CITY OF EDMONTON COMMERCIAL VEHICLE MODEL UPDATE USING A ROADSIDE TRUCK SURVEY

Matthew J. Roorda, University of Toronto
Nico Malfara, University of Toronto

Introduction

The movement of goods and services are central to the economy of the City of Edmonton. The City of Edmonton primarily relies on trucks for its urban goods movement. The City of Edmonton last developed a commercial vehicle model (CVM) based on data from an establishment survey and external truck counts from 2001. The model is a micro-simulation framework that simulates commercial vehicle tours, including both goods movements and service delivery tours. The City of Edmonton also conducted a roadside commercial vehicle survey in 2012. The goal of this project was to adjust the model to reflect the latest data collected in the 2012 Roadside Commercial Vehicle Survey as well as other information, such as land use data, other road counts, and updated network information. The lack of recent establishment-based survey data prevents a full-blown re-estimation of the tour-based micro-simulation model. A cost effective approach to upgrade the commercial vehicle model is to use an iterative procedure to adjust model parameters to better reflect current conditions.

This paper gives an overview of the project scope and study area, the original CVM structure and calibration process, a comparison of the original model outputs to the observed count data, the method used to re-calibrate model parameters, and the resulting model outputs from the re-calibrated model. Finally, the challenges and successes associated with this project as well as the lessons learned are discussed.

Study Area

The original Edmonton CVM was developed and calibrated in 2006. Recent updates to the City of Edmonton's Regional Transportation Model (RTM) have been made to include updated land use and road network information for 2012. Therefore, 2012 has been chosen as the study year and to coincide with the City of Edmonton's Roadside Truck Survey which was also completed in 2012. The study area includes the Edmonton Census Metropolitan Area (CMA), which is comprised of the City of Edmonton, St. Albert, Sherwood Park, as well as the Counties of Leduc, Strathcona, Sturgeon and Parkland.

Original Edmonton Commercial Vehicle Model

The City of Edmonton currently employs a tour-based microsimulation approach to estimate commercial vehicle movements based on a commodity flow study conducted in 2001. The microsimulation is executed using Java applications and two main sets of inputs: an EMME databank which provides information about the area being modelled and 30 coefficient files containing model specifications and parameter estimates. Hunt and Stefan (2007) developed a tour-based microsimulation model for the City of Calgary and many of the specifications and estimates for the City of Edmonton model were borrowed directly from the City of Calgary.

Figure 1 shows the framework developed by Hunt and Stefan (2007) that was applied to the City of Edmonton. First, aggregate tours are generated within EMME to create a list of tours using both logit and regression techniques. The aggregate tour generation consists of three parts: tour generation, vehicle type/ tour purpose, and tour start time. Second, individual tours generated from each zone are assigned a next stop purpose, next stop location and next stop duration using a micro-simulation process. In this process, Monte Carlo techniques are used to incrementally 'grow' a tour or end the tour by having a 'return-to-establishment' alternative within the next stop purpose allocation. If the next stop purpose is not 'return-to-establishment', then the tour extends by one more stop. The selection probabilities used in the micro-simulation processes are established using logit models which were estimated from the choice data collected in the surveys.

The model considers four truck types: light, intermediate (less than 8 tons), medium (greater than 8 tons) and heavy vehicles. Six establishment categories are used to classify business establishments: industrial (IN), wholesale (WH), service (SE), retail (RE), transport and handling (TH) and fleet allocator (FA). Five time periods are considered in the model: early off Peak (midnight – 7 AM), AM peak (7 – 9 AM), midday off-peak (9 AM – 4 PM), PM peak (4 – 6 PM), and late off-peak (6PM – midnight). The model also considers five land use types: industrial, residential, commercial, employment node, low density, and power centre.

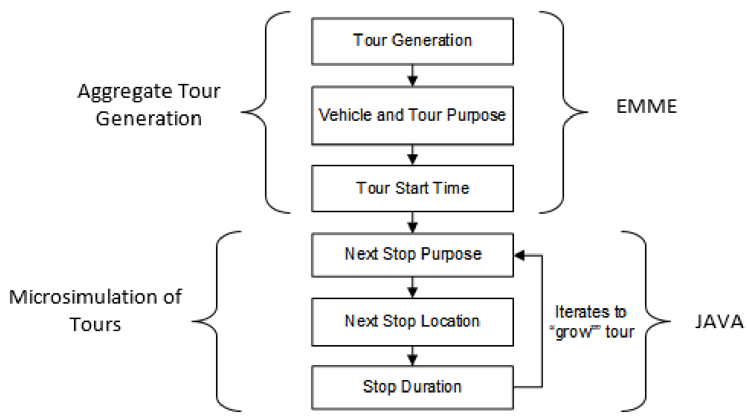

Figure 1: Tour-based Framework – Edmonton CVM Structure

The City of Edmonton commercial vehicle model can provide decision makers with a representation of commercial vehicle movements within the region for use in forecasting and policy analysis since the model is sensitive to changes in population, employment, transport supply conditions, and vehicle specific characteristics. As a result, impacts to model outputs such as traffic flow and vehicle travel times can be assessed. These outputs are analyzed to determine if policies such as truck route restrictions and land use distribution are effective or require revision.

Original Commercial Vehicle Model Calibration Process

Once all six sub-models presented in Figure 1 have been estimated and their coefficients determined, the CVM can be calibrated. Since the elements of the microsimulation are interdependent, adjustments to one element's coefficients can affect the output of another element. As a result, the calibration process uses a series of aggregate targets for fine-tuning of the model. In the calibration process, several iterations are performed to bring the model within an acceptable tolerance of the target values. The sets of aggregate targets considered are listed as follows: ratio of employees that ship to total number of employees; daily tour generation scaled by industry type and area, or time of day, or vehicle type; trips per tour scaled by industry type and tour purpose, average trip length (km) by industry type and vehicle types, destination sector factors by industry type and vehicle type, and intra-sector factors by industry type and vehicle type.

Comparison of Original Model to Observed Counts

Figure 2 presents the observed and original modelled daily truck totals categorized by vehicle type. The original model under-simulates the intermediate truck type by 77% and over-simulates the medium truck type by 85%. The original model has better correspondence for the heavy truck type compared to the other two types; over-simulating by 17%. Figure 2 highlights that the original model is resulting in incorrect vehicle type shares when compared with the observed counts. However, the original model is only over-simulating the number of trucks in total over all three vehicle types by 5%, which suggests that the discrepancy between observed and modelled values is primarily attributed to the vehicle type shares and not the generation of trucks.

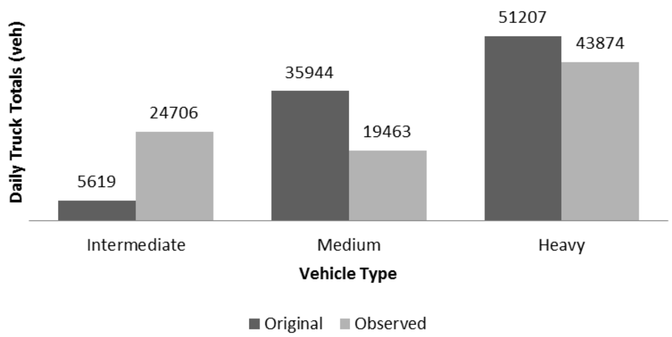

Figure 2: Observed vs. Modelled Count by Vehicle Type

To improve model correspondence to the observed count data, the following steps were taken:

i. The total truck volumes are within a reasonable degree of tolerance from the total observed counts. Therefore, changes to tour generation coefficients are not warranted.
ii. Re-calibrate the vehicle type alternative specific constants in the tour purpose and vehicle type model to adjust the shares of the truck types in accordance with the shares exhibited in the count data.
iii. The total truck volumes for each time period are also within a reasonable degree of tolerance from the counts. Therefore, adjustments to these coefficients are not warranted.
iv. If adjustments to the vehicle type alternative specific constants in the tour purpose and vehicle type model (ii) do not produce a sufficient improvement to the model; adjustments to the alternative specific constants in the next stop location model should be made.

Table 1 is a summary of the original model performance for each time period and vehicle type. To improve model correspondence to the observed count data, the following steps were taken:

v. The total truck volumes are within a reasonable degree of tolerance from the total observed counts. Therefore, changes to tour generation coefficients are not warranted.

vi. Re-calibrate the vehicle type alternative specific constants in the tour purpose and vehicle type model to adjust the shares of the truck types in accordance with the shares exhibited in the count data.

vii. The total truck volumes for each time period are also within a reasonable degree of tolerance from the counts. Therefore, adjustments to these coefficients are not warranted.

viii. If adjustments to the vehicle type alternative specific constants in the tour purpose and vehicle type model (ii) do not produce a sufficient improvement to the model; adjustments to the alternative specific constants in the next stop location model should be made.

Table 1 presents the percentage of count locations where the original model predicted the observed truck counts within an error of 40%. For six of nine categories the model reproduces less than half of the observed counts within an error of 40%.

To improve model correspondence to the observed count data, the following steps were taken:

ix. The total truck volumes are within a reasonable degree of tolerance from the total observed counts. Therefore, changes to tour generation coefficients are not warranted.

x. Re-calibrate the vehicle type alternative specific constants in the tour purpose and vehicle type model to adjust the shares of the truck types in accordance with the shares exhibited in the count data.

xi. The total truck volumes for each time period are also within a reasonable degree of tolerance from the counts. Therefore, adjustments to these coefficients are not warranted.

xii. If adjustments to the vehicle type alternative specific constants in the tour purpose and vehicle type model (ii) do not produce a sufficient improvement to the model; adjustments to the alternative specific constants in the next stop location model should be made.

Table 1 demonstrates that the model is performing poorly for the intermediate vehicle type in all time periods. Of the twelve vehicle type – time period categories, the model simulates the AM period with the least error compared to the other categories. Considering the 24 hour daily truck totals, the original model can only reproduce half of the heavy vehicles within an error of 40% and less than half for the intermediate and medium vehicles.

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xv. The total truck volumes for each time period are also within a reasonable degree of tolerance from the counts. Therefore, adjustments to these coefficients are not warranted.

xvi. If adjustments to the vehicle type alternative specific constants in the tour purpose and vehicle type model (ii) do not produce a sufficient improvement to the model; adjustments to the alternative specific constants in the next stop location model should be made.

Table 1: Percent of Count Locations for which Modelled Volumes are within 40% of Observed Volumes

Time Period	Vehicle Type	Percent of Values
AM	Intermediate	5%
	Medium	55%
	Heavy	50%
PM	Intermediate	5%
	Medium	32%

	Heavy	41%
OF	Intermediate	0%
	Medium	27%
	Heavy	55%
24 Hour	Intermediate	0%
	Medium	27%
	Heavy	55%

Vehicle Constant Re-Calibration Procedure

The vehicle type and tour purpose model assigns each tour both a purpose and a vehicle type. This is achieved using selection probabilities estimated for each establishment category using multinomial logit models with utility functions that include zonal-level land use, establishment location, and accessibility attributes. By adjusting the vehicle type alternative specific constant (ASC), the propensity of a tour to be made by a given vehicle type can be influenced. Therefore, the number of trucks for a given vehicle type at truck count locations can also be impacted.

A simplifying assumption made is that a change in the number of tours simulated by a given truck type will result in the same change in the number of truck trips modelled. We can influence the number of trips made by each vehicle type by modifying the logit model probabilities. The application of the CVM model leads to model traffic volumes by vehicle type at each count location.

From these model outcomes we can compute the ratio of total modelled trips (at the count stations) by one vehicle type to another. We would like the ratio of total modelled trips to reflect the ratio of total observed truck counts (at the count stations) by one vehicle type to another. The adjustment factor ($F_{k1,k2}$) to be applied to the alternative specific constant in the vehicle type and tour purpose model is formulated as the relative ratios of total modelled trips to total observed truck counts (at the count stations) by one vehicle type to another. If the model perfectly simulated the proportion of trips by vehicle type in the observed count data then the adjustment factor would equal one. We use the adjustment factor in an iterative process to modify vehicle type choice probabilities. Maintaining one vehicle type as the reference alternative, its utility function remains the same and the re-calibrated vehicle type constant can be calculated using equation 1.

$$\beta_{0k_1}^{new} = \ln\left(F_{k_1,k_2}\right) + \beta_{0k_1}^{old} \qquad (1)$$

Where,

β_{0k}^{old}	= current ASC for vehicle type (k)
β_{0k}^{new}	= new ASC for vehicle type (k)
$F_{k1,\,k2}$	= adjustment factor

The new constant replaces the old constant in the utility function. If the adjustment factor is less than 1, the new constant will be smaller than the old constant to ensure that fewer tours/trips by this truck type are made. Conversely, if the adjustment factor ($F_{k1,\,k2}$) is greater than 1, the new constant will be larger than the old constant to ensure that more tours/trips by this truck type are made. After several iterations using this method, the adjustment factor ($F_{k1,\,k2}$) will converge to 1.

Results

Figure 3 presents the observed and modelled daily truck totals categorized by vehicle type for the original and adjusted model as well as the observed counts. The adjusted model now over-simulates the intermediate truck type by 4% compared to under-simulating by 77% for the original model. The adjusted model now over-simulates the medium truck type by 7% compared to over-simulating by 85% for the original model. Lastly, the adjusted model over-simulates the heavy truck type by 7% compared to over-simulating by 17% in the original model. The overall number of trucks being over-simulated in the adjusted model is 6% compared to 5% in the original model. This increase in total number of trucks is negligible and within an error of 10% from the observed counts.

The vehicle constant re-calibration procedure was successful in correcting the vehicle shares simulated by the model. Furthermore, the method was able to converge on a reasonable answer relatively quickly, needing only five model runs to achieve the desired results.

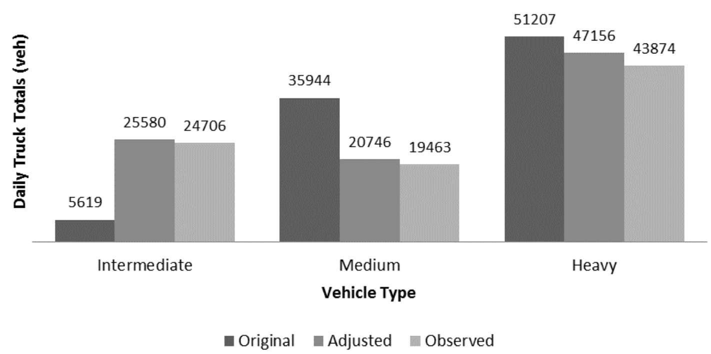

Figure 3: Observed vs. Modelled Counts by Vehicle Type

Table 2 is a summary of the comparison between the original and adjusted model performance for each time period and vehicle type. Table 2 presents the percentage of count locations where the original and adjusted models predicted the observed truck counts within an error of 40%. The adjusted model outperforms the original model in each category except in the AM period for medium trucks. Furthermore, the adjusted model makes the largest improvement in the intermediate truck type in each time period.

Table 2 demonstrates that the method was successful in correcting the vehicles shares and generating more intermediate truck trips. Furthermore, the method was able to bring the medium and heavy truck types into better correspondence with observed counts compared to the original model.

The calibration acceptance targets presented in Table 3 were used in this study to determine when to end the iterative re-calibration procedure.

Table 2: Percent of Count Locations for which Original and Adjusted Modelled Volumes are within 40% of Observed Volumes

Time Period	Vehicle Type	Original	Adjusted
AM	Intermediate	5%	55%
	Medium	55%	36%
	Heavy	50%	59%
PM	Intermediate	5%	86%
	Medium	32%	36%
	Heavy	41%	45%
OF	Intermediate	0%	82%
	Medium	27%	59%
	Heavy	55%	64%
24 Hour	Intermediate	0%	82%
	Medium	27%	55%
	Heavy	55%	68%

Table 3: Calibration Acceptance Targets

Measure	Target
Percent Error (Vehicle Type Distribution)	Less than or equal to 15%
Adjustment factor ($F_{k1, k2}$)	$0.95 \le F_{k1, k2} \le 1.05$
Percent of modelled volumes within 40% of observed counts	At least 50%

Table 4 presents the results of the final iteration of the re-calibration procedure.

Table 4: Re-calibration Acceptance Criteria Results

Measure	Target	Vehicle Type	Original	Adjusted
Sum of link volumes by vehicle type	Less than or equal to 15%	Intermediate	77%	4%
		Medium	85%	7%
		Heavy	17%	7%
Sum of link volumes	Less than or equal to 10%		5%	6%
Adjustment Factor ($F_{k1, k2}$)	$0.95 \leq F_{k1, k2} \leq 1.05$	Intermediate	-	1.007
		Medium	-	0.967
Percent of count locations where daily total model volumes within 40% of observed counts by vehicle type	Greater than or equal to 50% of locations	Intermediate	0%	82%
		Medium	25%	55%
		Heavy	55%	68%

The final iteration resulted in adjusted modelled volumes which showed an improvement over the original modelled volumes. The sum of link volumes by vehicle type is below the target value of 15% for all truck types and the sum of link volumes is also below the target value of 10%.

The adjustment factor $F_{k1, k2}$ is between 0.95 and 1.05 indicating that the ratio of total observed trips is nearly equal to the ratio of total modelled trips by one vehicle type another.

The percent of count locations within an error of 40% is greater than 50% for all vehicle types. This indicates that the adjusted model is able to predict more than half of count locations to within 40% of the observed counts. The largest improvement was observed for the intermediate and medium truck types. This was expected since the method was targeted to improve the shares of vehicle types according to the counts.

The goal of the re-calibration procedure was to increase the overall number of intermediate trucks generated and decrease the number of medium trucks generated to better match the distribution observed in the counts. The re-calibration procedure was successful in making the ASCs more positive for the intermediate truck type to facilitate more tours generated by this truck type and making the ASCs for the medium truck type less positive to decrease the number of tours generated. Since the heavy truck type was used as the reference vehicle type, its ASC remained unchanged.

Conclusions

The objective of this project was to improve the City of Edmonton's original commercial vehicle model developed in 2006 and calibrated to 2001 data with a cost effective approach by using new truck count data collected in 2012.

The Edmonton CVM has a complex model structure which was estimated using a large establishment-based survey collected in 2001. Since the original models that form the basis for the microsimulation of commercial vehicles are now outdated, the outcomes of the model do not reflect the current conditions on Edmonton's roadways. Since 2001, the Edmonton's land use, population, and employment have changed and grown. Due to these changes, the original model has shown poor correspondence to road counts conducted in 2012. The original model under-simulated intermediate trucks, over-simulated medium and heavy trucks, and were not able to predict most count locations within an error of 40% of the observed counts.

Since the original model was unable to reproduce the shares of vehicle types correctly, the method was focused on making improvements to the vehicle choice model. A novel approach was taken to adjust the vehicle type alternative specific constants in the vehicle choice model. The method utilized new road counts at 22 locations and the deviation between observed and modelled total daily truck volumes by vehicle type to adjust the alternative specific constants. The method improved model outcomes compared to the original model and showed close correspondence to observed values.

This research contributes to the literature on tour-based microsimulation of urban commercial vehicle movements by re-calibrating a commercial vehicle model using truck counts rather than simply matching high-level target values from a commodity flow survey (i.e. trip length, trips per tour). The adjusted model gives more reliable results for the study year. Furthermore, the method provides the user with an effective process for updating model parameters in future years when new road counts become available. This method also provides the City with a means to produce reliable truck volumes in the short term until a full commodity flow survey and full model re-estimation can be performed.

Although the method was able to make an improvement over the original model, the adjusted model continues to have shortcomings which are a result of the method's limitations. The method is limited to adjusting the alternative specific constants in the vehicle choice model. There is no mechanism to improve site specific count locations based on the deviation between observed and modelled volumes at the location. Furthermore, the method is highly dependent on the quality of the counts provided. In this research twenty-two locations were selected and the adjusted model has been calibrated based on the data provided for these select locations. Finally, this method is unable to calibrate light trucks since the provided counts did not capture this vehicle type.

As an extension to this research, the method presented can be further refined to address site specific issues. The method can be used to adjust constants in the next stop location model. This research is a short term solution – that utilizes available data that is relatively cost effective to collect – to improve the reliability of a model that is estimated and calibrated to outdated information. The larger solution to this problem would be to collect an updated establishment-based survey and re-estimate each component of the model structure. Furthermore, the newly estimated model should be validated using road counts unlike in the original development of the CVM.

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