THE DESIGN AND DEVELOPMENT OF LARGE-SCALE TRAFFIC ASSIGNMENT MODELS USING GEOGRAPHIC INFORMATION SYSTEMS

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Murtaza Haider, Ph.D.
School of Urban Planning
Department of Civil Engineering & Applied Mechanics
McGill University,
815 Sherbrooke St. West, Suite 403
Montreal, Quebec H3A 2K6
Tel: (514) 398-4079
Fax: (514) 398-8376
E-mail: murtaza.haider@mcgill.ca

Timothy Spurr
Department of Civil Engineering
McGill University
805 Sherbrooke St. W.
Montreal, Quebec,
Canada H3A 2K6
Tel: (514) 398-4079
Fax: (514) 398-8376
E-mail: timothy.spurr@mail.mcgill.ca

ABSTRACT

Traffic assignment models generate estimates for link-by-link travel flows and travel times. The output from these models is used in a variety of other transport models. In addition, transport infrastructure investment decisions are partly based on the output of these assignment models. Despite the critical role of traffic assignment models in transportation planning, operational details of large-scale (metropolitan-wide) traffic assignment models are seldom disclosed. For instance, the performance details of assignment models, such as the difference between the observed and forecasted travel volumes for various road types, are not widely available. Published research is even scarcer on how to design and develop new traffic assignment models. Only a handful of publications on design issues, such as how to delineate traffic analysis zones, what roads to include/exclude in the digital street network, or how to choose the appropriate volume-delay function are available.

This paper documents the development of a full-scale assignment model for the Greater Montreal Area using Geographic Information Systems (GIS). The digital street network developed for this model comprises 240,000 uni-directional links to replicate the entire street network in the study area. The assignment model has generated reliable traffic flows. This paper offers a detailed account of the methodology adapted for developing the full-scale model. This paper could serve as a reference for modelers who would like to refine or build new full-scale traffic assignment models. This paper concludes that GIS provide the quintessential platform to design and validate the traffic assignment models.

INTRODUCTION

Traffic assignment models constitute an integral part of the travel demand modeling framework. These models generate estimates for link-by-link travel flows and travel times. Conventionally, the assignments models are the last stage in the four-stage travel demand models. Lately, the assignment models inform land use models on accessibility in the integrated land use transport modeling frameworks. The output from the assignment models is instrumental in decisions regarding transport infrastructure investments, such as expanding road or transit networks, and in formulating transport policy, such as implanting tolls on bridges and freeways.

Despite the critical role of traffic assignment models in urban transportation planning, little research has been devoted to explain the performance of large-scale (metropolitan-wide) traffic assignment models. For instance, researchers and practitioners seldom disclose the accuracy of forecasts obtained from large-scale traffic assignment models. Similarly, the performance details of assignment models, such as the difference between the observed and forecasted travel volumes for various road types, are also not widely available. Published research is even scarcer on how to design and develop new traffic assignment models. Only a handful of publications on design issues, such as how to delineate traffic analysis zones, what roads to include/exclude in the digital street network, or how to choose the appropriate volume-delay function are available.

Traffic assignment models are available in numerous formulations. From a simple all-or-nothing formulation, which assigns all traffic between OD pairs to the shortest path, to more complicated dynamic formulations, traffic assignment models have evolved considerably over the past four decades. The fundamental principles behind the static models were defined by Waldrop (1), which were further refined by Frank and Wolfe and LeBlanc (2, 3). As the modeling techniques evolved, even probabilistic models of route choice were developed (4). However, probabilistic assignment models are not considered suitable for large congested networks (5).

More recently, dynamic traffic assignment models are becoming increasingly popular among researchers. Dynamic methods were first developed by Merchant and Nemhauser (6, 7). In the past three decades, dynamic models have been extensively researched and developed into complex mathematical formulations of route choices. Though dynamic models more adept at capturing the temporal distribution of choices and activities, these models, however, remain rather unworkable outside the theoretical settings because of concerns regarding tractability, extensive data and computational requirements (8). Recent availability of inexpensive but powerful computers has made it possible to run dynamic models for small networks.

Meanwhile, static models are criticized for inadequate representation of utility-maximization theory and for being unable to handle situations where the travel demand exceeds road capacity or where congestion is not continuous (9). Dynamic models are superior in operationalizing traffic flow theory; however direct comparisons of operational results of dynamic models with static models are rare (10, 11). Furthermore, metropolitan-level dynamic models based on detail street network are also far and few between. Therefore, large-scale traffic assignment models are often static in nature (12, 13, 14, 15).

GIS have revolutionized the way spatial data are collected, stored, manipulated, and used for modeling. GIS offer solutions to problems in transport modeling, including the modifiable areal unit problem (MAUP), boundary problems and spatial sampling, spatial dependency and spatial heterogeneity (16). Similarly, GIS mitigate problems inherent in delineation of TAZs and can be used to construct highly detailed transportation networks. Furthermore, GIS generate easily-decipherable visual output (17). Also, GIS interface is user-friendly and it greatly reduces time and money costs incurred in constructing transportation planning modules (18, 19). Finally, as the modeling practice becomes increasingly concerned with spatial and temporal disaggregation, GIS will play an ever more important role in spatial modeling (20).

Guidelines for designing new traffic assignment models are not readily available. Brief guidelines for delineating TAZs are available in textbooks or software manuals (21, 22, 23, 24 25). However, these guidelines are generic in nature and do not address the fundamental concerns about statistical biases that may result from spatial autocorrelation and MAUP.

The other major concern in designing new assignment models is how to determine an appropriate degree of detail in the digital street network. Again, only a handful of guidelines are available (26). Research has shown that increasing network detail and decreasing TAZ size indeed generate superior results, although the marginal improvement declines with further disaggregation (27). While other research has shown that model outputs are more sensitive to zonal disaggregation than network detail (28). Similarly, some guidelines are available on validating a traffic assignment model using certain quantifiable benchmarks for acceptable model performance (29).

This paper documents the design, development, and calibration of a large-scale traffic (automobile) assignment model for the Greater Montreal Area (GMA). The paper presents a detailed account of the design considerations in developing large scale assignment models. For instance, the process of simulating link-by-link traffic on a 240,000 uni-directional link network is explained. Furthermore, the paper offers a detailed account of calibration of the traffic assignment model.

Geographic Information Systems (GIS) were adapted for data storage & manipulation, delineation of TAZs, design of the digital street network, simulation and subsequent calibration of static traffic assignment models. This paper argues that GIS provide the quintessential tools to design and develop large scale traffic assignment models. In fact, GIS made it possible to approximate the real street network in the GMA in a highly disaggregate digital street network. Furthermore, GIS enables a flexible regime to delineate TAZs, which permits computing origin-destination (OD) matrices to any desired level of spatial disaggregation.

METHODOLOGY

The development of a large scale traffic assignment model for the Greater Montreal Area (GMA) addresses numerous design issues related to defining the study area, delineating TAZs, devising the detailed digital street network, assigning attributes to digital links, simulating traffic and finally validating the model. This research used GIS-based street network maps and a geo-coded OD database as the primary building blocks for the traffic assignment model. GIS were used further to delineate TAZs and later in the ongoing process of calibrating the model.

The study area comprises of the three Census Metropolitan Areas (CMAs), namely Montreal (population: 3,426,350), St-Jean-sur-Richelieu (population: 79,600), and Salaberry-de-Valleyfield (population: 39,028). Travel flows between Montreal CMA and the two neighboring CMAs dictated the need to expand the study area beyond Montreal. According to the 2001 census, the study area covers a total of 4,500 square kilometers with a gross population density of 790 persons per square kilometer. It should be noted that the population density for the Municipality of Montreal (a subset of the Montreal CMA with a population of 1.04 million) is much higher at 6,000 persons per square kilometer (30).

This study used TransCAD ® software, produced by Caliper Corporation, to develop the traffic assignment model. The methods presented in this section could be followed in any commercially available travel demand modeling software that is GIS-enabled or could be linked to a stand alone GIS package.

OD and Counts Data

The travel behavior data used in this study has been extracted from the origin-destination survey, which was conducted in the fall of 1998. The regional transportation authority, the Agence Metropolitaine de Transport (AMT) and the Quebec's Ministry of Transport (MTQ) administered the survey. Some 65,000 households containing 164,000 individuals, which correspond to a five percent sample of the population in the study area, were surveyed. These households recorded nearly 385,000 non-weighted trips during a 24-hour period (31, 31, 32). This study models trips made between 6:00 and 9:00 am. The study area depicting trip densities for the morning peak period is presented in Figure 1.

MTQ also provided the traffic counts data, which were used to validate the traffic assignment model. MTQ conducted traffic counts in the fall of 1998 and recorded traffic flows of automobiles and light trucks at 197 locations in the study area in half hour intervals between 6:00 am and 9:30 am.

Developing the Digital Street Network

The conventional modeling approach in a non-GIS environment has been to digitize paper-based engineering drawings. Thus traffic assignment models developed in non-GIS platforms, such as EMME/2, follow this convention. This process is very tedious, costly, and time consuming. Therefore, the non-GIS traffic assignment models only employ a skeleton digital street network to approximate the true street network. The time and money costs for coding the entire street network for large metropolitan areas have proven prohibitive even for large government organizations. In addition, updating networks in a non-GIS environment is equally cumbersome and the task becomes even more onerous for very detailed networks. More often than not, such updates are not performed regularly.

GIS are quite capable of addressing the above-mentioned shortcomings. In fact, the strength of a GIS-based approach is realized in its fullest while developing the digital street network. For almost all jurisdictions in North America and Western Europe, digital street network files are readily available from the government agencies or the private sector. Even in developing countries, such as India and Pakistan, digitized street networks are now available for major metropolitan areas. The digital street network becomes a ready input into the assignment model, which eliminates the need to digitize paper-based street maps.

This research relied on a commercially available digitized street network to base its traffic assignment model. DMTI Spatial Ltd. supplied a digital street network for the study area. This detailed and geometrically accurate network displayed every street, as well as other rights-of-way such as ferry routes, walking paths, cycling trails and some alleys. The tabular record associated with each link contained, among other attributes, road segment length, legislated speed, street name and the street's functional class (34). This street network map contained 134,954 non-directional (one- or two-way) links. The distribution of links by functional class is shown in Table 1.

Free-flow travel time was also computed based upon the link's length and the legislated speed. In addition, lane capacities (measured in passenger cars per hour per lane (pcphpl) and corresponding to level-of-service E) were assigned to each link based on the link's functional class. Horowitz (1991) recommends using the maximum link capacity corresponding to level of service E for optimal performance of the Bureau of Public Roads (BPR) volume-delay function (35). The study used Horowitz's guidelines and later modified link capacities after comparing results with observed counts (36).

The BPR volume-delay function has two parameters, alpha and beta, which vary between segments according to the links' functional class and the free flow speed. Global values of alpha equal to 0.6 and beta equal to 2 were used in the model. These values were later changed by link classification during model validation.

It is preferable to have estimates of intersection delays. In addition, the absolute delay values are less important than their relative values. Generally, right turn an intersection carries fewer delays than a left turn. Meanwhile, U-turns are usually illegal and even if they are permitted they are difficult to undertake in heavy traffic. Therefore, a penalty of 0.5 minutes (30 seconds) was applied to all left turning movements. Right turns received a global penalty of 0.2 minutes (12 seconds) and straight movements through intersections were assigned a delay of 0.05 minutes (3 seconds). U-turns were prohibited.

Centroid connectors were then created to link the zone's centroid to the street network. This process is automated in transportation GIS software, such as TransCAD. However, centroid connectors should be re-examined to ensure that the zone centroids are connected to the actual street network in a logical manner. To reduce the likelihood of U-turns being required to enter or leave the road network, two connectors per centroid were specified. The road density was sufficiently high that no limit needed to be set on centroid connector length.

The speed for centroid connectors was set at 40 km/h – the same as for local streets. The travel time over the link was computed by dividing the link length the fixed speed. Finally, each centroid connector was assigned a capacity of 99,999 vehicles per hour since congestion delays should not occur on fictional links.

Delineation of Traffic Analysis Zones

The Canadian Census geography demarcates CMAs into finer spatial units, such as Census Tracts (CT) and Dissemination Areas (DA). On average, a CT contains 2,000 to 8,000 individuals whereas a DA contains approximately a few hundred individuals. TAZs in the Montreal CMA were initially based on CTs, while DAs were used as TAZs in the CMAs of Saint-Jean-Iberville and Salaberry-de-Valleyfield. The following criteria were adapted for devising the zonal system.

1. The zonal system must be mutually exclusive and collectively exhaustive.
2. The zonal system must respect the boundaries of existing census tracts and dissemination areas. This condition was imposed in order to facilitate linkages between OD data and demographic data obtained from the census.
3. Trips must be distributed evenly throughout zones. Zones generating or attracting exceptionally large numbers of trips result in large assignment errors because trips whose ends in reality are distributed throughout the zone are directed to the zone's centroid.
4. While a spatially disaggregate zonal system is preferred, the disaggregation should be done with caution because a very disaggregate zone will result in a sparse OD matrix. For instance, when we divided the study are into 10,000 zones, the resulting OD matrix contained 100 million cells of which only 0.4% were populated for a 24-hour assignment routine.

Under the initially devised TAZ system comprising 873 zones, the average number of trips attracted was 8,935 trips and the standard deviation was 7,039 trips. The zonal system was further disaggregated to deal with zones attracting very large number of trips during the morning peak period. For instance, the zone representing the Central Business District (CBD) attracted 55,718 trips, which are approximately six standard deviations higher than the mean number of trips.

The concentration of a large number of trips would result in assignment errors because these trips will be directed to the centroid of the zone. GIS provide an efficient platform to deal with this problem. A spatial clustering routine was used to disaggregate trips into smaller zones. The procedure is as follows. First, the original census tract layer was superimposed over the point layer of trip destinations. Second, zones with high concentration of trips were selected. Third, Euclidean distances were calculated between all destinations within a zone and distances were stored in a matrix. The clustering tool used this matrix to group trip ends together into a user-specified number of clusters, which were color-coded. These zones were then sub-divided based on visual inspection of clusters within each zone. An example is presented in Figure 2. The original zone boundaries are thick lines whereas new zone boundaries (drawn by hand) are thin lines. The new zones, if merged, will again correspond exactly to their parent census tract. Zones containing large trip generators, such as shopping malls, universities, colleges and office towers, were disaggregated with this method.

The CMA of Salaberry-de-Valleyfield was subdivided into dissemination areas, which were found to be too small to generate a significant number of trips. Some of them were merged together in order to produce sufficiently large zones with due consideration for the distribution of trip ends and the layout of the road network.

The final zone system contained 947 zones with a corresponding O-D matrix comprising 896,809 cells. The mean number of trips attracted was 8,417 and the standard deviation was 4,549. The maximum number of trips attracted to a zone was 23,839, roughly three standard deviations from the mean.

Construction of Origin-Destination Matrices

For the AM peak automobile traffic model, only trips made by cars whose departure time were between 5:59 am and 8:59 am were extracted from the database. These trips were in turn separated, based on the stated departure time, into the three hours that make up the AM peak period: 6:00-6:59, 7:00-7:59 and 8:00 to 8:59. A separate O-D matrix was estimated for each hour segment corresponding to the zone system described above. Each trip record was accompanied by an expansion factor to elate the sampled trip to the underlying population. The OD matrices were in fact estimated by summing up the expansion factors.

In order to account for external trips, which either originate or terminate outside the study area but still use the road network within the study area, 34 external trip generators and receptors were also created. These trips cannot be accounted for in the OD matrix and hence need to be treated separately.

One of the strengths of GIS-based assignment modeling is that zone systems can be modified and improved in an efficient manner. In addition, the resulting OD matrix, which is based on the zone system, can also be readily computed. The process of assigning each trip to an origin and destination zone and then computing the OD matrix is a straightforward, one “click” operation in most GIS software designed for transport modeling.

The Traffic Assignment Model

This study applies the deterministic user-equilibrium algorithms for traffic assignment models. The present model uses the standard BPR function to describe the relationship between link volumes and travel times. The algorithm is iterative and approaches the optimal solution incrementally.

The models were estimated using a Pentium IV processor with 500 megabytes of Random Access Memory. A single iteration took four to five minutes and the number of iterations required to reach convergence varied between five and 12 iterations, depending upon the travel demand during the hour.

Techniques Used To Evaluate Model Performance

The use of GIS facilitates visual display of the forecasted traffic flows and other statistics, such as volume to capacity ratio. The visual inspection of traffic flows is extremely useful in detecting errors in the model. The link-by-link colour coded output is a valuable tool for a modeller, who is familiar with the study area, to detect anomalies. Statistical measures used to estimate the model fit are presented below.

This study introduced a 30-minute lag to compare the observed counts with the forecasted counts. For instance, flows generated by the 6:00 am to 6:59 am matrix were compared to counts observed between 6:30 am and 7:30 am. This time lag was deemed necessary to account for the delay between the stated departure time, and the time when the trip maker crosses the link where observed counts were taken. This methodology may not be ideal to account for the temporal delay between the trip start time and when the trip maker traverses through the observation point. However, repeated simulations revealed that the correlations between predicted and observed flows were consistently higher when the time lag was accounted for during validation.

The following statistics were used for model validation. The percentage error is the difference between observed and predicted counts divided by the observed counts. The percent root mean squared error (% RMSE) is expressed as follows:

$$\%RMSE = \frac{\sum_j \frac{(x_j - y_j)^2}{\sqrt{n-1}}}{\frac{\sum_j y_j}{n}} * 100$$

Where x_j is the forecasted flow at link *j*, y_j is the observed flow at link *j*, and *n* is the number of links. This is an aggregate statistic that measures the performance of the model. The U.S. Department of Transportation's Travel Model Improvement program recommends a %RMSE of less than 30 (29). Finally, a linear regression model was employed to measure the correlation between forecasts and counts. Ideally, the intercept of the linear function should be zero and the slope of the line should approach 1. The USDOT recommends a region-wide R-squared of at least 88% (29).

MODEL RESULTS

The traffic assignment model simulates traffic on each and every link in the actual road network. This full-scale modeling approach is inherently different from the conventional approach where traffic is simulated on a skeleton network comprising of freeways and major arterials. The ability to simulate traffic on small arterials allows efficient coupling of assignment models with spatially disaggregate land use models. The development of this highly disaggregate traffic assignment model, comprising of 130,000 bi-directional links, was made possible by the use of GIS in all development stages of the model.

The output from the assignment model is presented in Figure 3, which depicts a color-thematic map of volume-to-capacity ratios for the segment of the network covering parts of Island of Montreal (CBD) and Longueuil neighborhood on the South Shore. The Island of Montreal is to the left and South Shore is to the right on the map. Also visible in the map are the three bridges. Champlain Bridge is at the bottom, Victoria Bridge is in the middle and Jacques-Cartier Bridge is at the top of the map. The map legend explains that the thickness of the link represents traffic flow and the color represents the intensity of traffic.

Champlain Bridge at the bottom of the figure represents the two-way flow of traffic. Since the simulated traffic is for the morning peak period, traffic flow from South Shore to Montreal CBD on the island is higher than the flow in the reverse direction. It is interesting to note that Montreal CBD-bound flow on Champlain Bridge is higher than the flow on Victoria Bridge in the same direction. However, the red-color depicting the flow on Victoria Bridge suggests that even with relatively lower traffic volume, the flow is relatively more congested on Victoria Bridge than the flow on Champlain Bridge.

The network loadings and average simulated trip characteristics corresponding to the three OD matrices are presented in Table 2. In the first hour corresponding to the period 6:00 to 6:59 AM the travel demand is around 194,000 trips. The demand reaches a peak in the next hour at 378,000 trips. In the third hour, covering the period 8:00 am to 8:59 am, the travel demand declines to 352,700 trips. The total travel demand for the three-hour morning peak period is around 925,000 trips.

The forecasted trip characteristics reveal that the average trip distances and travel times are the highest for the first hour and then they decline for the second and third hour. It appears that trip-makers with larger trip distances leave early in the morning (between 6:00 and 6:59 AM) to avoid traffic congestion and those with shorter trip distances leave in the second and third hour, during 8:00 and 8:59 AM. The shorter trip distances in the third hour also correspond to the highest percentage of intra-zonal trips. Because of the highest travel demand during 7:00 and 7:59 AM, the average speed is also the lowest for this period.

The highest forecasted average trip time is 22 minutes, which may be lower than the actual travel times. These under-predictions are in fact typical of the deterministic user-equilibrium models because of their underlying assumption that trip makers have perfect knowledge about routes and therefore they choose the route that minimizes their travel time. In reality, drivers do not have perfect information and minimal travel time may not be the sole consideration in route choice (4, p.85).

The change in trip distances and travel times has some relation with the trip purposes, which also change considerably between the three modeled hours (Table 2). In the initial hour starting at 6:00 AM, 80% trips were work (commute) trips, which declined to 57% in the third hour starting at 8:00 AM. Similarly other trip purposes, such as school and shopping trips purposes increase significantly in the second and third hour. The higher percentage of work trips in the first hour and large number of non-work trips in the subsequent hours suggest that workers commute for longer distances while trips undertaken for non-work purposes are of relatively short distances during the morning peak periods. The distribution of trip lengths for the three peak hours is presented in Figure 4, which shows that the percentage of short trips (less than 10 km) increases from 35% in the first hour to 63% in the third hour.

The model performance varies slightly between the three simulations for the corresponding hours. The techniques used to evaluate model performance have been discussed earlier in the methodology section. The R-squared for the regression model regresses the observed counts over the forecasted counts for links with available observed traffic counts. The value for R-squared varies between 82 and 87% (Table 2). The overall fit for the regression model for the three hour counts taken together is 88% and the %RMSE is 30.3%. These statistics satisfy the minimum thresholds suggested in the literature (29).

The first hour forecasts traffic flows 15% below the observed flows on the selected links (Table 2). The forecasted flows are nearly 6% higher than the observed values in the second hour. Whereas in the third hour, the forecasted flows are yet again 2.5% less than the observed flows. The missing forecasted trips between 6:00 and 6:59 AM are being investigated at the moment. However, the “excess” traffic forecasted between 7:00 and 7:59 AM may be due to the inability of the static equilibrium model to cope with queues. During the second peak hour, numerous arterials experience demand well above their capacity resulting in queue formation upstream of the link and forced flow on the link itself. The static model cannot deal with either of these phenomena. The flow continues to appear on links even though the absolute capacity has been reached. The static model, however, performs well when all three hours are taken together where the model under predicts trips by only 3%.

Table 3 presents the average link speeds and volume to capacity ratios for different road types. The data reinforce some of the general trends outlined earlier. For instance, travel demand is the lowest between 6:00 and 6:59 AM. As such, the link volumes tend to be low and speeds are closer to free flow speeds during the same time period. However, the average volume to capacity (v-c) ratio exceeds 0.5 for all road classes except primary and secondary highways, and arterial roads. This is due in part to the fact that freeways that extend to the edge of the study area are loaded by external trip-generator nodes.

As travel demand increases during the second hour (7:00 to 7:59 AM), v-c ratios rise and speeds drop (Table 3). Average speeds on most link classes appear reasonable although data to verify this are not currently available. The simulated average speed on arterial roads may be too high, but it does not account for global movement delays imposed at every node. All link types, except for primary highways, depict volume to capacity ratios above 0.5. Former provincial highways converted to arterial roads return the highest average v-c ratio, followed closely be freeways. This is indicative of the concentration of traffic on high-capacity links. Arterials converted from provincial highways (Carto 50) return a higher v-c ratio than other arterials (Carto 4) because the former are located exclusively in high density city environments. Many regular arterials are dispersed throughout the surrounding hinterland as well as in the urban agglomerations and so their average V-C ratio is lower. Finally as the demand subsides in the last hour (8:00 and 8:59 AM), v-c ratios drop to levels comparable to those observed in the first hour.

Other guidelines for assessing modal fit suggest that a link carrying 8,000 vehicles per hour should have a forecasted volume within 10% of observed levels (37). Similarly, for a link carrying 2,000 vehicles per hour, a 30% error is acceptable. Link volumes in between these two values may be interpolated linearly. When this approach is applied to the 165 links with observed traffic counts, 139 links were found to be within acceptable range.

MODEL VALIDATION

Model validation involved detecting errors in the network, OD matrix, and the like in an iterative manner. The same procedure was repeated for simulating traffic in the three one hour slices. Table 4 presents results for the 12 iterations for the first hour (6:00 to 6:59 AM) only. In trial 1, the %RMSE was 49.5% and the r-squared was 0.82. By the 12th trial, the %RMSE had been reduced to 37.8% and the R-squared increased to 0.88. Note that the size of the improvement increment varies significantly between trials.

The model performance improved significantly with the modifications to the BPR parameters, alpha and beta (trial 5). The second most important element was the addition of external trips and their distribution throughout the region. This process reduced the % Error in trials 5 and 6. Individual link capacities were adjusted in all 12 trials in addition to other model improvements. Therefore, it is difficult to isolate the impact of adjustments to link capacities on model performance. Similarly, it is difficult to discern the importance of small measures, such as the addition or elimination of erroneous turning restrictions, which were made along with other major changes.

The marginal increase in model performance declined as the model performance levels improved. For example, trial 5 displayed a decrease in the %RMSE of over 10 percentage points from trial 4. A seven point decrease occurs between trials 7 and 8. However, subsequent decline in %RMSE was around 2 or 3 percentage points.

DISCUSSION

The validation of traffic assignment models is an ongoing process. The model is being continuously refined as new data on traffic counts or network/intersection details become available. Numerous methodological and other shortcomings were discovered during model design and validation. First, the zone system is not optimal. Many large zones still generate a large number of trips. The zone system is being modified to dissect large zones into smaller spatial units. More work is needed on defining the optimal zone system or to do away with the TAZ approach and assign trips to the network using actual trip origins and destinations.

Second, the method of connecting TAZs to the network is being modified. The conventional approach has been to connect the centroid of a TAZ with the street network. Instead, the connection point should be determined by the land use pattern and the location of transportation infrastructure within a zone.

Third, the automatic generation of centroid connectors increases the likelihood of unrealistic distribution of demand. The connectors are being redrawn with due consideration for the connector length (which should be minimized) and the location of the connecting nodes in the actual street network. However, the goal for the future versions of this model is to do away with centroids and centroid connectors entirely and adopt a completely disaggregate approach. This process involves the elimination of the O-D matrix and the assignment of individual trips using their actual locations for origin and destination rather than using the centroids of the TAZs.

Fourth, the link capacity indicated in the BPR function is the absolute maximum flow that can pass over the link. Additional demand will result in forced flow. The BPR function cannot restrict flow from being assigned to a link even when the capacity has been exceeded. Traffic speed on the link declines, but link flow continues to increase. In reality, the unmet link demand results in queue formation upstream of the link.

CONCLUSIONS

The traffic assignment model described in this paper builds a full scale model of the street network in the Greater Montreal Area. The model successfully simulates traffic on all streets comprising the actual road network. The use of GIS has allowed for an efficient, inexpensive development of a detailed and geographically accurate road network.

The traffic assignment model developed in this study will be linked to a land use model to capture the interdependencies between accessibility and land use. The highly disaggregate nature of this model allows linking the output of travel demand models with the land use models at a spatially disaggregate level. This will fill the gap in the modeling practice where researchers have focused on disaggregating the land use models to parcel size level, while the assignment models are still based on skeleton street networks. The use of detailed street networks will make it possible to capture the heterogeneity in accessibility within a TAZ.

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LIST OF TABLES AND FIGURES

Table 1 Montreal Network Links by Functional Class Before Modifications

Cartography designation	Functional class	Count	Length	Speed limit
1	Freeway	5473	2148.15	100
2	Primary highway	4217	1089.84	80
3	Secondary highway	3567	1282.81	60
3	Ramps	48	6.81	50
4	Arterial road	14410	2673.37	60
4	Ramps	513	64.24	50
5	Local road	102189	20237.61	50
6	Trail	4496	1022.36	10
20	Ferry route	16	89.49	10
21	Ferry ramp	23	2.33	10
	TOTAL	134952	28617.01	

Table 2 Performance of AM Peak Hour Models

			Trip characteristics			Trip Purpose				Model Performance		
Hour	Total trips	% Intra-zonal trips	Minutes	Kilo-metres	Avg. Speed	Work Trips (%)	School Trips (%)	Shopping Trips (%)	Other (%)	R-squared	% RMSE	% Error
6:00 to 6:59 am	193,559	7.6	22.4	21.1	56.3	79.7	1.6	0.4	18.4	86.9%	35.9%	-15.2%
7:00 to 7:59 am	378,600	8.8	20.1	16.6	49.7	67.9	4.4	1.2	26.8	83.1%	36.5%	6.2%
8:00 to 8:59 am	352,772	11.4	14.2	13.5	57.2	56.6	4.3	5.2	36.1	82%	35.3%	-2.5%
AM Peak (all 3 hours)	924,932	9.6	18.4	16.4	53.6					87.6%	30.3%	-3.3%

Table 3 Link Performance by Functional Class

				0600-0659		0700-0759		0800-0859	
Functional Class	Carto	Count	Length (km)	AB Speed by AB Flow	AB volume-capacity ratio	AB Speed by AB Flow	AB volume-capacity ratio	AB Speed by AB Flow	AB volume-capacity ratio
Freeway	1	3111	1568.84	82.29	0.62	76.28	0.73	87.51	0.56
Primary highway	2	2190	812.15	76.39	0.23	73.74	0.33	76.69	0.23
Secondary highway	3	4076	1360.91	51.21	0.41	49.00	0.51	53.67	0.32
Arterial Roads	4	15111	2674.33	45.87	0.34	42.07	0.53	44.78	0.40
Local Roads	5	102964	20245.97	34.10	0.51	32.35	0.63	33.69	0.54
Arterial provincial highways (formerly Carto=2)	50	1294	157.76	42.00	0.61	39.76	0.75	46.08	0.48
Ramps	51	3358	704.52	42.69	0.57	39.72	0.66	43.90	0.53
Centroid connectors	100	1894	319.28	40.00	0.00	40.00	0.00	40.00	0.00

Table 4 Changes in Model Performance Over Successive Trials

Trial	R-squared	% RMSE	% Error
6:00 – 6:59 AM			
1	0.8178	49.45086	-13.33778248
2	0.8187	49.56457	-13.39477752
3	0.8239	49.09624	-13.47378833
4	0.8094	52.07972	-13.50189539
5	0.8724	40.03511	-6.161721561
6	0.8728	38.5982	-8.762521381
7	0.8719	44.67398	-10.95417657
8	0.8753	37.85573	-9.285062388
9	0.8751	37.87904	-11.42500772
10	0.8755	38.52175	-11.1218334
11	0.871	38.82136	-13.68288967
12	0.8788	37.79538	-14.59235797

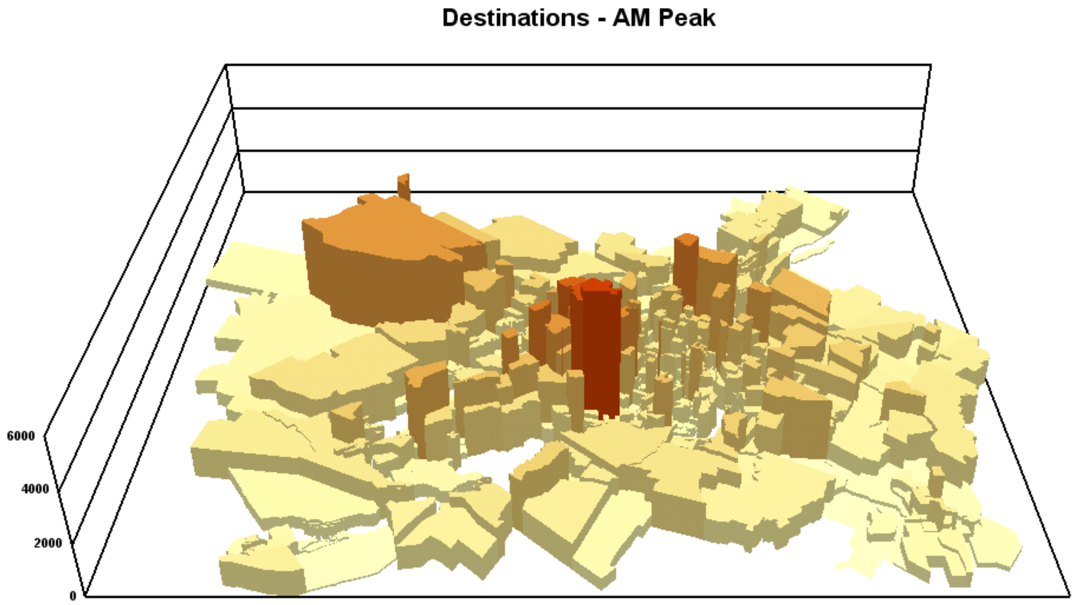


Figure 1 Number of Trips Attracted To Each Zone Between 08:00 And 08:59 AM

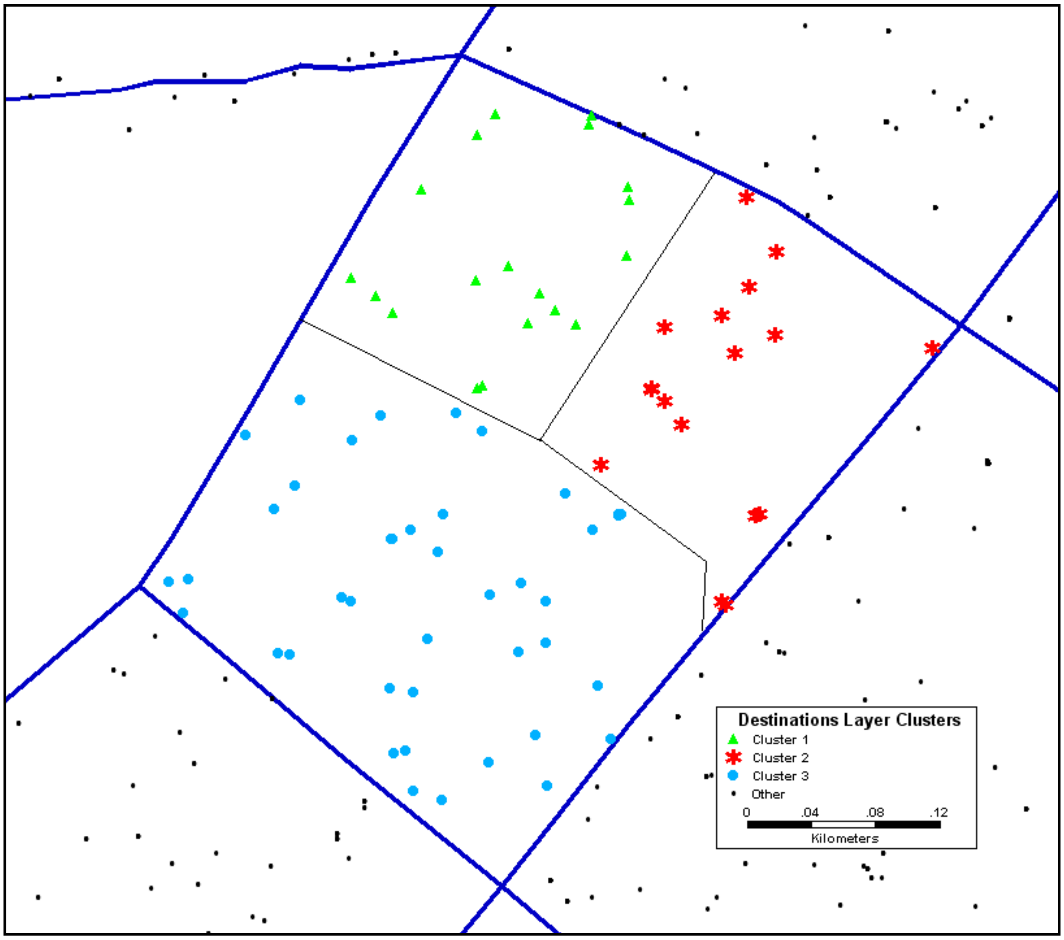


Figure 2 Destination Clusters Appear As Different-Shapes Points

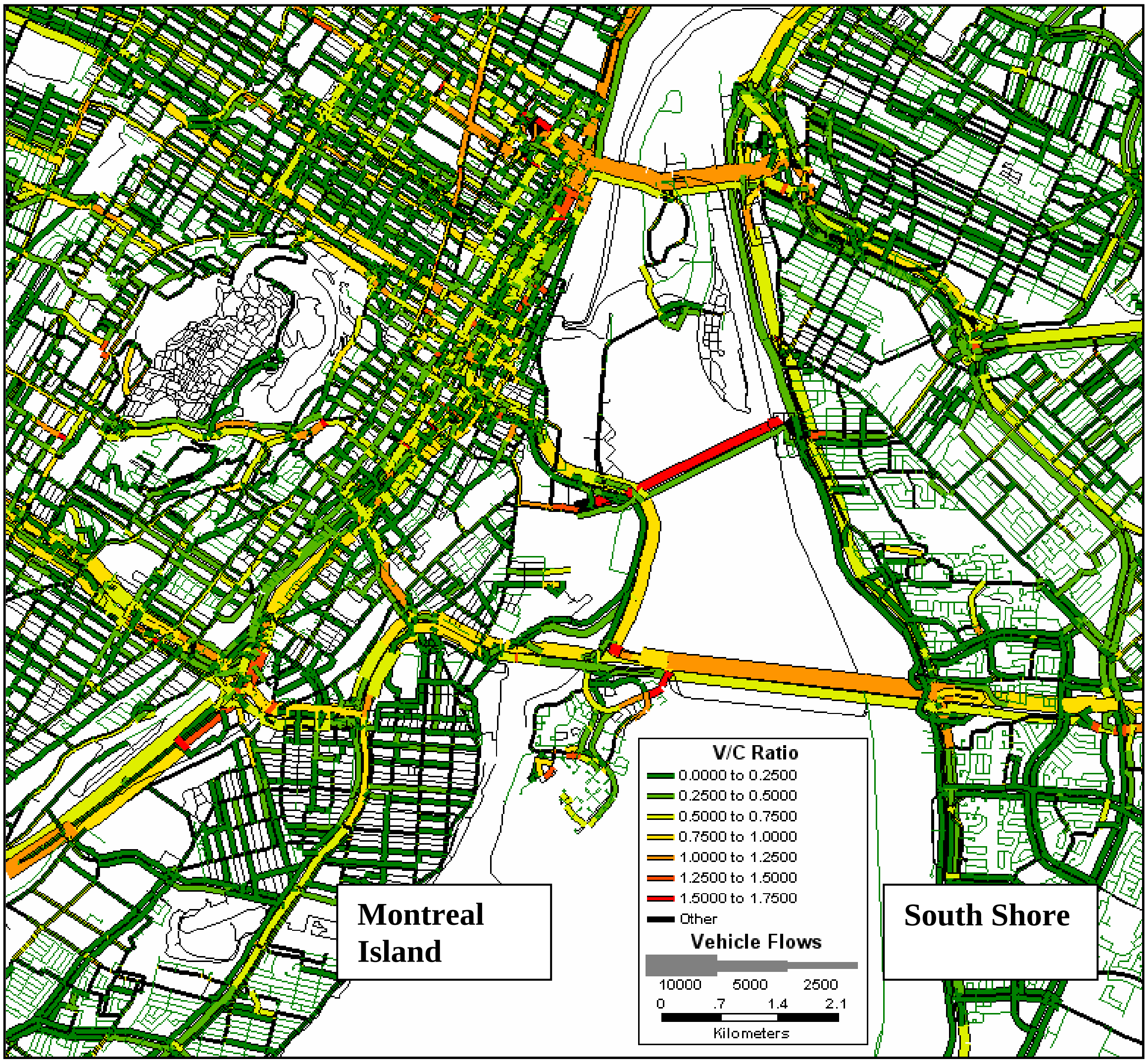
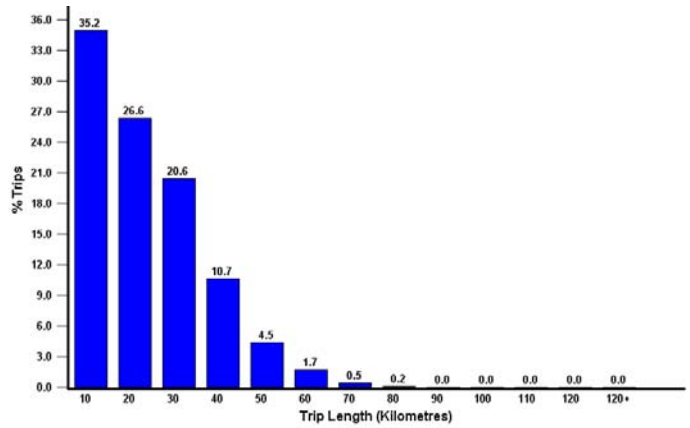
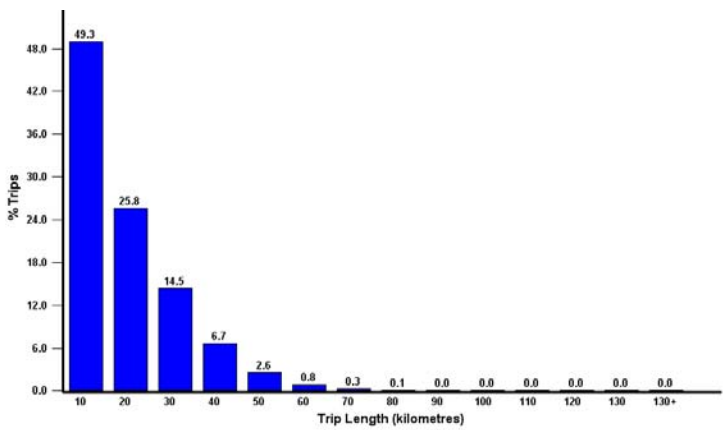


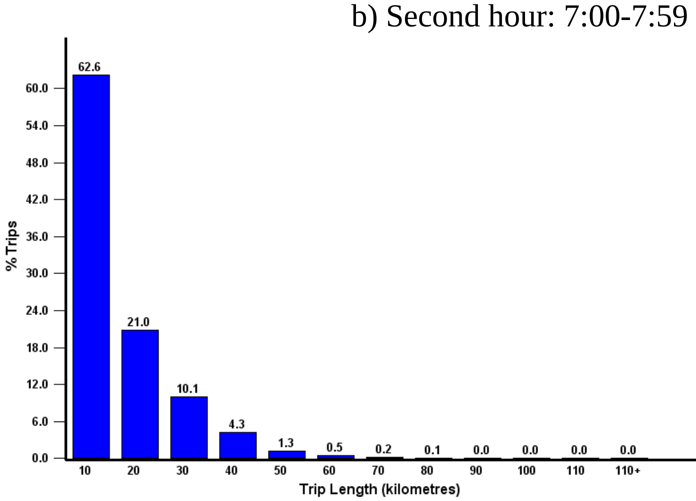
Figure 3 Color-Thematic Map of Volume to Capacity Ratios Displayed For Each Link



a) First hour: 6:00-6:59 AM



b) Second hour: 7:00-7:59 AM



c) Third hour: 8:00-8:59 AM

Figure 4 Trip Length (In Kilometres) Frequency Distributions