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GIS-based travel demand modeling for estimating traffic on low-class roads

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Traffic count data are useful for many purposes, but often not available for significant portions of road networks. It would be prohibitive to cover all roads with traditional sensor-based traffic monitoring system, particularly for rural, low-class roads. In cases where traffic volumes are needed but unavailable, travel demand models (TDMs) can be used to estimate such information. A literature review indicates that research work for estimating traffic volumes for low-class roads using TDM is scarce. The majority of previous research used traffic count data-based regressions. The problem of such an approach is that it relies on available traffic counts to develop, calibrate, and validate regression models. Nevertheless, few or no traffic counts are collected on low-class roads, and therefore make it inapplicable. This study implements TDMs for two regions in the province of New Brunswick, Canada to estimate traffic volumes for low-class roads. Geographical Information System-based TDMs using census data and Institute of Transportation Engineers (ITE) Quick Response Method produce forecasted traffic for a significant portion of road network previously without any traffic information and limit the average estimation errors for low-class roads to less than 40%. Available traffic data were increased by 45% in York County and 144% in the Beresford area. The traffic estimation errors are comparable to or better than those reported in the literature, and the forecast traffic volumes provide a solid foundation for identifying high-volume road segments and prioritizing funding. Study results clearly show TDM is a practical, useful, cost-effective way for estimating traffic parameters on low-class roads.

Keywords: traffic counts; travel demand modeling; forecasting; GIS; low-class roads

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Introduction

Like many others, the traffic monitoring program in the Canadian Province of New Brunswick has traditionally focused on the higher functional class highway system (collector and above). There are limited traffic volume statistics available for low-class local highways. Low-class highways account for the majority (65% or more) of system kilometers in the province. Although it is not practical to establish regular traffic count sites along the lower class roads, it is important to establish traffic estimates or traffic volume ranges for these highway segments especially in the context of the asset management initiative.

An alternative to the installation of new traffic counters on low-class roads is to estimate traffic volumes via a travel demand model (TDM). Development information and socioeconomic data could be used in conjunction with established trip generation techniques to estimate travel demand among different zones in a region. The travel demand is assigned to different routes, which in turn is used to estimate traffic volumes for highway segments.

Our literature review indicates that there is limited research of applying TDMs for estimating traffic volume on low-class roads. Highway agencies usually collect very limited data on low-class roads. Some studies use regression techniques to estimate travel demand based on the socioeconomic characteristics of adjacent land use and the distance to higher functional class roads (e.g. arterials), and they show varying degrees of success. A few studies investigated the possibility of using TDMs to estimate traffic volumes, but most have focused on higher functional classes. This paper reports the study results of using TDM to estimate traffic volumes on low-class roads in the Province of New Brunswick, Canada.

Literature review

This section details the issues related to traffic volume estimation on lowclass and low-volume roads. Traffic data collection practices for low-volume/ low-class roads are briefly reviewed. Various studies were profiled to review the state-of-the-art in the areas of traffic estimation for these roads.

Traffic data collection practices for low-volume low-class roads

Traffic count data are extremely useful in many applications, particularly in asset management. Most jurisdictions assign traffic volumes to roads based on sample counts from adjacent areas or those for a particular road class. Actual count data are often not available for large portions of the network. In the case of low-class/low-volume roads, traffic count data are almost non-existent (Seaver *et al.* 2000).

A literature review of traffic count collection practice in the USA, Canada, and Australia indicates that sensor-based traffic monitoring activities on low-class roads in general are very limited (Hanson 2007) and that low-class road traffic counting practices vary widely among highway agencies. How effectively these roads are managed depends on two factors: the current state of the asset management program and the amount of funding available. This is largely constrained by available resources. The practitioners call for obtaining traffic information for low-class roads via another cheaper and more efficient way (NBDOT 2006). This study tries to use TDM for estimating traffic along these roads.

Estimating traffic summary statistics for low-class roads with traffic count data-based regression

Most annual average daily traffic (AADT) estimates in research are made using a short-term traffic count and either a factor method or a more advanced method, such as neural networks (Sharma *et al.* 2000). Literature on estimating AADT for roads that do not have traffic counts is limited (Zhao and Chung 2001). In most cases they are low-class roads and thus not included in traffic counting programs. The few attempts that have been made use traffic count data-based regression techniques show varying degrees of success. They are outlined as follows.

Seaver et al. (2000) was the only study that looked at estimating traffic volume specifically on rural local roads. The study was based on very detailed data; various combinations of 45 variables (typically 7-8 for each stratum) were used in the analysis. Initial results were not very good for rural roads within or outside metropolitan statistical areas (MSAs), indicating that additional subgroups may be needed within each road type. Regression clustering on rural paved roads outside MSAs yielded three strata. Models for each one had R^2 values of at least 0.90 and a predictive R^2 of at least 0.74. The regression models for the two strata within MSAs had an R^2 of 0.80–0.93 and a predictive R^2 of 0.57–0.61. The study concluded that it is possible to mathematically model traffic volumes on low-volume roads. However, their study aimed to estimate traffic volume for certain road groups or subgroups. It did not address the volume variations within a group and thus not useful from asset management point of view. In addition, no estimation errors were reported and only R^2 were used as indications of modeling accuracy.

A study at Purdue University, Indiana, developed a multiple regression method using data from 89 count stations to predict AADTs on county roads in Indiana. The four predictors used were: county population, location type (urban/rural), a dummy variable for indicating whether an easy access to state roads exists, and total arterial mileage in the county. An R^2 of 0.75 was achieved. The AADT prediction errors range from 1.56% to about 35%

(Mohamed *et al.* 1998). Close examination to the final model from the study indicates that local roads within a county would in general have very similar estimated traffic. It is clear that the study cannot address volume variations of local roads within same counties.

Zhao and Chung's study (2001) also used the geographic area of Broward County, Florida. The following variables were used in regression analysis: function classification, number of lanes, direct access from a count station to expressway access points, accessibility to regional employment in Broward County, employment in a variable-sized buffer around a count station, and population in a variable-sized buffer in a count station. Four regression models were used with R^2 values ranging from 0.66 to 0.82. The model with the highest R^2 used all variables except the population buffer. For the four methods applied in their study, 73–79% of study sites have a prediction error of less than 40%. The maximum estimation errors for the four regressions are all more than 150%.

A regression model was developed for non-state roads in Broward County, Florida, using the following predictors: function classification, number of lanes, area type, auto ownership, presence of non-state roads nearby, and service employment. The model has an adjusted R^2 of 0.5961 with a minimum/maximum prediction error of 1.31%/57% (Xia *et al.* 1999). The low estimation errors in their study can be contributed to the generally higher traffic volumes (more than 3000 vehicles/day) on these roads as they are within the urban area.

Eom *et al.* (2006) applied a spatial regression model to estimate AADT for roads in Wake County, North Carolina. The study used observed traffic counts from 200 of the County's 1200 monitoring stations to estimate traffic volumes. The estimates were compared to the remaining stations that were not used in the model. Traffic was assigned based on the observed values from the closest monitoring stations and several socioeconomic factors. This model worked fairly well in an urban setting where the density of counting stations was high; however it showed mediocre performance in more rural areas. An overall R^2 value of 0.6613 was obtained. Some scatter diagrams were used to present estimation accuracy and no prediction errors were reported.

In summary, previous research used traffic count-based regressions for estimating traffic volumes for various types of road (Xia *et al.* 1999, Zhao and Chung 2001, Eom *et al.* 2006) or road groups (Mohamed *et al.* 1998, Seaver *et al.* 2000). Most of them focused on high-class roads, as traffic counts are usually not available for low-class roads in general. Research for low-class roads (Mohamed *et al.* 1998, Seaver *et al.* 2000) was limited to road groups, rather than individual road segments, which makes it not useful from asset management and operation point of view. Regression approaches also fall short in that some data has to be prepared for individual road sites (Xia *et al.* 1999, Zhao and Chung 2001, Eom *et al.* 2006). The independent

variables selected in the final models may not be readily available. They may only be obtained by processing data from a Geographical Information System (GIS) (such as 'Direct access to state roads or not' and 'Total service employment within a certain distance of a count station') or combine data from various sources (e.g. those containing 'Number of lanes' or 'Road functional class').

Travel demand modeling for estimating low-class road traffic

Literature on using a TDM to estimate low-class road traffic is scarce. Blume *et al.* (2005) implemented a model that used census data and sample counts to estimate vehicle miles traveled (VMT) on urban local roads, rural local roads, and rural minor collectors. Sample counts were taken for eight strata and an AADT based on median traffic volumes was estimated for each group. The estimated AADT was assigned to all the roads in the respective strata and VMT was calculated. The study identified the required number of sample counts to reach certain accuracy levels, ranging from 158 for 70–15 (15% error at the 70th percentile), to 881 for 95–10. This study did not address the issue of estimating traffic volumes for individual road links.

Many US jurisdictions have implemented statewide TDMs. Horowitz and Farmer (1999) performed a critical review of the statewide travel forecasting methods used in practice by US Departments of Transportation (DOTs). The model used by Michigan is considered to be an indicator of the 'state of the practice.' It is a three-step model that omits the mode choice portion of the traditional four-step process, and retains the characteristics of an urban model. The model forecasts trips between 2392 Transportation Analysis Zones; 2307 of which are within Michigan and 85 of which represent the other 47 contiguous states, Canada, and Mexico. Most of the modeling work was done using the *TransCAD* and its built-in modeling tools.

Michigan's statewide TDM may be the most advanced but it still falls short in addressing the issue of low-class/low-volume roads. Roads classified as collector or above are generally included in the network, with local roads occasionally included for the purpose of connectivity. The vast majority of local roads are omitted (Michigan DOT 2007).

Case studies

Two areas in the Province of New Brunswick are selected for this study, which are York County and Beresford Census Consolidated Subdivision (CCS), as shown in Figure 1. The York County is in the middle of the province and encompasses the provincial capital – Fredericton. The Beresford CCS is located in the northeast region of the province and it is a popular tour area.



Figure 1. Geographic location of York County and Beresford CCS.

The New Brunswick Department of Transportation (NBDOT) manages a total of 1420 km of roads in York County, of which 643 km (45%) are included in the traffic counting program (NBDOT 2006). The AADT on each of these roads is derived from 55 locations throughout the county using either short-term counts or data from permanent count sites. All numbered roads (freeways, arterials, collectors, and local numbered) are covered by the traffic counting program. Local named roads represent 345 km of the provincial road network in York County. This represents 24% of the total York County road network and 35% of all paved roads. Except for one small segment, local named roads are not included in the traffic counting program.

Figure 2(a) shows the York County dissemination areas (DAs) and road network with labeled highways. Arterial highways are numbered 2–99. Collector highways are numbered 100–199. Local numbered highways are numbered 200+. Arterial highways are highlighted in dark red. Collector highways are highlighted in purple. Local numbered highways are represented by a red dashed line. All other parts of the road network, including local named roads are shown in grey. Roads across the province are all numbered using this practice, including the Beresford area.

In order to examine the TDM at a smaller scale, the analysis area was reduced to the CCS level. The CCS of Beresford encompasses an area for which available traffic counts could be intuitively linked to local traffic, i.e. it encompasses a central business district (CBD) and the entire urban influencing area. There are a total of 224 km of road in the Beresford area. The NBDOT manages 178 km of these roads. Traffic count data were available for the one arterial, one collector, and two local numbered roads. This represented 45 km (25%) of the provincial road network which comprised one permanent count site and two short-term count sites on the arterial highway; two short-term count sites on the collector; and one



Figure 2. (a) York County and (b) Beresford area road network.

short-term count site on each of the local numbered roads. Figure 2(b) shows the Beresford area road network and DAs. Numbered highways include arterial highway 11, collector highway 134, and local numbered highways 315 and 322, and they are labeled and represented with the same color-coding scheme as the York County.

Study data and method

The TDM was developed using *TransCAD*'s built-in four-step model and omitting the mode choice step. Three GIS road networks: national network, provincial network, and the network covered by the provincial traffic counting program, were used at the various points of this study. The smallest census units, DAs, were directly used as traffic analysis zones (TAZs) to take advantage of readily available socioeconomic data from the 2000 census. The Quick Response Method (QRM) (NCHRP 1978, *TransCAD 2005*) was used for trip generation, trip attraction, and trip balancing. The following section details this process.

TransCAD offers three methods of trip production: cross-classification, regression, and discrete choice. The QRM uses a cross-classification trip-rate table with parameters from the National Cooperative Highway Research

Program (NCHRP) Report 187 (NCHRP 1978). The table includes triprates for three trip purposes: home-based work (HBW), home-based nonwork (HBNW), and non-home-based (NHB). Data required for this method included the total number of households (HH) in the zone and the average income per household for the zone, which were obtained from the census data. Since the trip rate table in NCHRP 187 is based on 1970 US dollars (US\$), an inflation index was applied. Using the Consumer Price Index to calculate the inflation, a factor of 4.69 was applied to the 1978 numbers.

The number of trips generated per household is a fundamental parameter and is inherently subject to high variation. Miller *et al.* (2006) acknowledged this and performed a study to investigate discrepancies between residential trip generation rates in the context of borrowing national average rates (NCHRP rates) for local application. The study concluded that there are no significant differences in mean rates attributable to the use of an average value instead of a site-specific value, so these rates were directly applied in this study.

The QRM uses an attraction model from NCHRP Report 187 (NCHRP 1978). The model is a regression equation that estimates the number of person trips attracted to a zone based on the number of dwelling units in a zone and the zone's work activity. Data required for this method included the total number of HH in the zone, retail employment in the zone, and non-retail employment in the zone. Balancing productions and attractions was done by holding the productions constant (recommended).

The gravity model was used to distribute trips among the zones. In order to do this, an impedance matrix needed to be created. The distance between centroids was used to fill the matrix. The value in the diagonal cells of the matrix (i.e. Zone 1 to Zone 1) was manually changed from 0 to 9999 to force trips to be distributed to other zones. The friction factor matrix was created using this impedance matrix. Person trips were converted to vehicle trips using the default recommended average occupancy value of 1.62 persons per vehicle (NCHRP 1978). Then an impedance function was used to distribute trips among zones. This study used a Gamma function with the parameters shown below:

$$f(d_{ij}) = a \cdot d_{ii}^{-b} \cdot e^{-c(d_{ij})} : a > 0, \ c \ge 0$$
(1)

where $f(d_{ij})$ is the friction factor between each *ij* pair of zones; d_{ij} is the impedance between each *i*, *j* pair of zones; *a*, *b*, *c* are calibrated parameters. The parameters recommended in the NCHRP 365 – 'Travel Estimation Techniques for Urban Planning' (NCHRP 1998) were used in this study. Although some of the study areas were considered rural, the overall traffic flow was still expected to follow the urban model as most areas are within the influencing areas of urban centers, so it was felt that these parameters

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were appropriate in this context. The result of this step was an O–D matrix for all zone-to-zone trips for each type of trip: HBW, HBNW, and NHB.

The final step was to assign each trip to the road network and generate traffic volumes. Several formatting steps were required before this could be achieved. These included cross-referencing the centroid nodes to the nodes they represent in the road network; indexing the O–D matrices with the road network nodes (rather than centroids nodes); and replacing links in the road network that had a length of zero with a non-zero value.

The STOCH method (Sheffi 1985) was used to perform the traffic assignment for the QRM. This method distributes trips between O–D pairs using the shortest path, but also assigns a portion of the trips to other 'reasonable' routes based on probabilities calculated by a logit route choice model. This method was chosen over the all-or-nothing method in order to increase the range of roads on the network that would be assigned traffic. Although typically used to model congestion, an equilibrium method (Sheffi 1985, *TransCAD 2005*) was also implemented in an attempt to improve on the results obtained from the stochastic assignment. The observed NBDOT traffic volumes were manually entered as capacity constraints on the corresponding road segments in the network. Traffic assignment was performed for each trip type resulting in total traffic volumes on each link for each trip type. The sum of traffic volumes for all trip types represents the total estimated daily traffic volume on each link, which in turn serves as AADT estimate of the link.

Study results and discussion

York county study

Traffic volumes were estimated for 935 km (66%) of the 1420 km of provincial roads in the county. The NBDOT currently has 645 km (45%) of the road network covered by the traffic counting program. Traffic volumes were estimated for 290 km of road that previously did not have any traffic count data available. This represented an increase in available data of 45% compared to the current traffic count data. Traffic volumes were estimated for 183 km (52%) of local named provincial roads.

There are four arterial highways in the York County. Traffic counts from the hardcopy map provided by the NBDOT were used to compare with the traffic volumes estimated by the TDM. Nine counts were used in the comparison for the arterial road segments. The estimates for the arterial highways had a fairly low average error. The average error was 9% with only one of the nine comparisons made had an error greater than 10%. Since these trunk roads are expected to carry the majority of the traffic throughout the zone, the low percentage error indicates that the trip productions and attractions being modeled are reasonably well. There was no clear tendency toward over or underestimating traffic. A regression analysis was performed resulting in an R^2 value of 0.9807, which emphasizes that there is a strong linear relationship between the estimated and observed values.

There are six collector highways in the county. Sixteen traffic counts were used to compare with the estimated collector volumes. Collector volumes were overestimated on all but two cases, which indicates that the traffic did not get assigned appropriately at this level. Average error for the class was 44% with a 90% percentile error of 104%. Low-volume roads tended to have the worst estimates, while high-volume estimates had a relatively low error.

There are 11 local numbered highways in the county. Ten observed traffic counts were used to compare with the estimated traffic volumes on local numbered roads. It was found that the estimates for local numbered roads were all overestimated and had the highest average error of all the road classes (174%). The R^2 value for local numbered traffic estimations was 0.5414 which indicates a moderately weak correlation between observed and estimated values.

In all cases the volumes were significantly overestimated with errors ranging from 11% to over 700%. This reinforces the indication that traffic did not get widely assigned to the road network; only 65% of roads were assigned traffic and thus traffic volumes on these roads were significantly overestimated.

Trip assignment was initially performed with an 'all or nothing' type assignment. This means that the majority of travel between zone centroids will be assigned to shortest paths regardless of the number of centroid connectors. There are two possible solutions to this problem. The number of generating sites within each TAZ could be increased or a different assignment scheme could be developed. Although both solutions increase the amount of manual input to the model, which may make large-scale implementation impractical, changing the trip assignment method is likely the easier solution.

To test this theory, the assignment method was changed to 'Stochastic User Equilibrium' (SUE), which incorporates capacity constraints into the trip assignment. The observed values of collector traffic were manually added to the corresponding road segments as the capacity in the road network file. The traffic assignment was performed and the estimates on the local numbered roads were again compared with the observed values.

Generally traffic volumes were still largely overestimated, but the implementation of a user equilibrium traffic assignment improved the overall predictions on local numbered roads. The average error was reduced by about 14% and the 90th percentile error was reduced by 59%. The results from the regression analysis were also improved. The R^2 value increased to 0.6965, which indicates a stronger correlation between the estimated and observed values. The Sum of Squared Error (SSE) for the TDM output was reduced by 97% from 25,424,339 to 861,461 based on the adjusted estimates.

The fairly large R^2 indicates that regression could be used to remove the consistent overestimation bias and improve the accuracy of local road estimates from the TDM. Four traffic counts were removed so they could be used for model validation and the regression analysis was performed on the remaining six, which produced the following equation:

$$Observed = 0.4375 \times Output \text{ from TDM} + 67.237$$
(2)

The average error for the test group estimates was reduced by 115% to 38.6%. The 50th, 75th, and 90th percentile errors were all reduced by over 120%. These results clearly show that using regression to modify the TDM estimates on local roads without traffic data can increase the accuracy and reduce the overall bias in the estimations on these roads.

One explanation for the large overestimation on local roads could be that the trip distribution was not done effectively. Trips generated in a zone were forced to end in another zone, meaning there was no internal zone traffic. While this was not a problem in urban areas where the DAs were small, in rural communities where DAs were larger, inter-zone travel was overrepresented. Traffic was then distributed to areas with large attractions, mainly Fredericton's business districts. Since a large portion of the greater Fredericton area in the east of the study area was not included in the model (e.g. the town of Oromocto), there was a surplus of trip attractions generated in Fredericton that would normally have been paired with productions from the missing area. In order to keep productions and attractions balanced, productions from the other parts of the zone were paired with the surplus attractions. Combine this with the apparent over-representation of rural inter-zone trips, and an overestimation of traffic volumes on local roads can be expected. Therefore, the study results indicate that selection of an appropriate study boundary which includes the entire influencing areas of adjacent cities or towns is critical.

Beresford CCS study

The above analysis to York County indicates that the analysis zone should be limited in an area for which the majority of the traffic in the region was generated within the zone. Therefore, another area – the Beresford CCS is chosen for further study, which is located on the waterfront of the Baie des Chaleur in the northeast part of the province. The TDM implemented in the study produced traffic volumes for 110 km (62%) of the provincial road network in the Beresford CCS. This represents an increase in available data of 65 km (144%) compared to the existing traffic count data.

The main road, which services the CBD, is collector Highway 134, which runs north–south along the waterfront. The population density is highest close to the water on the east side of the zone and becomes progressively lower heading west. Arterial Highway 11 runs through the zone parallel to Highway 134. On both highways, observed traffic volumes on sections to the north and south of the zone were significantly lower than traffic volumes in the center of the zone, particularly on the collector highway, where the traffic volume went from 1240 vehicles per day at just north of the zone to 12,400 vehicles per day in the CBD. This indicates that the majority of traffic is being generated within the zone.

In order to compare the observed traffic counts with the estimated traffic volumes, it was necessary to account for through trips in this case due to the fact that both Highway 11 and Highway 134 traverse the entire study area. Since observed traffic volumes in the north of the zone were lower than volumes in the south of the zone, the observed volumes in the north of the zone were taken as a better representation of through traffic. On Highway 134, the observed value of 1240 vehicles per day on the north section was used as the through traffic value. On Highway 11, the observed value of 3510 vehicles per day from the permanent count station in the north of the study area just before the first interchange was used as the through traffic value.

The observed traffic volumes at the two short-term count sites on Highway 11 (arterial) were 4500 and 7060 vehicles per day, respectively. With through traffic removed, the expected volumes on these two segments were 990 and 3550. The traffic volumes estimated using the TDM were 1032 and 3132 vehicles per day. In the first case traffic was overestimated with an error of 4%; in the second case traffic was underestimated with an error of 12%. These results clearly show the TDM performed reasonably well at the arterial level.

The observed traffic volumes at the two short-term count sites on Highway 134 (collector) were 9430 and 12,400 vehicles per day, respectively. With through traffic removed, the expected volumes on these two segments were 8190 and 11,160 vehicles per day, respectively. The traffic volumes estimated using the TDM were 6290 and 9925 vehicles per day, respectively. Volumes in both cases were underestimated with respective errors of 23% and 11%, respectively. This may indicate that through trips were slightly underestimated at both locations. It is reasonable to speculate that additional traffic was generated between the edge of the analysis zone and the location of the base counts used to estimate through traffic.

There are two local numbered highways in the zone: Highways 315 and 322, both running north–south. Highway 322 branches off 315, runs parallel, and then rejoins 315, as shown in Figure 2(b). The short-term count sites were both located at the southern juncture of the two highways. This juncture was located just south of the study area. The observed traffic volumes were 1400 vehicles per day for Highway 322 and 2660 vehicles per day for Highway 315, respectively. Since these were local roads, no through traffic modifier was applied. The traffic volumes estimated using the TDM were 1951 vehicles per day on Highway 322 and 2992 vehicles per day on Highway 315, respectively.

Both volumes were overestimated, with an associated error of 39% for Highway 322 and 12% for Highway 315, respectively. The averaged estimation error for local numbered roads is about 25%.

The largest error occurred on Highway 322. Traffic on both local numbered roads was overestimated. This could also be attributed to the location of the short-term counts. The counts were taken at the junction of the two roads, which occurred south of the analysis zone. Since there are residential dwellings along these roads, and several intersecting local named roads, these counts may not be indicative of actual traffic volumes on the road segments within the zone because traffic that has entered or discharged from the road before the location of the estimate will not be captured.

The R^2 value was 0.9785, which indicates a strong correlation between observed and estimated traffic. Like the previous example, a regression model could be developed in the future as a calibration tool to reduce the overall overestimation bias for other links within the area. In this case, the small sample size makes this impossible and therefore no analysis was carried out.

Overall, the TDM was able to capture the travel patterns of the zone fairly well. Intuitively, Highway 134, which serves as the main street for the CBD, should have the highest traffic volumes in the zone. This behavior was successfully captured by the TDM and confirmed by the observed traffic counts. The estimated volume of locally generated traffic was also fairly close to observed values.

Surface-treated local named roads under the jurisdiction of the province represented 84 km of road in the analysis zone. The TDM used in this study estimated traffic volumes for 50 km (60%) of these roads. There is currently no way to assess the accuracy of individual estimations on these roads without taking additional traffic counts for comparison. It should be noted that with a reduced study area size, the magnitude of the estimation error on low-class roads will be reduced, as it is the case here.

The analysis to the higher class roads indicates that the model has provided a good estimate of the total volume of traffic generated within the zone and has captured the overall pattern of traffic movement in the zone. Since these local named roads feed the traffic from the generating sites to the higher class roads, it can be inferred that the estimated traffic volumes on these links are indicative of the actual traffic volumes. Regardless of whether or not the error in the estimated traffic volumes can be quantified, this process has made data available for a significant portion of the road network for which no data were previously available.

In order to address the issue of variability in the estimates, roads could be classified into a volume range rather than be assigned a specific traffic volume. This can be useful for identifying high-priority road segments within the same road class. Table 1 shows the identified local named road groups by traffic volume for the Beresford CCS area. It can be found the results look

Identified road groups	Traffic volume range (veh/day)	Kilometers of road	% of total
Very low	0–500	45	54
Low	500-1000	7	8
Medium	1000-2000	19	23
High	2000 +	13	15

Table 1. Identified Beresford local named road groups by traffic volume.

reasonable in that most road segments (62%) are identified as low or very low classes with an AADT less than 1000 vehicles/day. Thirteen roads (15%) are identified as high-volume ones and 19 (23%) are assigned into medium volume group. GIS presentation reveals these medium or high-volume roads are close to the CBD or waterfront areas. The forecasted traffic is quite fit with the expected distribution. Study results show that, rather than assigning a specific value, a relative classification scheme could be used (e.g. low-high) to describe road links. Prioritizing these roads based on the estimated volume classes could significantly improve operations from an asset management perspective.

Conclusions

Our literature review indicated that previous research mainly used traffic count data-based regressions to estimate traffic volumes. However, the majority of them focused on high-class roads (e.g. collector or above) as traffic counts are usually not available for lower class roads. The remaining work for local roads falls short in addressing the volume variations within individual groups. Statewide TDM have been developed and implemented in many jurisdictions and they can be used to estimate traffic volumes. However, they are not useful for addressing the issue of low-class/low-volume roads as the local roads are generally not included in these models.

This study examined the feasibility of using a TDM to estimate low-class road traffic volumes. Two regions in New Brunswick were chosen to test and implement a TDM: York County and the CCS of Beresford. The results from the county case showed that estimates for arterial roads had the lowest average error (9%), followed by collectors (45%), and local roads (160%), as compared to observed traffic counts. An overall overestimation trend was found across nearly all study sites and thus indicates traffic was not effectively distributed at the collector and local road level. Existing traffic counts were used to develop the regression models for calibration purposes. Regression analysis was used to analyze the correlation between the forecasted traffic from the TDM and observed traffic counts, and linear regressions were developed to recast the forecasts from the TDM to more

reasonable ones. It was found that the calibrated models were useful to remove overall overestimation trend from the TDM. In the case of York County, the overall average error for the collector roads was reduced to 36% and that for the local roads was limited to less than 40%.

Reducing the study area size resulted in increased estimation accuracy. The overall average error of the Beresford CCS estimates was 17%. In particular, the estimation errors for local roads were limited to less than 40% and the average error was reduced to 25%.

The following conclusions were made based on the study results:

- (1) Travel demand modeling for estimating traffic on low-class/ low-volume roads is practical and useful. The average estimation errors for local low-class roads were limited to less than 40% and that is comparable to or better than those reported in the literature.
- (2) For local roads, the relative magnitude of traffic estimates is more important than the accuracy of individual links. TDM provides an effective way to identify high-priority segments within the local road class. That is, those roads with assigned traffic, especially high volume, should be given priority.
- (3) Using a TDM increases the amount of traffic information available for a road network. Traffic information does not exist for the majority of low-class roads. A TDM is non-invasive financially feasible, cost-effective method to obtain these data. Census data, traffic counts, and travel demand modeling software are readily available for almost all highway agencies and thus the cost for developing such a tool can be very low.
- (4) Study area boundaries should be chosen to reflect the entire urban influencing area. Using an arbitrary jurisdictional area, such as a county, may result in inaccurate areawide travel patterns as it is shown by the York County study in this paper. Boundaries should be chosen such that the majority of local traffic in the area can be assigned to one or more CBDs, regardless of whether the area is urban or rural.
- (5) The TDM approach does not assign traffic to some roads and tends to overestimate traffic on the rest. Regression can be used to calibrate the estimates in order to remove this bias and increase the overall accuracy, particularly for lower class roads (collector and local).
- (6) Choosing an appropriate method of traffic assignment is important. The SUE assignment method provides a better distribution of traffic on the road network than traditional all-or-nothing methods. The addition of available traffic counts as capacity constraints improves the model accuracy.

Several potential areas for further research can be identified. Low-class road traffic can be modeled most effectively by reducing the size of the analysis zone; however, this limits the model's application. It may be desirable for areas with a well-established statewide TDM to find a way to incorporate local estimates into the model. This could be done by developing an advanced assignment scheme. A method to assign a percentage of zone traffic to local roads based on factors such as functional class, roadway density, and proximity to trunk roads could be developed. Including other characteristics that may be available, such as the number of driveways per kilometer or resource road access, may also be useful for estimating local road traffic. Also, the development of a more complex scheme for creating an impedance matrix or adjusting the parameters of the gamma function could provide a more accurate representation of the trip distribution. Particularly in rural areas, a method to assign internal zone traffic to the road network should be investigated.

A comprehensive model could also be created by increasing the resolution of trip generating sites. Further disaggregation of socioeconomic data to smaller areas (such as at the household level) and create a virtual 'real world' model would serve as the most accurate and versatile method. Currently this is limited by the available resolution of census data. In this way, rather than assigning traffic to road links based on trips from a single generating site, trip generations could be spread over the entire road network. While detailed models like this exist, they are typically fairly difficult to develop. The use of GIS and land-use information from remote sensing data could play a significant role in developing detailed models like this quickly and effectively.

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