MULTI-OBJECTIVE SPEED OPTIMIZATION FOR HEAVY GOOD VEHICLES IN INTERRUPTED TRANSPORTATION NETWORKS

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Introduction

In essence, logistic companies and HGV travelers choose their journey paths after considering a variety of factors including route boundaries, network traffic condition, travel costs and time. There is a set of approaches utilized to efficiently integrate fleets, operation centers and infrastructure midway nodes, in order to minimize system-wide costs while satisfying service level requirements. The approach introduced here is in the framework of *Advanced Traveler Information Systems* (ATIS) appointing; first, time factor (interruption time), secondly, fuel economy and last but not least, finding the correlation between interruption time and fuel economy.

In terms of travel time, possible interruption points during pre-haulage, post-haulage and main haulage will affect estimated time of arrival (ETA). This information can be obtained by several means: travelers' and operators' own experience, radio broadcasts, Internet websites and variable message systems (VMS). Also it might be accessible for the operators or drivers as well, as it can be incorporated into pre-trip and/or on-trip data. The accuracy of ETA can be increased by accumulating the estimated interruption wait times. However, like traffic data, stochastic approaches are required to be deployed over the historical data.

The cost factor encapsulates a variety of aspects such as fuel consumption, vehicle operation costs, labor costs, overhead costs and environmental impacts. The simplest methods for cost reduction are finding the shortest path and best speed adjustment for fuel economy. There are a great number of algorithms to compute the shortest path based on mathematical approaches (Ittai et al., 2011), which is beyond the scope of this study. For fuel consumption, usually the travelers adjust their speed range from minimum to maximum allowed in a link during their journey. Speed-cautious driving behaviors and eco-driving will result not only in lower risk of accident, fewer traffic violations, less vehicle wear and fewer break-downs, but also significantly reduce both fuel consumption and emissions. In order to minimize fuel consumption and hence emissions, it is necessary to provide drivers with advice and feedback while driving. The results of Shiaw-Shyan et al. (2010) on eco-driving studies in Southern California present how deployment of on-board eco-driving devices affects driving behavior, and the resulting fuel economy. Their study examines instantaneous fuel economy feedbacks provided to the driver under real-world driving conditions.

Finally, data fusion in ITS architecture is a true asset and added value for existing stand-alone information systems. The physical and logical interoperability between systems has been employed to improve operation of systems and by optimization methods, more robust and reliable information is provided to transportation problems.

Problem Statement and Objective

Basically, the FLS considers tradeoffs between a variety of factors including travel time and fuel economy. The supply chain competitive market trend, with fast and timely based services, requires rapid responsive and reactive transportation system with real-time accurate information to avoid extra costs.

If the fleet's travel plans take into account both fuel economy and travel time, but ignore variation in the services at terminals and interruption nodes, then it might lead to many long delays, and hence the FLS won't function at its optimum level. Lack of communication between these interruption points and FLS is a major cause of these irregularities. Variation in the infrastructure service load may cause uninformed utilization and decrease the optimum performance. Avoiding variation in demand is a critical objective in process and operation management (Slack, 2009). For instance, Figure 1 shows a scenario in which the vehicle *i* is heading toward interruption point *n* with average speed $\bar{S}$ and distance *l*. The driving behavior will be eco-drive as far as it is ahead of its schedule. This will lead to saving fuel up to the arrival to point *n*. At interruption point *n* there will be a queue waiting for vehicle *i* at time $\frac{X_l}{\bar{S}_i}$. If the interruption point *i* collects expected duration of time arrival based on duration of HGVs headways with implementation of ITS telematics (inductive loops, radar, DSRC[1], etc) then it was possible to guide the driver in advance to adjust the speed more accurately (Mannering, 2008). After interruption point *n* the driver may speed up to recover lost time and reach point *n*+1. Again, if the driver is not aware about the expected queue at *n*+1 then it lead again to another increase in cost by consuming more gas and arriving at the time of higher service load at *n*+1.

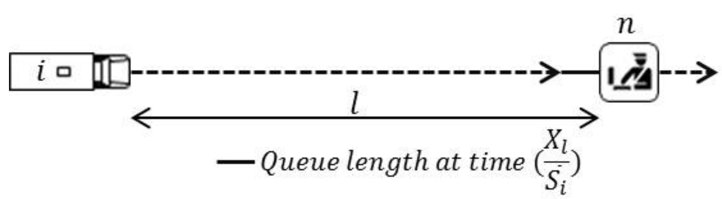

Figure 1

Methodology

Two data sets are required in this application: estimation of cost factors and estimation of wait time at interruption points.

Cost factors

As mentioned earlier, fuel cost, vehicle operation costs, labor costs, overhead charges and environmental costs are some elements in cost analysis. Fuel economy considers all of these factors with excessive attention to emission factors. According to the EU Commissioner for climate action studies, HGV represent about a quarter of EU road transport CO_2 emissions and some 6% of the total EU emissions with a rising trend mainly due to increasing road freight traffic (European Commission, 2011). The data collected from a location-based services (LBS) mobile app over 10,000 journeys uploaded to a web portal over nine months show the tradeoff between the speeds that the participants drove, the fuel they used and their total journey time. Summary of results published by developer presents maximum speed reduction to 100 km per hour could reduce fuel consumption by 9%, but add less than two minutes to the average hourly journey time (DriveGain, 2012).

Each vehicle reaches its optimal fuel economy at a different speed (or range of speeds) depending on engine design, vehicle age, weight, make, driver behavior, road topography, fuel properties, resistive forces on the vehicle, temperature, humidity level, and many other factors. In general, gas mileage decreases rapidly at speeds above 80 km/h.[2] Driving behavior in accelerating and decelerating between posted speed limits and roadway grades have a significant impact on vehicle fuel consumption and CO_2 emission rates. Maintaining a desired speed by adjusting the vehicle throttle and brake level can improve the result. Implementation of advanced driver assistance systems (ADAS) can result in excessive fuel usage by attempting to maintain a desired speed on roadway segments. Added to conventional cruise controls, adaptive cruise controls systems are available in the market bringing more enhancements. Research in 2011 at Virginia Polytechnic Institute led to the development of an eco-cruise control system that is adaptive and responsive to road topography information. The idea was based on an old principle used by experienced truck drivers: "travel faster in downgrades and slow down along upgrades". The result of their test performed at Interstate 81 with vehicles equipped with onboard unit (OBU) and eco-cruise control system shows that, on average, the eco-cruise control system can save 10.33 percent in fuel consumption and correspondingly CO_2 emissions for different vehicle types (Kyoungho et al., 2011). Adding to topographic profiles, gear-shifting information was considered by researchers from Linkőping University (Fröberg et al., 2008). With a macroscopic approach the system is trying to minimize the total aggregation of costs factors as presented in Equation 1 where ρ is fuel consumption rate for vehicle i at time t which can be extracted from popular fuel consumption models (Mannering, 2008) in the mechanical engineering Equation 2. α is aggregation of overhead costs including vehicle operation costs, labor costs and other overheads for fleet company j. and finally γ is environment impedance.

$$min\left[\sum_{t=1}^{t}\sum_{i=1}^{n}(\frac{x_l}{s_i})\rho_i + \sum_{t=1}^{t}\sum_{i=1}^{n}(\frac{x_l}{s_i})\alpha_j + \sum_{t=1}^{t}\sum_{i=1}^{n}\rho_i\gamma\right] \quad (1)$$

$$\rho_i = \mu\left[\frac{k\omega_t d}{2000} + P_{i,t}\right] \quad (2)$$

In Equation 2, μ is the fuel consumption factor, which varies with the engine make and condition, k is the engine friction, ω is the engine speed in revolutions per second at time t, d is engine displacement and P is total power used by the vehicle driveline at time t for vehicle i. The variables affecting P are: total resistance force (aerodynamic, rolling, and grade resistance forces for vehicle i), vehicle mass, vehicle acceleration at time t, the vehicle speed at time t; gear ratio at time t, and driveline efficiency of vehicle i.

Interruption points wait time estimation

Fleets cannot avoid interruption points in longer journeys such as stops at customs control or POE on an interstate or international trip. These stations are interrupting trips in order to provide required and necessary services. Restricted capacity at stations means limitations in serving vehicles during a time period. Having an insight about the real-time and estimated service level at these points is as important as having traffic data for journey planners. These stations include: terminals, border crossing, point of entries, custom inspections, police inspections, loading and offloading stations, weigh scales, rest stations, tolling, refueling stations and so on. At these stations vehicles' engines burn fuel either if working idle or "stop and go" without earning any mileage. Estimated fuel consumption of an idling engine is 0.6 liters per hour per liter of engine displacement and this figure rises in "stop and go" patterns. Implementations of new technologies hand in hand with systems interoperability have reduced these impacts but it's not vanished yet. Fleet management and telematics, real-time planning and operations are reducing wait times at terminals and loading and offloading stations. Different techniques such as weight in motion, open road tolling (ORT), electronic toll collection systems, HGV parking information at motorway service and rest areas, and finally systems like SENTRI[3] and IBCC[4] can automate the operation and hence reduce wait times. Even with these systems, there are still many interruption points with information unavailable for FLS. Difficult terminal and operator cooperation, lack of intersystem equipment, old systems, infrastructure and rolling stock, uneven utilization of terminals, underdeveloped information and communication infrastructure are the main reasons for the failure.

Using ITS for reducing delays and increasing the reliability of crossing and wait times at POEs was among several objectives mentioned in the proposed freight Act of 2010 (U.S. Senate, 2010).

The operators and drivers usually use estimation of wait time based on historical data available and real-time information presented to them. The Niagara border crossing between Ontario and New York with two major POEs (Peace Bridge and Queenston-Lewiston Bridge) is an example with available historical data to FLS.

In addition to historical traffic data, Alice Kam et al. proposed application of artificial neural networks (ANN) to predict travel times for real-time control of a VMS motorist information system at the Canadian-U.S. border crossing areas. The ANN traffic flow prediction models comprise one functional module in the motorist delay awareness systems for border crossings concept. The travel times used for Advanced Traffic Management and Information Systems may be based on historical (Weissmann et al., 2007), current, or predicted traffic conditions. Historical traffic data are unlikely to provide an appropriate indication of evolving, day-specific traffic conditions. Alice Kam et al. have indicated that the use of historical data as the basis for real-time control is significantly inferior to the use of current or predictive information (Alice Kam et al., 2004).

By implementation of detection and sensor systems such as DSRC, radar and inductive loops in the pathway toward POEs it's possible to aggregate the headways between HGVs and traffic information. This data can be fed into the simulation model and, combined with filtered historical data, will produce a reliable estimation of wait time for vehicles already in the network. The sensor locations have to be just before or after major bifurcation points and interchanges along the highway and adjacent network (Figure 2). Moreover, the distances between sensors generally needed to be shorter near the POE. Alice Kam et al. propose installation of 19 inductive loops in order to gather information about the vehicle types, flow, speed and queuing data along the route to each bridge. These have been used as input parameters in the neural networks design where flow and speed could be readily collected by loop detectors on the roadways. The queuing data could be obtained indirectly from the number of vehicles in each individual queue link at POE. Also it is important to consider the queue mixture whether the trucks queue is separated from passenger vehicles queue or there mixed queue of traffic.

Since the service rate at stations varies due to different factors such as security level at border control or inspection capacities (number of open channels) on one hand, and on the other hand the demand is not constant because arrival of HGVs to the station changes over time, therefore stochastic analysis is required for the queue and consequently wait time. Usually we have multilane queues at stations. For the queue, exponentially distributed time intervals and departure (derived from assumption of Poisson distributed arrivals and departure) will be used, with N number of departure channels. This queue model is known as M/M/N. The simulation software used is based on the same traffic flow distribution. First in first out (FIFO) queuing discipline is applicable for interruption points.

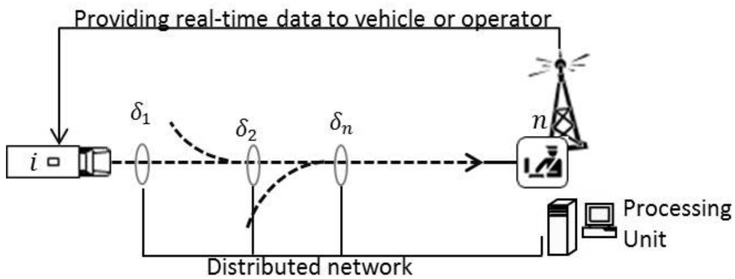

Figure 2

δ_1 to δ_n are showing the sensor units. Information from these sensors is provided both to the traffic center to compute level of service and the station *n* in order to calculate the expected service rate. These sensors are parts of distributed network in the ITS architecture. The processing unit will provide information based on each section to the driver (to OBU) or operator (processing unit) and raw data can be used to extract estimation of wait time. The expected wait time for driver *i* can be compute based on average time spent in the system $\bar{t}$ in unit time per vehicle as follows:

$$\bar{t} = \frac{\rho + \bar{Q}}{\lambda} \tag{3}$$

The estimation waits time for vehicle *i*, t_i can be computed based on Equation 4:

$$\dot{t_i} = \left(\frac{Q_0}{\mu_0}\right) + \left[\sum_{\delta=1}^{n} \frac{\lambda_{t.\delta}}{\mu_{t.\delta}}\right] * \bar{t} \tag{4}$$

Q_0 is the queue at current time, μ_0 is the average departure rate in vehicles per hour at current time. This will be the estimation of wait time based on queue left if there is no more HGV between vehicle *i* and station n. λ Shows the average arrival rate in vehicle per unit time according to each sensor unit δ at time $t = \left(\frac{\boldsymbol{X}_\delta - \boldsymbol{X}_n}{\bar{\boldsymbol{S}}}\right)$.

The matrix produced during travel time will be updated at future times $\ddot{t}$; this will include possible HGVs overtaking vehicle *i* (which will pass the next sensor unit).

The transfer function for vehicle i to drive at maximum posted speed S_{Max} or follow optimum speed orders according to eco-drive S_{opt} will be:

$$if\ t_i < \left(\frac{X_l}{S_{Max}} - \frac{X_l}{S_{Min}}\right) \wedge\ t_i \geq \left(\frac{X_l}{S_{Max}} - \frac{X_l}{S_{Min}}\right) + \left(\frac{X_{\delta_n} - X_n}{\bar{S}}\right)$$

$$then\ S_{Max}\ else\ S_{opt} \qquad (5)$$

In this model, service level has highest priority in respect to echo-drive other criteria. With calibration it is possible to include station service level into echo-drive variables rather than overriding it.

Simulation

Two routes have been selected for this simulation. Both connect Montreal central as the starting point to Boston city center as the destination. Route I (Figure 3) with 587 km length via I-89S and I-91 passing through Highgate Springs on QC-133. Route II (Figure 4) with 623 km leaves Montréal on A-15 and, via I87S and I90-E, reaches Boston. There is a trip interruption for customs and border check on both routes (Canada–U.S. point of entry) called St-Armand/Philipsburg and St-Bernard-de-Lacolle, accordingly.

The simulation in this study has been conducted by VISSIM micro-simulation software. The traffic condition of the highway has been selected at three different times of the week with average free flow, stable flow and unstable flow. Two separate service levels and expected wait-time dataset were available at each point of entry dedicated to commercial vehicles and passenger cars. These data are available to drivers and operators online or via other means such as "wireless version" at Canada Border Services Agency website.[5] The update interval is 30 minutes. These data have been used as the basis of current average wait times in the simulation environment, considering 90 seconds standard deviation.[6] In order to have the estimation of wait times in the network, sensor units (inductive loops) were placed just before or after major bifurcation points and interchanges along the journey path. The queue length at POE was monitored with sensor units actuating speed changes for HGV travelers and taking into account HGV traffic ahead.

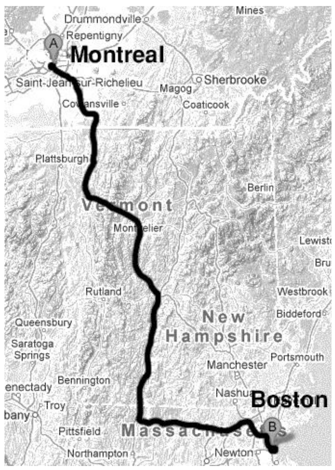

Figure 3

Figure 4

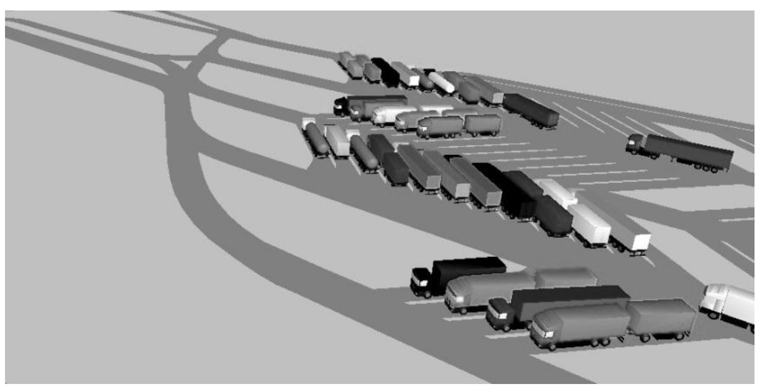

Figure 5

Figure 5 is a snapshot of simulation at POE during unstable traffic flow, showing HGV waiting for customs clearance to leave the station. Fuel consumption is based on databases of different types of vehicles (passenger and HGV) that could be imported into VISSIM simulation environment.

The summary of results for routes I and II (Tables 1 and 2) presents a minor effect on average travel time and, consequently, fuel consumption reduction. The point is that the fuel consumption reduction is not just due to travel time reduction but also the speed pattern of vehicles. Under normal conditions, for instance, there are cases where a driver drives more aggressively with more wait time at POE. On the other hand, in the same scenario under the optimized model simulation, the driver could drive normally considering some time to be saved at POE caused by giving enough time to queue for its reduction. Although the travel times for both drivers are almost the same, less fuel has been consumed by the second driver.

This is not an "always true" statement without having sufficient information and, as mentioned earlier, the traffic ahead of the driver will change the input level of the future queue. Even though under the optimized simulation environment we have more shifts between max and min posted speed, which is against eco-drive principles, in general the result was better. It is very important to combine other variables improving eco-drive as mentioned earlier.

Table 1

route I	Traffic Condition					
	Free flow		**Stable flow**		**Unstable flow**	
Speed	**TT***	**ρ***	**TT***	**ρ***	**TT***	**ρ***
Normal	6h10'	209.64L	6h55'	236.27L	8h15'	284.27L
Optimum	6h08'	204.23L	6h42'	223.5L	8h07'	278.3L
Difference	2'	5.41L	13'	12.77L	8'	5.97L
%	0.5%	2.7%	3.2%	5.7%	1.5%	2.2%

Table 2

route II	Traffic Condition					
	Free flow		Stable flow		Unstable flow	
Speed	TT*	ρ*	TT*	ρ*	TT*	ρ*
Normal	6h17'	226.54	6h40'	245.04L	7h55'	324.04L
Optimum	6h14'	221.13L	6h29'	231.73L	7h49'	317.81L
Difference	2.5'	5.41L	11'	13.31L	6.5'	6.23L
%	0.70%	2.65%	2.83%	5.80%	1.48%	1.96%

*The average for travel time "tt" and fuel consumption "ρ" for all HGVs in the simulation and in 10 times simulation runs under each scenario.

Conclusion

In fleet logistics systems one of the key strategies for improving vehicle fuel efficiency is obtaining more miles from each liter or gallon of fuel. Vehicle idle times and trip interruptions are double losses because extra fuel is burned without earning mileage and there is extra travel time for trip. This is in contradiction to supply chain responsive transportation requirements designated for just-in-time and other time-based applications. According to fuel economy and eco-driving, it is better to drive at a steady pace than to jack-rabbit between high and low posted speeds. Conventional cruise controls help drivers follow more constant patterns in their course. Integrating factors such as road topography, gear to drive, resistive forces on the vehicle, temperature and humidity level into cruise control will enhance efficiency in fuel economy. Adapting vehicle speed with real-time information received from expected queue length at time of arrival to interruption points is another added value that enhances eco-drive with incentives for speeding up whenever queue trend is positive, or slowing down if queue trend is negative.

As a multi-objective approach this will reduce fuel consumption and travel time for FLS and consequently reduce CO_2 emissions and smooth load distribution and temporal service at stations.

In this study, results for average fuel consumption, CO_2 emissions and average travel time for two journey plans from Montreal to Boston have been simulated under dynamic traffic conditions and triggering HGV speed based on estimated queue at POE. Further studies for calibrating the method, data fusion technics and real world test need to be conducted.

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Endnotes

[1] Dedicated short range communication
[2] Fuel economy www.eia.gov April 2013
[3] Secure Electronic Network for Travelers Rapid Inspection
[4] International Border Crossing Clearance
[5] http://www.cbsa-asfc.gc.ca/bwt-taf/menu-eng.html - Accessed March 07, 2013
[6] "No delay" means less than 10 minutes. We considered no delay as 10 minutes delay according to CBSA instruction in order to neglect negative variables.