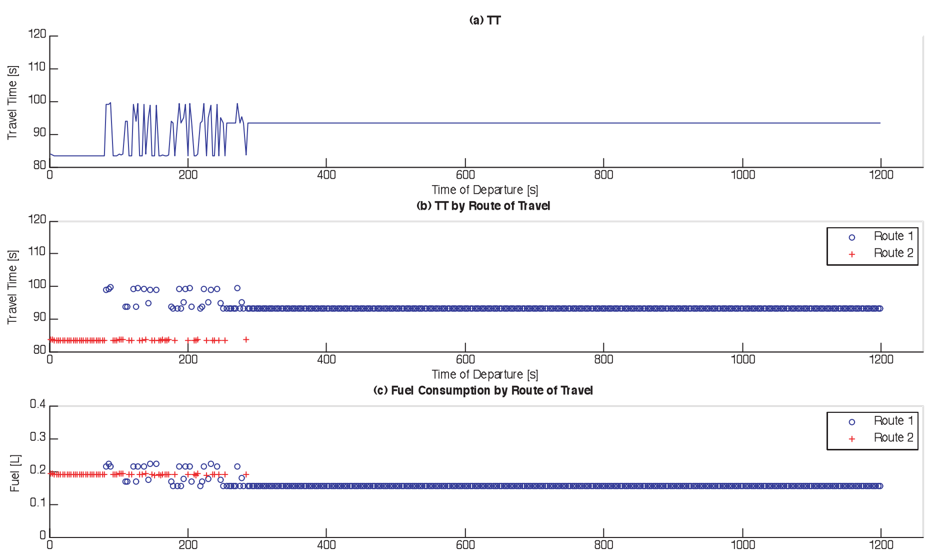

Figure 3. Run 3 Temporal Variation in Individual Vehicle Travel Time and Fuel Consumption Levels

When vehicles are routed using the ECO-IFA mechanism all vehicles travel along route 1, as illustrated in Figure 4. This results in a further reduction in the vehicle fuel consumption level from 0.16 L (run 3) for the ECO-SFA mechanism to 0.15 L (run 5) for the ECO-IFA mechanism, as summarized in Table 2.

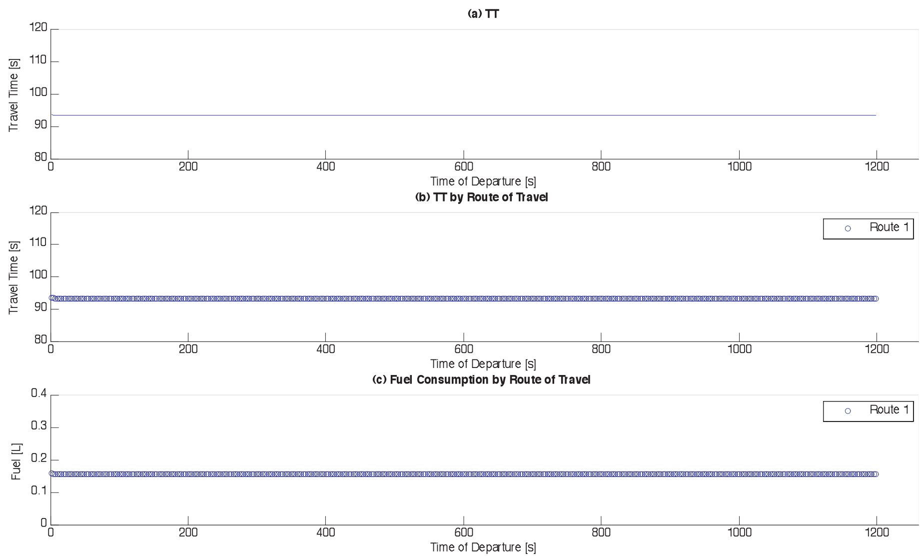

Figure 4. Run 5 Temporal Variation in Individual Vehicle Travel Time and Fuel Consumption Levels

Scenario 2: Freeway with Arterial Diversion (Run 7 – 10)

In scenario 2 links 1 and 5 are made freeway links instead of arterial links and thus the free-flow speed on links 1 and 5 are 100 km/h instead of 77 km/h as was the case in Scenario 1. This example, entails traveling on a freeway and having the option to continue on the freeway or exit the freeway to travel on a slower but more fuel efficient arterial roadway.

As was the case in Scenario 1, the SFA and IFA routing strategies would entail continuing to travel on the freeway roadway (traveling on links 3 and 4). This produces an average travel time of 71.7 s. In the case of ECO-IFA (run 9) all 400 drivers select the more efficient arterial route (route 1). The vehicles increase their average travel time from 71.7 s to 83.6 s, as would be expected. However, what is not expected is that the average fuel consumption actually increases from 0.17 to 0.19 L by selecting the more fuel efficient arterial route. This increase in fuel consumption, while might appear counter intuitive as first glance, results from the fact that vehicles the vehicles that enter the freeway from the more efficient arterial route have will accelerate from a speed of 77 km/h to 100 km/h on link 5. Consequently, although the drivers select the more fuel efficient route they incur and acceleration penalty on the freeway and thus increase their overall fuel consumption level. Had the length of the arterial and freeway routes been slightly longer the savings in fuel consumption would have outweighed the penalty associated with the vehicle accelerations on the freeway on link 5.

CONCLUSIONS

The paper presented the INTEGRATION microscopic traffic assignment and simulation framework for modeling eco-routing strategies. Two eco-routing algorithms are developed: one based on vehicle sub-populations (ECO-Subpopulation Feedback Assignment or ECO-SFA) and another based on individual drivers (ECO-Agent Feedback Assignment or ECO-AFA). Both approaches initially assign vehicles based on fuel consumption levels for travel at the facility free-flow speed. Subsequently, fuel consumption estimates are refined based on experiences of other vehicles within the same class. This stochastic, multi-class, dynamic traffic assignment framework was demonstrated to work for two Scenarios. Savings in fuel consumption levels in the range of 15 percent were observed and potential implementation challenges were identified.

REFERENCES

[1] G. H. Tzeng and C. H. Chen, "Multiobjective Decision-Making for Traffic Assignment," *Ieee Transactions on Engineering Management*, vol. 40, pp. 180-187, May 1993.

[2] C. M. Benedek and L. R. Rilett, "Equitable traffic assignment with environmental cost functions," *Journal of Transportation Engineering-Asce*, vol. 124, pp. 16-22, Jan-Feb 1998.

[3] L. R. Rilett and C. M. Benedek, "Traffic assignment under environmental and equity objectives," *Transportation Research Record*, pp. 92-99, 1994.

[4] S. Sugawara and D. A. Niemeier, "PART 2 - AIR QUALITY - How Much Can Vehicle Emissions Be Reduced? Exploratory Analysis of an Upper Boundary Using an Emissions-Optimized Trip Assignment," *Transportation research record*, p. 9, 2002 2002.

[5] A. Nagurney, "Congested urban transportation networks and emission paradoxes," *Transportation Research, Part D: Transport & Environment*, vol. 5, pp. 145-151, 2000.

[6] A. Nagurney, et al., "Multimodal traffic network equilibrium model with emission pollution permits: Compliance vs noncompliance," *Transportation Research, Part D: Transport & Environment*, vol. 3, pp. 349-374, 1998.

[7] A. Nagurney and J. Dong, "A multiclass, multicriteria traffic network equilibrium model with elastic demand," *Sage Urban Studies Abstracts*, vol. 30, pp. 415-517, 2002 2002.

[8] K. Ahn and H. Rakha, "The Effects of Route Choice Decisions on Vehicle Energy Consumption and Emissions," *Transportation Research Part D: Transport and Environment*, vol. 13, pp. 151-167, 2008.

[9] M. Van Aerde and S. Yagar, "Dynamic Integrated Freeway/Traffic Signal Networks: A Routeing-Based Modelling Approach," *Transportation Research*, vol. 22A(6), pp. 445-453, 1988.

[10] M. Van Aerde and S. Yagar, "Dynamic Integrated Freeway/Traffic Signal Networks: Problems and Proposed Solutions," *Transportation Research*, vol. 22A(6), pp. 435-443, 1988.

[11] M. Van Aerde and H. Rakha, "INTEGRATION © Release 2.30 for Windows: User's Guide – Volume I: Fundamental Model Features," M. Van Aerde & Assoc., Ltd., Blacksburg2007.

[12] M. Van Aerde and H. Rakha, "INTEGRATION © Release 2.30 for Windows: User's Guide – Volume II: Advanced Model Features," M. Van Aerde & Assoc., Ltd., Blacksburg2007.

[13] H. Rakha, et al., "Traffic signal coordination across jurisdictional boundaries: Field evaluation of efficiency, energy, environmental, and safety impacts," *Transportation Research Record*, vol. n 1727, pp. 42-51 2000.

[14] H. Rakha, et al., "Estimating vehicle stops at undersaturated and oversaturated fixed-time signalized intersections," *Transportation Research Record*, vol. n 1776, pp. 128-137 2001.

[15] F. Dion, et al., "Comparison of delay estimates at under-saturated and over-saturated pre-timed signalized intersections," *Transportation Research Part B-Methodological*, vol. 38, pp. 99-122, 2004.

[16] H. Rakha, et al., "Requirements for evaluating traffic signal control impacts on energy and emissions based on instantaneous speed and acceleration measurements," *Transportation Research Record*, vol. n 1738, pp. 56-67 2000.

[17] H. Rakha, et al., "Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions," *Transportation Research, Part D: Transport & Environment*, vol. 9, pp. 49-74, 2004.

[18] K. Ahn, et al., "Estimating vehicle fuel consumption and emissions based on instantaneous speed and acceleration levels," *Journal of Transportation Engineering*, vol. 128, pp. 182-190, 2001.

[19] K. Ahn, et al., "Microframework for modeling of high-emitting vehicles," *Transportation Research Record*, pp. 39-49, 2004.

[20] A. Avgoustis, et al., "Framework for estimating network-wide safety Impacts of intelligent transportation systems," in *Intelligent Transportation Systems Safety and Security Conference Miami*, 2004.

[21] H. Rakha and B. Crowther, "Comparison of Greenshields, Pipes, and Van Aerde car-following and traffic stream models," *Transportation Research Record*, pp. 248-262 2002.

[22] H. Rakha and B. Crowther, "Comparison and calibration of FRESIM and INTEGRATION steady-state car-following behavior," *Transportation Research*, vol. 37A, pp. 1-27, 2003.

[23] H. Rakha, "An Evaluation of the Benefits of User and System Optimised Route Guidance Strategies," M.Sc., Civil Engineering, Queen's University, Kingston, 1990.

[24] H. Rakha, et al., "Evaluating alternative truck management strategies along interstate 81," *Transportation Research Record*, vol. n 1925, pp. 76-86, 2005.

[25] H. Rakha, et al., "Construction and calibration of a large-scale microsimulation model of the Salt Lake area," *Transportation Research Record*, vol. n 1644, pp. 93-102, 1998.

[26] S. Park and H. Rakha, "Energy and Environmental Impacts of Roadway Grades," *Transportation Research Record*, vol. 1987, pp. 148-160, 2006.

[27] H. Rakha, et al., "Microscopic modeling of vehicle start emissions," *Transportation Research Record*, pp. 29-38 2003.

[28] L. R. Rilett, et al., "Simulating the TravTek route guidance logic using the integration traffic model," in *Vehicle Navigation & Information Systems Conference Proceedings Part 2 (of 2)*, Dearborn, MI, USA, 1991, pp. 775-787.

[29] L. R. Rilett and M. W. van Aerde, "Modelling distributed real-time route guidance strategies in a traffic network that exhibits the Braess paradox," in *Vehicle Navigation & Information Systems Conference Proceedings Part 2 (of 2)*, Dearborn, MI, USA, 1991, pp. 577-587.

[30] L. Rilett and M. Van Aerde, "Routing based on anticipated travel times," in *Proceedings of the 2nd International Conference on Applications of Advanced Technologies in Transportation Engineering*, Minneapolis, MN, USA, 1991, pp. 183-187.

[31] L. Rilett and V. Aerde, "Modeling Route Guidance Using the Integration Model," in *Proceedings of the Pacific Rim Trans Tech Conference*, Seattle, WA, USA, 1993, pp. 258-264.

[32] H. Rakha, et al., "Vehicle dynamics model for predicting maximum truck acceleration levels," *Journal of Transportation Engineering*, vol. 127, pp. 418-425, 2001.

[33] H. Rakha and I. Lucic, "Variable power vehicle dynamics model for estimating maximum truck acceleration levels," *Journal of Transportation Engineering*, vol. 128, pp. 412-419, 2002.

[34] H. Rakha and Y. Zhang, "INTEGRATION 2.30 framework for modeling lane-changing behavior in weaving sections," *Transportation Research Record.*, pp. 140-149, 2004.

[35] H. Rakha and Y. Zhang, "Analytical procedures for estimating capacity of freeway weaving, merge, and diverge sections," *Journal of Transportation Engineering*, vol. 132, pp. 618-628, 2006.

[36] H. Rakha and K. Ahn, "Integration modeling framework for estimating mobile source emissions," *Journal of Transportation Engineering*, vol. 130, pp. 183-193, 2004.