SURFACE TRANSIT SPEED UPDATE REPORT

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Surface Transit Speed Updating

Background

An important element of transit assignment modelling that TMG, nor arguably regional demand modellers in general, have not previously addressed is the updating of surface transit speeds as a function of roadway congestion. Currently, transit segment speeds for non-exclusive right-of-way use average line speeds normalized by the length of the section. This method uses GTFS data that specifies trip times in order to calculate the average line speed. For exclusive right of way lines, stop to stop speeds are averaged from stop times in the GTFS data and encoded into the network. These speeds are then used to calculate transit times along that section.

Though this approach has been standard for a number of years, it is not forecastable. The process of generating this GTFS data would also be time intensive and subject to a number of assumptions, making it not feasible to create. Currently, applying the base year GTFS line speeds to future scenarios can lead to unrealistic results. In particular, failure to account for shared right-of-way (SROW) congestion effects on transit speed and times may bias model assignments in favour of SROW routes relative to exclusive right-of-way (EROW) routes. Therefore, a new forecastable dynamic method is required for use in future scenarios that is relatively simple to avoid more detailed future inputs, which can become an entire issue to obtain as well.

Literature Review

A literature review searching for existing surface transit speed updating implementations was undertaken. Various past implementations took account congested link travel time, added with dwell time. Two approaches to the modelling of link travel time were observed: a) travel time as a function of various parameters such as area type (AT), land type (LT), and facility type (FT), and b) travel time as a function of congested automobile speed [1-6, 10-13, 16]. The former utilized a lookup table of travel time with independent variables of AT, LT, and AT. Although this method stood out for its feasibility, it was not used in this surface transit travel time model as it would not produce a forecastable model. This is because determining future, new land use patterns for every transit link would be extremely difficult to do with any reliability, as well as extremely labour intensive. The second approach linearly correlates automobile and transit congested speeds. Studies conducted in Jacksonville, Florida strongly demonstrated the linear relationship between automobile and transit congested speed at all speeds [16]. TMG model development proceeded with the latter approach, as it would produce a forecastable model that more closely represents reality.

Further literature review was conducted to review existing surface transit delay models, namely for dwell time and intersection delay. Dwell time models that were commonly observed a) assumed constant dwell time by service type, such as local and express transits, or b) produced dwell time as a function of number of boarding and alighting passengers (examples of the latter include the TCQSM method or Levinson's approach [1, 14, 16, 17]). Studies done in the District of Columbia indicated that the number of boarding and alighting passengers do in fact play an important role in dwell time [17]. It was decided to proceed with the latter method to better represent the characteristics of dwell time. The former method would not reflect the true nature of dwell time and the results obtained would be excessively aggregated. Although various intersection delay models were found, it was decided to remove intersection delays from the model as a) intersection delays would not have significant impact on our macroscopic model, and b) it would be very difficult to implement in a static EMME network [7-9, 15].

Proposed Model

In order to update transit speed for future scenarios, the following model is proposed. For each segment in the transit line, the travel time on that section is assumed to be a function of the Auto Travel Time on that section, plus an additional dwell time to account for the number of stops and the number of passengers boarding and alighting.

$$Transit\ Travel\ Time = \beta_1 Auto\ Travel\ Time + Dwell\ Time$$

Where β_1 is a conversion factor to account for the fact that transit vehicles travel at different speeds than auto vehicles. Auto travel time is obtained for an EMME Road assignment and is then used in this model. Dwell time is further modelled as

$$\begin{aligned} Dwell\ Time = & [Number\ of\ Boardings\ Passengers][Boarding\ Time\ Per\ Passenger] \\ & + [Number\ of\ Alighting\ Passengers][Alighting\ Time\ Per\ Passenger] \\ & + \sum\nolimits_{Stops} Default\ Duration\ Per\ Stop \end{aligned}$$

Where the number of boarding and alighting passengers is obtained from a transit assignment in EMME and then normalized by how many runs there were in the time period. For example, if a line had a headway of 30 minutes during the 3-hour AM period, there would have been 6 runs during that time. If the total number of boarding passengers was 1200 at the node, the normalized boarding number would then have been 200 at the node. The $\sum_{Stops} Default\ Duration\ Per\ Stop$ term is there to account for the number of stops in the route. Since in the GTAModel workflow, extra cosmetic nodes (including transit stops) are removed to add space for the hypernetwork, there needs to be a term that reflects the fact that in real life, busses do stop at these removed stops and have a "constant" dwell time on top of which boarding and alighting passengers add to.

This model, which closely represents the nature of surface transit travel behaviour, is implemented to the network with two assumptions: a) automobile travel time from EMME road assignment is representative,[1] and b) the number of boarding and alighting passengers from EMME transit assignment is true. The potential flaw these assumptions may cause is that the model may not converge if the assignment results are inaccurate.

Calibration

The parameters that need to be estimated in this model are the conversion factor (β_1), the Boarding time per passenger, alighting time per passenger, and the default duration per stop. The remaining transit assignment parameters were assumed to be the same as the regular GTAModel transit assignment.

The first attempt at calibrating these parameters was to conduct a Particle Swarm Optimization algorithm using eXtensible Travel Modelling Framework (XTMF), a modular program developed and maintained by TMG. This attempt involving trying to calibrate parameters such that they would fit the

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[1] Note that the number of surface transit vehicles operating in the shared-ROW link is included in the calculation of roadway congestion levels within each link.

GTFS stop times data. However, because the EMME transit assignment requires segment speeds to generate boarding and alighting numbers, which would then change the segment speed, this approach led to a very turbulent hyperplane in which parameters failed to converge.

An alternate approach was then found with the help of the Toronto Transit Commission's (TTC) Automated Person Count (APC) data. The TTC has outfitted APC technology on approximately 10% of its busses which are then rotated across the network to collect data over time on all its routes. The TTC was kind enough to provide 1 days' worth of APC data to TMG in order to help with the analysis. This data set consisted of 972 csv files, one for each bus on the road.

This data was first cleaned to ignore the first five entries in every file as these corresponded to the time the bus spent in the bus bay. Furthermore, any entry that had no latitude and longitude for stop location was removed as well as any entry that had a dwell time of greater than 90 seconds was removed to adjust for midblock and other longer layovers. In order to account for the fact that dwell time at certain stops will be affected by the intersection delay (drivers could be leaving the doors open while waiting), stops at intersections were removed. The remaining entries were analysed to determine dwell time as well as total boardings and alightings, and multiple linear regression using OLS with the statsmodels api in python was performed. The following regression models were attempted

$$Dwell\ Time = \gamma_1(Boardings + Alightings)$$

$$Dwell\ Time = \gamma_2(Boardings + Alightings) + Default\ Duration$$

$$Dwell\ Time = \gamma_3(Boardings) + \gamma_4 Alightings)$$

$$Dwell\ Time = \gamma_5(Boardings) + \gamma_6 Alightings) + Default\ Duration$$

$$Dwell\ Time = \gamma_7 \max(Boardings, Alightings)$$

$$Dwell\ Time = \gamma_8 \max(Boardings, Alightings) + Default\ Duration$$

Where γ_x is the parameter being estimated and Default duration is the constant in the model. The model with the best fit is shown in Figure 1 with it generating dwell time in seconds.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             dwell_time   R-squared:                       0.324
Model:                            OLS   Adj. R-squared:                  0.324
Method:                 Least Squares   F-statistic:                 2.145e+04
Date:                Thu, 16 Nov 2017   Prob (F-statistic):               0.00
Time:                        16:58:20   Log-Likelihood:            -3.0395e+05
No. Observations:               89598   AIC:                         6.079e+05
Df Residuals:                   89595   BIC:                         6.079e+05
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.4331      0.032    231.412      0.000       7.370       7.496
boardings      1.9577      0.011    175.053      0.000       1.936       1.980
alightings     1.1219      0.010    111.403      0.000       1.102       1.142
==============================================================================
Omnibus:                    84018.272   Durbin-Watson:                   1.745
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          4112354.235
Skew:                           4.539   Prob(JB):                         0.00
Kurtosis:                      34.924   Cond. No.                         4.28
==============================================================================
```

Figure 1 Best fitting regression model using the TTC APC dataset

This results in the following model

$$Dwell\ Time\ (at\ each\ stop) = 1.96(Boardings) + 1.12(Alightings) + 7.43$$

With this dwell time model, the auto coonversion factor still needs to be estimated. Two different approaches lead to similar results.

In order to determine the auto conversion factor, the average line speeds of the EMME lines was utilized. As a reminder, these line speeds were generated from GTFS trip data which specifies start and end time for each trip. Since each unique trip is inputted into EMME as a separate line, these lines can then have average speeds depending on the time period (AM,MD,PM,EV). Since the speed and length of the lines is known, average time in seconds can be calculated for each line. This represents the Total Transit Time, which can be represented in the following way

$$Total\ Transit\ Time = Dwell\ Time + Transit\ Running\ Time$$

Since the number of boardings and alightings can be modelled using EMME and the number of stops is known (again due to EMME), the dwell time can be calculated as follows

$$Dwell\ Time = 1.96\left(\frac{Total\ Boardings\ in\ Time\ Period}{Runs}\right) + 1.12\left(\frac{Total\ Alightings\ in\ Time\ Period}{Runs}\right) + \sum_{Stops} 7.43$$

The total number of runs is calculated using number of minutes in time period (ex. AM is 3 hours or 180 minutes) divided by the headway (in minutes). This then gives us the total dwell time on that line. Rearranging the above equation we get

$$Total\ Transit\ Time = Dwell\ Time + Transit\ Running\ Time$$

$$Transit\ Running\ Time = Total\ Transit\ Time - Dwell\ Time$$

This will then allow us to calculate the running time in seconds for each line. Using EMME, we can model how long a car would take to travel along the same route as the bus. On locations where auto vehicles were not allowed, such as inside stations etc, auto time was assumed to be 20 km/hr. This would then give us Auto Time. The correlation factor would then be equal to

$$\beta_1 = \frac{Transit\ Running\ Time}{Auto\ Time}$$

When averaging this parameter across all lines in the EMME network, other than GO trains, Subways, and Streetcars, an average β_1 of 1.825 was obtained. However, it was decided not to use a global average here but to instead separate it out between different time periods. Therefore there would be an auto conversion factor for each time period.

In addition to the TTC dataset, York Region Transit was also able to provide an APC dataset of their busses. This dataset was to be used to help calibrate the so called “905 Regions” that surround Toronto, rather than simply using TTC numbers for the entire GTA region.

However, when estimating a regression model on the dataset, it showed a much worse fit than the TTC Model as shown in Figure 2.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             dwell_time   R-squared:                       0.118
Model:                            OLS   Adj. R-squared:                  0.118
Method:                 Least Squares   F-statistic:                     8224.
Date:                Thu, 18 Jan 2018   Prob (F-statistic):               0.00
Time:                        13:26:53   Log-Likelihood:            -5.2386e+05
No. Observations:              123410   AIC:                         1.048e+06
Df Residuals:                  123407   BIC:                         1.048e+06
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         20.7671      0.064    322.982      0.000      20.641      20.893
boardings      2.4353      0.022    110.446      0.000       2.392       2.478
alightings     1.2512      0.022     58.107      0.000       1.209       1.293
==============================================================================
Omnibus:                    39809.632   Durbin-Watson:                   1.876
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           105989.722
Skew:                           1.772   Prob(JB):                         0.00
Kurtosis:                       5.837   Cond. No.                         4.29
==============================================================================
```

Figure 2 Regression results for the best fitting model using the YRT dataset

The large constant value shown was also worrying as it is theoretically troubling as to why a bus would stop for a minimum of 21 seconds at a stop to let a single person alight. This figure may have some bleeding of the traffic signal effect into the dwell time calculations. Nevertheless, an attempt was made to find the auto conversion factor but it was found that transit vehicles travel 42% faster than auto vehicles. It is known that transit vehicles cannot travel faster than auto vehicles especially in a macro model, thus a different approach was need to model vehicles in York Region.

An attempt was made to simply transfer over the TTC dwell time and instead of using a global auto conversion, use a separate conversion factor for the different line groupings present in the GTA. However, when looking at the standard deviations of the auto conversion factor as shown in Table 1, it shows that while the averages for the line groupings are different, they are within the standard deviation from each other for all cases other than GO Bus. Therefore, only GO Bus was given its own auto correlation ratio for use in the model.

Table 1 - Auto Correlation Factors for all Agencies

Service & Time Period	Average of factor	StdDevp of factor
AM	**1.663156817**	**0.401992592**
Brampton	1.839546954	0.36547983
Durham	1.644706092	0.375871363
GO Bus	1.226575054	0.223644081
Halton	1.622832129	0.358320525
Hamilton	1.839556825	0.333099982
Mississauga	1.691439052	0.284806287
TTC Bus	1.749014034	0.429402755
York VIVA	1.654791706	0.328115269
YRT	1.525285827	0.335356205
EV	**1.923648799**	**0.41217722**
Brampton	2.158933035	0.281247738
Durham	1.891922371	0.367679759
GO Bus	1.477074233	0.187206079
Halton	1.935310706	0.505510866
Hamilton	1.867344464	0.370408653
Mississauga	1.890103472	0.228122715
TTC Bus	2.050018881	0.426032959
York VIVA	2.084797198	0.238398283
YRT	1.756330238	0.365145457
MD	**2.055619866**	**0.481192679**
Brampton	2.211268508	0.340129675
Durham	1.895153316	0.357235864
GO Bus	1.554290607	0.226851532
Halton	1.898389565	0.424583505
Hamilton	2.035704292	0.375937911
Mississauga	2.025729562	0.318286406

TTC Bus	2.225772712	0.436116333
York VIVA	2.272269742	0.350778998
YRT	2.016443691	0.708281777
PM	**1.637378565**	**0.438409066**
Brampton	1.845373985	0.333026595
Durham	1.591210046	0.342351024
GO Bus	1.179986807	0.224650256
Halton	1.629150828	0.450549762
Hamilton	1.809206969	0.357433109
Mississauga	1.589550242	0.285744866
TTC Bus	1.711252369	0.473374901
York VIVA	1.703099741	0.361828829
YRT	1.598641776	0.441310637

Due to the fact that GO Busses have now been removed from the average conersion factor, new conversions are summarized in Table 2 below, along with the boarding and alighting times.

Table 2 - Auto Correlation Parameters

Parameter	Value
Boarding Duration per Passenger	1.9577
Alighting Duration Per Passenger	1.1219
Default Dwell Time	7.4331
Auto Conversion Factor AM (Bus)	1.704750704
Auto Conversion Factor MD (Bus)	1.965837753
Auto Conversion Factor PM (Bus)	2.118648855
Auto Conversion Factor EV (Bus)	1.684546052
Auto Conversion Factor AM (GO Bus)	1.226575054
Auto Conversion Factor MD (GO Bus)	1.477074233
Auto Conversion Factor PM (GO Bus)	1.554290607
Auto Conversion Factor EV (GO Bus)	1.179986807

The final model (for the AM period on a TTC Bus line) then looks like

$$Transit\ Travel\ Time\ (on\ a\ segment) = 1.70(Auto\ Travel\ Time) + Dwell\ Time$$

Where Dwell Time is equal to the following

$$Dwell\ Time = 1.96(Boardings) + 1.12(Alightings) + \sum_{Stops} 7.43$$

Streetcar Model

Streetcars in Toronto presented a different problem as they represent behaviour that was not found in the TTC dataset. However, before estimating new parameters for the transit assignment, it was crucial to apply a dwell time model to streetcars as that would lead to more people using the streetcars as they face no penalties in terms of boarding and alighting. Since streetcar data was not available, it was assumed that the bus dataset model would be applied, but with a few tweaks. Streetcars in 2011 did not have all door boarding in operation so the model disregards this, but in 2016 all-door boarding in streetcars had come into affect. This blurs the lines between boarding and alighting since it is inherently assumed that in busses there are only two doors. Therefore, we estimated a new model using the bus dataset that used the total number of boardings and alightings at stop leading to the model shown in Figure 3.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             dwell_time   R-squared:                       0.300
Model:                            OLS   Adj. R-squared:                  0.300
Method:                 Least Squares   F-statistic:                 3.847e+04
Date:                Thu, 18 Jan 2018   Prob (F-statistic):               0.00
Time:                        13:26:53   Log-Likelihood:            -3.0547e+05
No. Observations:               89598   AIC:                         6.110e+05
Df Residuals:                   89596   BIC:                         6.110e+05
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          7.5002      0.033    229.732      0.000       7.436       7.564
total          1.4960      0.008    196.148      0.000       1.481       1.511
==============================================================================
Omnibus:                    81995.929   Durbin-Watson:                   1.751
Prob(Omnibus):                  0.000   Jarque-Bera (JB):          3780048.912
Skew:                           4.382   Prob(JB):                         0.00
Kurtosis:                      33.590   Cond. No.                         5.86
==============================================================================
```

Figure 3 Regression results when estimating a streetcar model

When the 2016 model is estimated the total number of boardings and alightings can then be divided by the number of doors available on the streetcar (in multiples of two).

This model also requires a new auto conversion factor. This presents a new issue whereupon streetcars often travel through segments of road where they have exclusive right of way, which means no auto times on that segment. This was solved using the following formulas

$$Total\ Transit\ Time = Transit\ Running\ Time - Total\ Dwell\ Time$$

Since dwell time is known, we can then find the Transit Running Time

$$Transit\ Running\ Time = Total\ Transit\ Time - Dwell\ Time$$

Since the length of the line is known as well as the length of the EROW sections and the length of the SROW sections, we can then obtain the line running speed

$$Average\ Running\ Speed = \frac{Transit\ Running\ Time}{Total\ Line\ Length}$$

We can then obtain the time spent in the EROW and SROW sections respectively using the following

$$EROW\ Time = \frac{EROW\ Length}{Average\ Running\ Speed}$$

$$SROW\ Time = \frac{SROW\ Length}{Average\ Running\ Speed}$$

The auto time can then be calculated from EMME on the SROW sections and the ratio can then be used.

$$Ratio = \frac{SROW\ Time}{Auto\ Time\ on\ SROW}$$

Table 3 then gives us the following parameters for streetcars over the time periods:

Table 3 - Streetcar Auto Correlation Factors

Time Period	Auto Conversion Ratio
Default Dwell Time	7.5002 s
Time to Board/Alight	1.496 s
AM	1.841448614
EV	2.064731175
MD	2.253656208
PM	1.689979987

The numbers provided above are for two-door streetcars. To forecast for the future, the total number of boardings and alightings for each vehicle must be divided by the number of doors and then multiplied by two. This will naturally assume that all doors are used equally in the streetcar, however that is a relatively minor assumption.

Implementation and Testing

In order to implement this model in an EMME and XTMF Framework, a new module was created for Transit Assignment. Since the EMME congested transit assignment algorithm already utilizes an iterational approach to transit assignment as it attempts to find convergence on congested lines, it seemed inefficient to have a larger loop that updates dwell times after each assignment. Therefore, TMG utilized the congested transit assignment algorithm from EMME but inserted a dwell time updated script which updates the dwell times between each iteration of the extended transit assignment. This allows for much faster transit assignment converging times and a much more efficient algorithm.

In order to test the Surface Transit Updating model, it was decided to run future year forecasted demand from GTAModel V4.0 through the model in order to determine whether the results are acceptable for a heavily congested scenario. Therefore the following steps were taken:

1. A check for the model was done to see if the line speeds reverted back to the original line speeds that they were based on. This was done by comparing the original line speeds (calculated from GTFS) to the line speeds calculated from a Transit Assignment utilizing Surface Transit Speed Updating. The speeds and times were then plotted and are shown in Figure 4 and Figure 5 below.

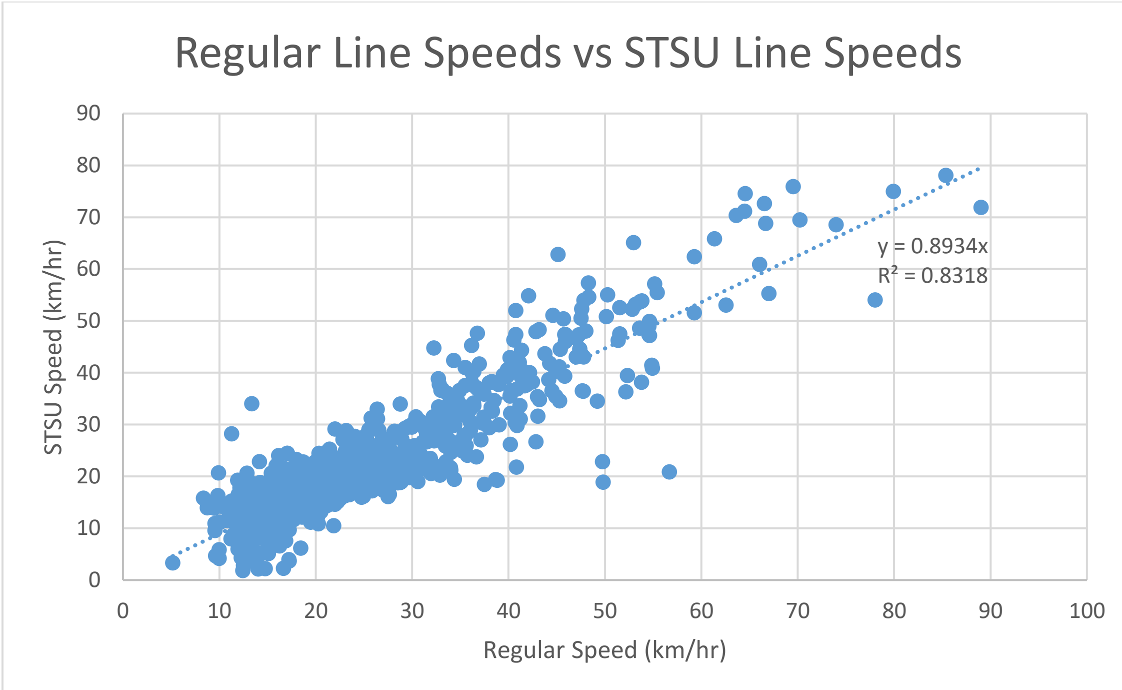

Figure 4 Graph showing the difference in line speeds between the two assignments

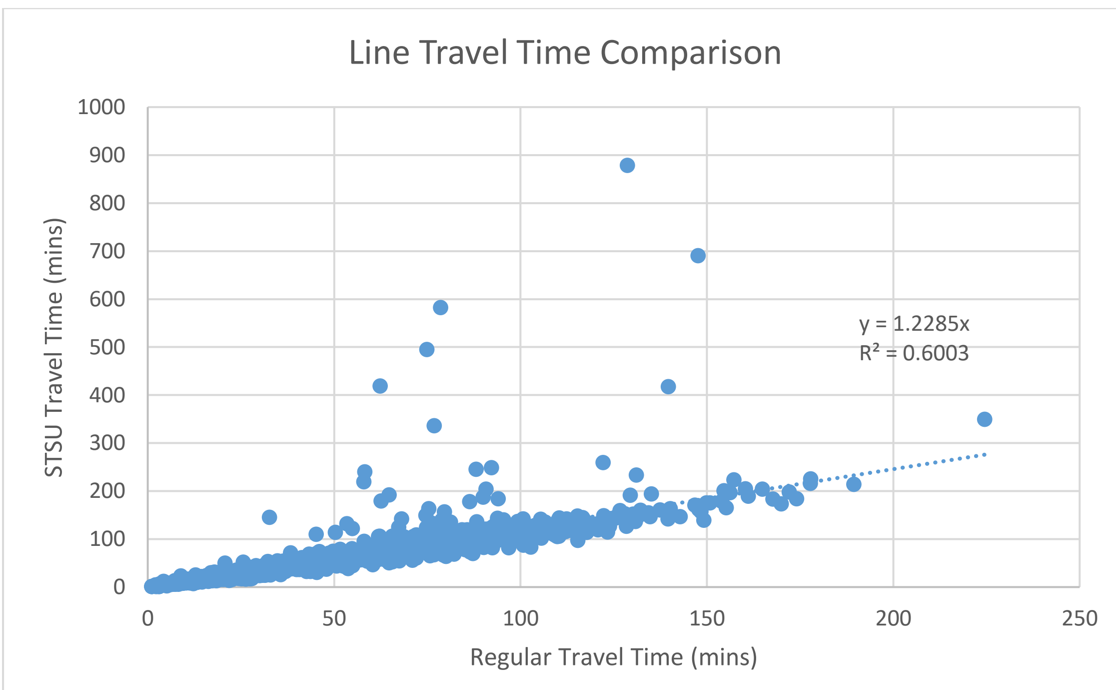

Figure 5 Graph showing the difference in transit line travel time between the two assignments

There appears to be on the whole, a good fit to the trend lines, however the model does appear to be slightly under-predicting line speeds, leading to longer total travel times on the transit lines.

2. Since the parameters that were used for the transit assignment were not calibrated with Surface Transit Speed Updating, it is necessary to calibrate them. This was done using a Particle Swarm Optimization within the XTMF Framework to generate the new parameters. The assignment was calibrated to the TTS boardings for the AM and PM time periods. After calibration, the assignment performed slightly better than the regular assignment. This was expected because the Surface Transit Speed model was assembled to recreate the current data, but have the ability to generate better forecasts. Therefore, it wasn't expected to be too much better than the current assignment for the base year. The parameters as well as the fitness values is given in Table 4 below. The fitness value is the RMSE of the observed boardings subtracted by the modelled boardings. The lower the value is, the closer the model is to representing the true data.

Table 4 - Parameters after PSO calibration

Parameter	Value
Fitness	502.5708
Wait Time Perception	1.766078
PD1.Walk Perception Value	1.093058
Toronto.Walk Perception Value	2.623971
Non-Toronto.Walk Perception Value	1.884335
Toronto Centroid Connectors.Walk Perception Value	1.072108
Non-Toronto Centroid Connectors.Walk Perception Value	2.304927
Subway.Walk Perception Value	3.977788
Fare Perception	7.50832
Boarding Penalties.Brampton.Penalty	12.40961
Boarding Penalties.Durham.Penalty	11.27182
Boarding Penalties.GO Bus.Penalty	5.817453
Boarding Penalties.GO Train.In Vehicle Time Perception	0.833476
Boarding Penalties.GO Train.Penalty	5.424176
Boarding Penalties.Halton.Penalty	11.94058
Boarding Penalties.Hamilton.Penalty	9.817667
Boarding Penalties.MiWay.Penalty	7.190769
Boarding Penalties.YRT.Penalty	5.229805
Boarding Penalties.VIVA.Penalty	12.27566
Boarding Penalties.Streetcar.Penalty	11.25108
Boarding Penalties.TTC Bus.Penalty	11.66129
Subway and GO Rail Congestion Exponent	3.53439
EROW Streetcar Congestion Exponent	5.316258
SROW Streetcar Congestion Exponent	4.609741
Regular Bus Congestion Exponent	5.8552
GO Bus Congestion Exponent	4.810059

3. GTAModel V4 has a number of modules that have parameters that are calibrated to the EMME utils from a base year transit assignment. In the interest of time, all of these were not re-calibrated for Surface Transit Speed Updating (STSU), but instead a scale parameter calculated by dividing the Regular utils and the Surface Transit Speed Updating utils was found and applied. This scale parameter was found to be 0.97. This means that the perceived costs of travelling by transit were found to be slightly lower when surface transit speed was applied.
4. A full run of GTAModel V4 with STSU was then run for the base year and compared to a run without STSU. This produced the results summarized in Table 5.

Table 5 - GTAModel trips by mode for 2011

Mode	Reg-Trips-2011	STSU-Trips-2011	Change in Value (Reg-STSU)	Percentage Change (using Reg as the Base)
Auto	6,685,710	6,613,182	72,528	1%
Bicycle	234,216	202,395	31,821	14%
Carpool	598,158	566,117	32,041	5%
DAT	192,272	225,135	- 32,864	-17%
Passenger	938,161	931,483	6,678	1%
RideShare	493,847	488,311	5,536	1%
Schoolbus	227,148	218,147	9,001	4%
Walk	775,491	736,268	39,223	5%
WAT	1,832,457	1,999,006	- 166,548	-9%
Total	**11,977,459**	**11,980,044**		

As can be seen, the total number of trips has not changed much in the model, as the synthetic population that was used was the same across both scenarios. Furthermore, all other employment and trip generation parameters had the same value. Where the model differs the most is in the gain in Walk Access Transit (WAT) and Drive Access Transit (DAT) trips when STSU is implemented. These trips are redistributed across the other modes with bicycle and walk seeing the greatest relative change, while auto sees the most trips gained. This is due to the perceived costs of travelling by transit has decreased by a scale parameter of 0.97 as mentioned above.

Note that these numbers are after one iteration of the model with no feedback from EMME. Once the feedback from EMME starts, it is expected that the additional riders on the transit system will once again increase the costs of travelling on the transit system, leading to a redistributing of the trips, most likely back to around the same number as the regular scenario. Furthermore, in the interest of time, the mode choice model has not been recalibrated with the new transit assignment. Instead, the scale parameter was used on the Perceived Travel Times coming out of EMME in order to perform a rough recalibration.

5. A future year forecast population was generated based on a simple growth factor. According the Government of Ontario, the population in the GTAModel area is expected to grow 157% by

2041 from the base year of 2011. This growth factor was applied as an expansion factor in the synthetic population of persons and households for a 2041 Scenario.

6. This future year scenario was run through GTAModel and generated the following results shown in Table 6

Table 6 - GTAModel trips by mode for 2041

Mode	Reg-Trips-2041	STSU-Trips-2041	Change in Value (Reg-STSU)	Percentage Change (using Reg as the Base)
Auto	10,686,903	10,585,415	101,487	1%
Bicycle	367,562	317,620	49,941	14%
Carpool	939,320	888,871	50,448	5%
DAT	302,033	353,291	- 51,259	-17%
Passenger	1,475,055	1,463,940	11,115	1%
RideShare	776,427	767,656	8,771	1%
Schoolbus	354,215	340,048	14,168	4%
Walk	1,217,059	1,154,376	62,682	5%
WAT	2,915,117	3,185,172	- 270,055	-9%
Total	**19,033,690**	**19,056,389**		

The numbers in the 2041 scenario show almost the same trend as above. As this is only one iteration of GTAModel with no feedback from EMME, it is expected that due to the massively congested nature of the transportation system, transit will be massively affected. This means that further iterations of the model will cause a significant change in the number of transit riders.

7. The demand from this future assignment was assigned to EMME to determine the level of congestion in the system. Figure 6 shows the perceived travel times extracted out from the 2011 scenario of GTAModel with surface transit speed updating divided by the perceived travel times from the regular run of GTAModel. This has been aggregated to a PD level and shown in the form of a heat map, where the red cells indicate that the surface transit updating network is presenting longer perceived travel times, green cells indicate that the regular assignment has longer perceived travel times, and white cells indicate that they both are perceived to take the same amount of time. The heat map shows that even though the initial mode choice has assigned more transit trips, the feedback from EMME will rebalance the mode choice by changing the utils of the transit choice.

Figure 6 Heat map showing the differences in perceived travel times between the regular assignment and the surface transit speed assignment for 2011

Figure 7 shows the same kind of heat map as above, but instead for the 2041 scenario. As this scenario is more congested, we expect there to be a greater difference between the regular model run and the surface transit speed model run and this can be clearly seen as the heat map is much redder than Figure 6. As above, red indicates higher perceived travel times for the surface transit speed model, green indicates higher perceived travel times for the regular run, and white indicates that both the assignments are perceived to take a similar amount of time. Again this shows that the mode choice will rebalance the transit users by changing the travel times associated with transit and is anticipated to lead to less users of the transit system in general.

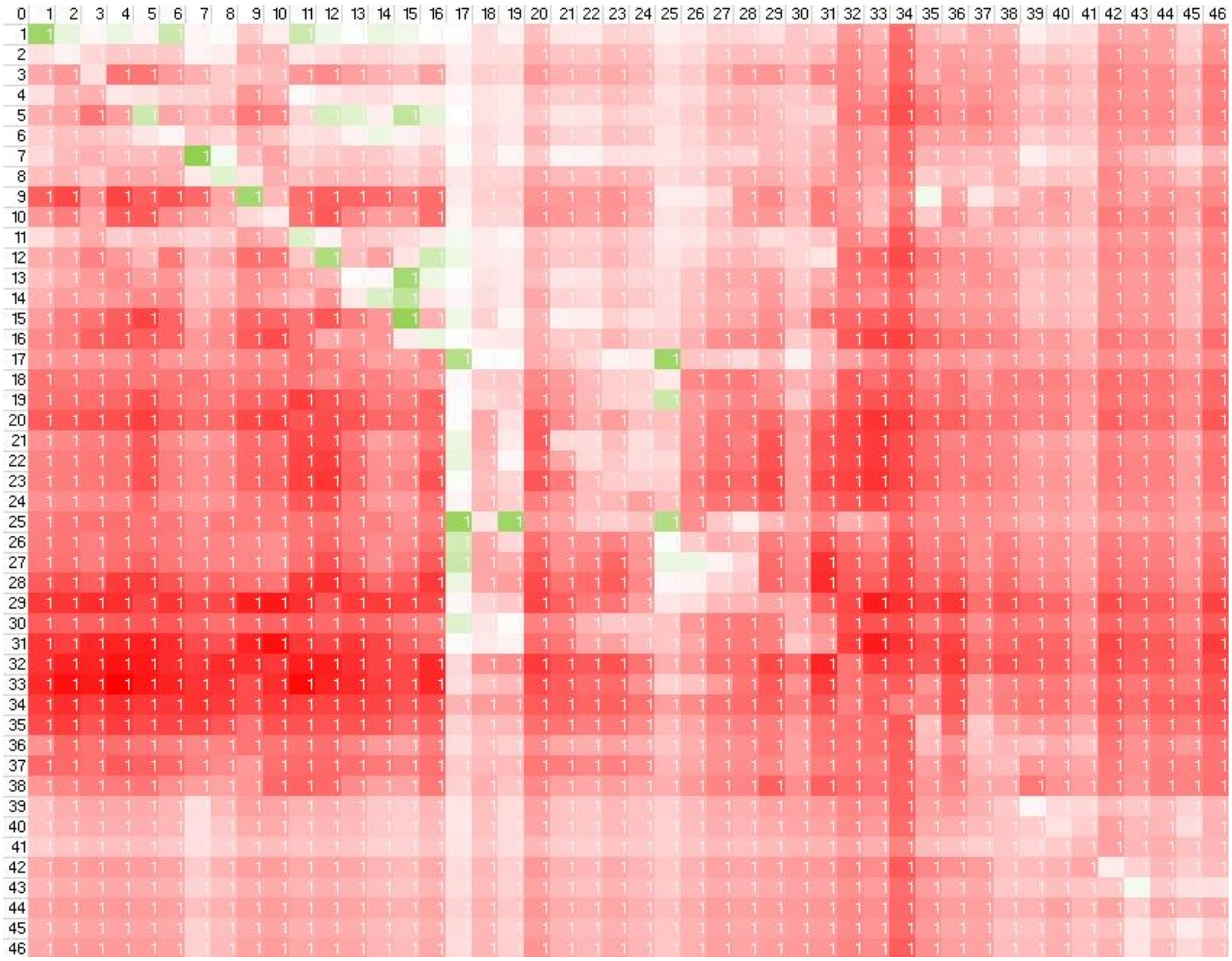

Figure 7 Heat map showing the differences in perceived travel times between the regular assignment and the surface transit speed assignment for 2041

Conclusion

The current GTAModel has had a problem with forecasting transit users in the future due to the neglect of dwell times and other auto vehicles on its surface transit system. This is why the Surface Transit Speed Updating model has been developed that actively takes into account congestion on the roads and the number of transit users to determine the speed of transit vehicles. This model is based on a combination of observed APC data obtained from the TTC as well as GTFS data that is provided by all agencies in the GTHA. Dwell times were obtained from the APC data and then used to generate auto congestion parameters in combination with GTFS data. Testing of this model was done with GTAModel V4, however, due to limited time and resources, in depth testing could not occur. A scale parameter was used to try to recalibrate GTA for use with STSU instead of manually recalibrating all of the parameters present in the model. Furthermore, only 1 iteration of the model was used. The demand from this iteration was assigned in EMME and compared to each other. It was seen that the surface transit speed updating assignment algorithm does in fact lead to greater perceived travel times for future year congested assignments, which is to be expected and can then perhaps lead to more accurate transit results.

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