EXPLORING SIMULATION BASED DYNAMIC TRAFFIC ASSIGNMENT WITH A LARGE-SCALE MICROSCOPIC TRAFFIC SIMULATION MODEL

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ABSTRACT

With better computational resources, microscopic transportation models are beginning to reach size and scale similar to regional macroscopic models. Calibrating complex large-scale transportation models is not trivial and is typically performed using observed traffic counts to simultaneously calculate demand and path choice. One issue that needs further exploration is the use of simulation based dynamic traffic assignment (DTA) techniques to determine route choices between origin and destination pairs. In this paper, we test the implementation of DTA in a commercial tool on a large-scale microscopic model. Performance of the DTA is quantified for two conditions – normal traffic flow and a future flow with heavy congestion. Results reveal why current DTA techniques may struggle and suggest mitigating. This paper does not offer a complete solution, but contributes to the research of utilizing microscopic models in a larger scale by providing evidence and discussing the challenges of current commercial DTA techniques.

Keywords: microscopic simulation, forecast, dynamic traffic assignment, calibration, and model development.

1 INTRODUCTION

Macroscopic models have been the "go to" tool for transportation modeling from a regional perspective. The choice to use the macroscopic model is often because of the regional size needed would take too long to run in a microscopic environment. New computational hardware and more efficient software is now in the hands of transportation modelers. With developments in this new technology, large-scale microscopic models are becoming more popular as shown in the literature (Xiong et al. 2015, Smith et al. 2008, Toledo et al. 2004, Lawe et al. 2009, Jha et al. 2004, Zhao and Sadek 2012, Rakha et al. 1998).

There are several issues with the use and development of large-scale microscopic models. An issue associated with calibration is the ability to find an appropriate distribution of demand for each origin and destination (OD) pair that utilizes a particular path. The more complex the road network is, the more available paths there are between an OD pair. A method commonly used to determine a reasonable level of

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trips per path is traffic assignment. This paper focuses on the difficulties faced when using simulation based dynamic traffic assignment (DTA).

Static traffic assignment techniques are used in macroscopic modeling in order to determine a user equilibrium of paths between each OD pair. User equilibrium is considered a point in calibration at which each vehicle does not have a better path to take in order to improve its particular trip. Because microscopic models use time varying demand, DTA is employed instead of the static version. The DTA process is iteration-based where paths are adjusted based on the results of prior iterations for each simulated time step. The process continues until a user-defined threshold is met. The threshold is often a point of acceptable path distribution, often quantified by a measure of relative gap. Relative gap is computed as an aggregate measure of how close the paths for each OD pair are to the shortest travel time path.

In a smaller model with less complexity, the DTA process works well converging to a point of equilibrium. As the scale of a model grows in size, complexity, and congestion, the DTA process becomes more difficult. A key cause of degraded performance is the result of queuing that occurs in the model and which may reflect real world conditions. As networks become overly congested, grid-lock can occur; this may prevent demand from entering the network. During the DTA process, earlier iterations see higher congestion as the selected paths are not the best for user equilibrium. As the DTA begins to balance demand over the paths in the network, more vehicles are able to enter the network, negating much of the information that the system has discovered in the prior iterations.

Traditional calibration tends to modify network and demand parameters at the same time while running simulation based DTA (Ben-Akiva et al. 2012). This type of process typically utilizes observed road count data or travel time data to compare with simulation results throughout the process of calibration. Measures of model error are then minimized throughout the process resulting in a better fitted model. This process is not possible in forecasted scenarios, therefore a process of demand generation and user equilibrium is relied upon.

Within the past year a large-scale microscopic simulation model of Virginia Beach, Virginia was completed to assist in transportation operations planning for the city. The model was developed with both a 2012 base year and forecasted 2034 future year. Traffic demand for the 2034 model was approximately 25% greater than the base year and obtaining adequate path results from simulated DTA was challenging. Running the model to what was believed to be a good relative gap of 0.05 or better resulted in instability within the network and strange paths that appeared to result in gridlock. In this paper convergence is measured in the DTA process by the measure of relative gap, and stability is identified in the final simulation by how efficient the transportation performs (amount of vehicles queued outside the network or gridlocked situations). Due to the heavy congestion, a strategy was adopted that slowly increased the demand throughout the DTA process. This process has shown success in smaller models as described in (Levin et al. 2015) and yielded favorable simulation based DTA paths that resulted in more realistic conditions in our model. Interestingly, the final relative gap remained similar to the DTA runs performed prior to the demand modification.

This paper investigates the process of simulation based DTA and presents results from DTA tests performed on the large-scale city-wide microscopic model of the City of Virginia Beach Virginia. The model and simulation were built in Transmodeler®, a microscopic modeling and simulation tool produced by the Caliper Corporation. The large-scale model utilized two road networks and time dependent demand sets, one for the 2012 base year and the other for the 2034 forecasted future year. The model provides a relatively uncongested base year and heavier congested future year allowing for performance comparisons of the DTA methods to be tested. In this study, the 2012 roadway network was used with both the base and future year demand. Details of the development of the models are described in greater detail by (Jordan et al. 2017).

The results from the DTA tests are documented in this paper to show how the DTA process performs with the model as congestion increases. The paths are analyzed for each iteration of the DTA to better understand how well it is performing throughout the process. New strategies are tested and documented to provide a reference for others working with large-scale microscopic models. The conclusions in this paper and data further define the issues with current DTA applications in large scale microscopic transportation simulation.

2 BACKGROUND

Simulation based DTA is a method that is used to determine the allocation of paths between each time dependent OD pair based on the congestion of the model at that time in the simulation. Much of the DTA process is outlined and explained in the DTA primer and is a good reference to the background and workings of DTAs (Chiu et al. 2011). The DTA process is similar to the static traffic assignment process (STA) except that the DTA handles time dependent matrices. DTA is used in dynamic simulations where traffic is modeled over time. These simulations can be microscopic where each vehicle in the system is modeled or mesoscopic where a compromise is made somewhere in between macroscopic and microscopic modeling. Mesoscopic modeling often models the flow of packets or pods of vehicles rather than every individual vehicle.

The traffic assignment process uses an iteration-based approach. During each iteration, demand is assigned a path based on the information from both the prior iteration and current simulation congested travel times. To determine the average travel times from each assignment iteration, the simulation utilizes measures of road segment travel time and turning delays. Equation 1 shows the calculation to determine the average travel time for each time segment. Where X_i is the segment travel time or turning flow input, $f[X_i]$ is the segment travel time or turning movement output (f representing simulation model), and α_i is the factor used to average input and output.

$$X_{i+1} = (1-\alpha_i)X_i + \alpha_i f[X_i] \tag{1}$$

Calculation of the α_i factor can be done with several different algorithms. The most common algorithm used is the Method of Successive Averages (MSA). Algorithms such as MSA are used to reduce the amount of path changes that can happen each iteration of the DTA. Equation 2 is the simple approach where i is the iteration or simulation run within the DTA process. As the value of i increases the factor becomes smaller resulting in

$$\alpha_i = \frac{1}{i+1} \tag{2}$$

The objective of STAs and DTAs is to achieve a state of user equilibrium. User equilibrium is the point at which the path between each OD pair cannot be changed in a way that improves the individuals trip travel time. Progress in a DTA is traditionally measured as relative gap. The relative gap is an aggregate measure calculated as the difference between travel time of the current paths and the best possible path travel time in the simulation. A relative gap of zero would mean that the travel time of the paths used are equal to the travel time of the best possible path in the system at that time. Equation 3 was used to calculate the relative gap. In this equation, Gap^{τ} is the relative gap in time interval τ, I is the set of all OD pairs, K_i is the set of paths used by trips traveling between OD pair i, f_k^{τ} is the number of trips taking path k in time interval τ, t_k^{τ} is the travel time on path k in time interval τ, d_i^{τ} is the demand departing in time interval τ, and $t_{min,i}^{\tau}$ is the travel time on shortest path between OD pair i in time interval τ.

$$Gap^{\tau} = \frac{\sum_{i\in I}\sum_{k\in K_i} f_k^{\tau} t_k^{\tau} - \sum_i \in I d_i^{\tau} t_{min,i}^{\tau}}{\sum_{i\in I} d_i^{\tau} t_{min,i}^{\tau}} \tag{3}$$

The size and complexities of a model will dictate acceptable levels of relative gap. Identifying this acceptable measure of relative gap is difficult and is often determined after extensive tests of DTA with the model. The relative gap, although a good measure of convergence by comparing current versus optimal travel time, does not measure network stability, a trait that is greatly desired from the resulting DTA. The DTA primer describes the importance of observing network stability in DTA results in addition to convergence with relative gap(Chiu et al. 2011). Other measures should be observed in addition to relative gap such as the number of completed trips and the number of trips queued outside the network. This can occur when the network is highly congested with queues preventing vehicles from entering the network.

Comparisons have been made of DTA applications for microscopic and mesoscopic simulations. Case studies have been done to compare the performance of applications that have DTA implemented (Gliebe and Bergman 2011). Other research has focused mostly on the type of algorithms used within DTA such as MSA, gradient based, and time-varying step size algorithms (Mahut et al. 2008). Most comparisons focus on the measure of relative gap and how quickly the systems can achieve certain levels of relative gap for small to medium sized networks. These comparisons are useful in identifying the processing time of DTA applications and their effectiveness for creating results with low relative gaps, but do these results apply to large-scale models where congestion might be very high with a great number of vehicles queuing outside the network?

3 METHODOLOGY

To better understand the effects of the DTA on large-scale microscopic models, a large number DTA iterations were computed several times. The tests were performed to help understand the effectiveness of the relative gap measure to indicate equilibrium. In addition, the tests will be performed to understand other measures to assist in the stopping criteria of DTA that indicate equilibrium. The researchers were able to observe simulation results for each iteration of the DTA from an aggregate measure to see the performance of the DTA as it progresses.

Using the large-scale microscopic simulation of Virginia Beach described in (Jordan et al. 2017), two scenarios were run using the demand level for the year 2012 and the demand forecast for the year 2034. The network consisted of 3,403 links with 874 intersections, 438 of them signalized, and 1,808 nodes. The 2012 base year model ran a total of 558,436 vehicles within a 4 hour pm peak period. The 2034 future year forecast model ran a total of 694,528 vehicles within the 4 hour pm peak period. Figure 1 shows the modeled areas road network and signalized intersection nodes. For this study the signal timing will be the same for all scenarios. It should be noted that though there is a signal timing plan associated with each signal there are actuator sensors associated with the signals to allow them to change based on demand.

The two levels of demand (2012 and 2034) are specified as lists of origin destination (OD) matrices. Each OD matrix is demand representative for a 15 minute time period as the amount of vehicle trips leaving a node (origin) and destined for a node (destination). The 2012 demand level is considered the base year demand and the 2034 is considered the future year. The model used in this study created the base year demand utilizing observed data on road segments and an origin destination matrix estimation process to calibrate the model to an acceptable level. The future year demand was then built using traditional macroscopic transportation forecasting models, then using a downscaling process to disaggregate the macro level 4 hour data to 15 minute data. The process of initial calibration and future year calibration of the Virginia Beach model is documented and was presented in the following (Jordan et al. 2017).

Two strategies were performed based on the literature and what is known. The two strategies are described in detail below and later tested.

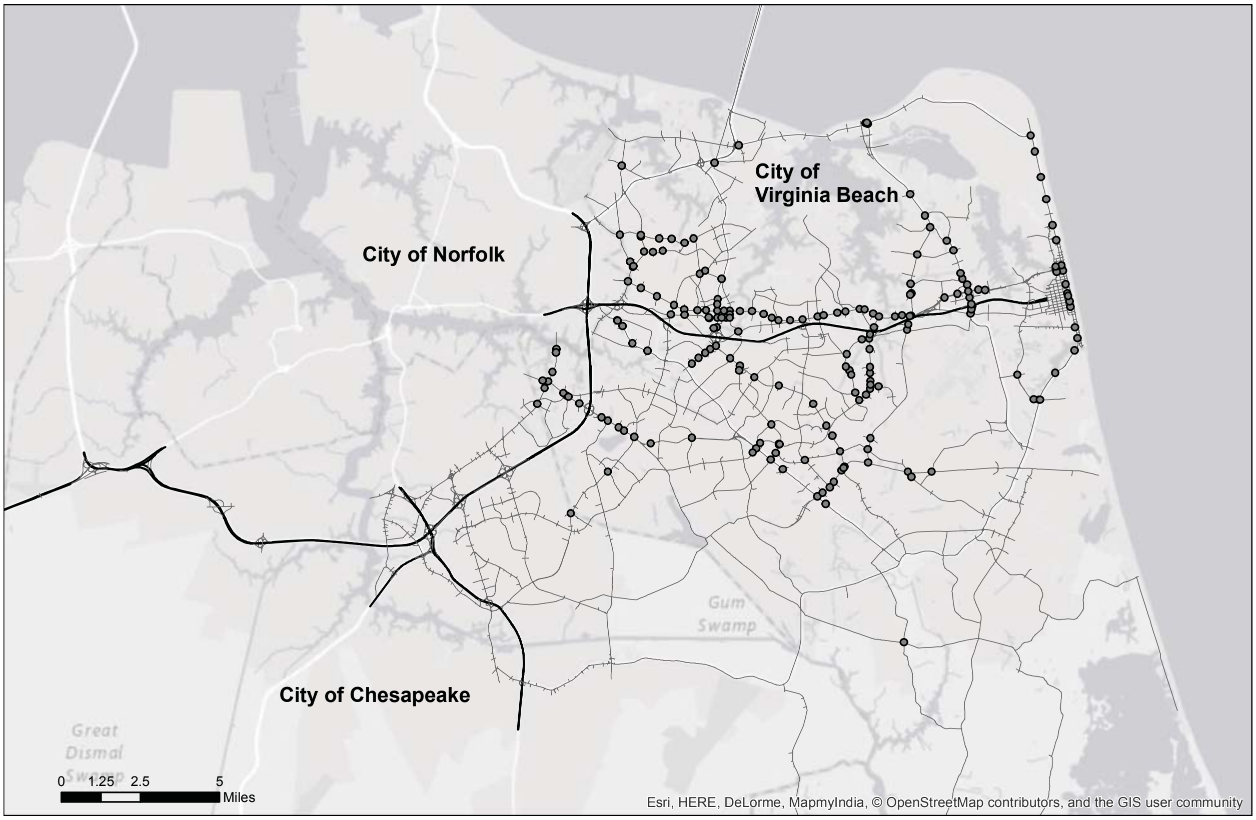

Figure 1: Road network used for the study. *Note: Background map created with ESRI ArcGIS.

3.1 Strategy 1: High iteration

An initial test of DTA with a stopping criteria of 200 iterations was run in order to gain a starting point of best case scenario for comparison. The number of iterations was chosen based on the models ability to converge based on the relative gap for 50 iterations; four times the original stopping criteria was a point well beyond the original but still obtainable based on the runtime of the model.

A problem identified from prior runs and from (Levin et al. 2015) with the DTA process involved too much congestion preventing vehicles from entering the network. The issue might be related to situations when congestion clears from a better path distribution, the queued traffic off the network then enters the network causing more congestion. This added demand made user equilibrium harder to find as the problem space that the DTA is trying to solve changes. To try and work around this issue, another strategy involved the same approach of resetting the MSA but to start the DTA with a reduced demand that slowly increases throughout the DTA process. This type of strategy allowed the DTA to allocate good paths before congestion occurred preventing traffic from queuing off the network.

3.2 Strategy 2: Partial Demand Loading

To accomplish the easing of demand over the period of DTA, the application was scripted to stop after 50 iterations for the same reasons explained earlier in the document. The first set of DTA iterations used 10% of the total demand. After running 50 iterations, the application paused the DTA and increased the demand to 20% of the total. Similar increases were completed until the final DTA used 100% of the model demand. The demand occurred evenly throughout the OD matrix to ensure that proportionality was retained as demand changed on different paths.

The simulation tool reported a historic travel time file and a turning delay file for each iteration of the DTA. These files were used by the simulation to determine the path choice for each OD pair based on the DTA results. A single simulation run was executed for each iteration of the DTA using the output files from the DTA. Doing this allowed the researchers to output simulation results for each iteration of the DTA and to test the reduced demand paths with the full demand. This test provided a comparison of the how well the path choice performed for each iteration of the DTA by testing it with the same demand. Quantitative measures observed were relative gap values, queued vehicles, incomplete vehicles, aggregate trip statistics values.

4 SIMULATION RUNS

DTA was performed for a total of 1300 iterations with the large-scale microscopic model of Virginia Beach. 650 iterations of the model used the 2012 base year demand and 650 iterations of the model used the 2034 future year forecasted demand. Each iteration of the DTA was re-run as a single simulation to generate output files used in this analysis. The process time was roughly one hour to run 4 hours of simulation time using an 8 core desktop computer. Approximately, 142 days of computation time were distributed over multiple computers in order to obtain the result data sets to observe the effects of the DTA process on a large-scale microscopic model.

The data sets included two tests performed for the 2012 base year and the 2034 forecasted year. The two tests are labeled as the 200 dta run for the normal DTA process for 200 iterations. The data labeled scripted DTA is for the scenarios that had the partial demand loading where the total demand is increased throughout the process. The results are presented in the order of 2012 200 dta run, 2012 scripted DTA, 2034 200 dta run, and 2034 scripted DTA. After the results, a comparison identifies similarities and differences between the results.

In the following subsections, charts are presented showing the convergence of the model reflected in values of relative gap based on the DTA runs with the values shown on the primary y axis (left side of the chart). The other measure that is shown in the plots is a bar graph reflecting the number of queued vehicles outside the network waiting to enter for the modeled period with the values shown on the secondary y axis (right side of the chart). The queued vehicles data comes from the single simulation runs completed after the DTA. These single simulation runs were performed with 100% demand in order equal demands and DTA path results on the system. The queued vehicles provide an alternate measure of the systems convergence that can be observed along with relative gap.

4.1 Datasets

The 2012 base year demand was used in DTA for 200 iterations and its results are showing in Figure 2. This model was the least congested of the two scenarios but still contained congestion. The relative gap dropped to its lowest point at around 10 iterations and then slowly increased. Many modelers might consider the 10 iteration point a good place to stop DTA with the relative gap is just under 0.05. As more DTA iterations were run, the value for queued vehicles outside the network continued to decrease meaning that more trips entered the network. Though the relative gap increased slightly after the 10 iterations, it stays below 0.05 indicating that the measure of 0.05 might be the best value of relative gap that can be achieved with the modeled demand.

The scripted DTA shown in Figure 3 attempted to ease the demand on to the network while simultaneously building an understanding of the paths through the DTA process. The 2012 results show a relative gap line

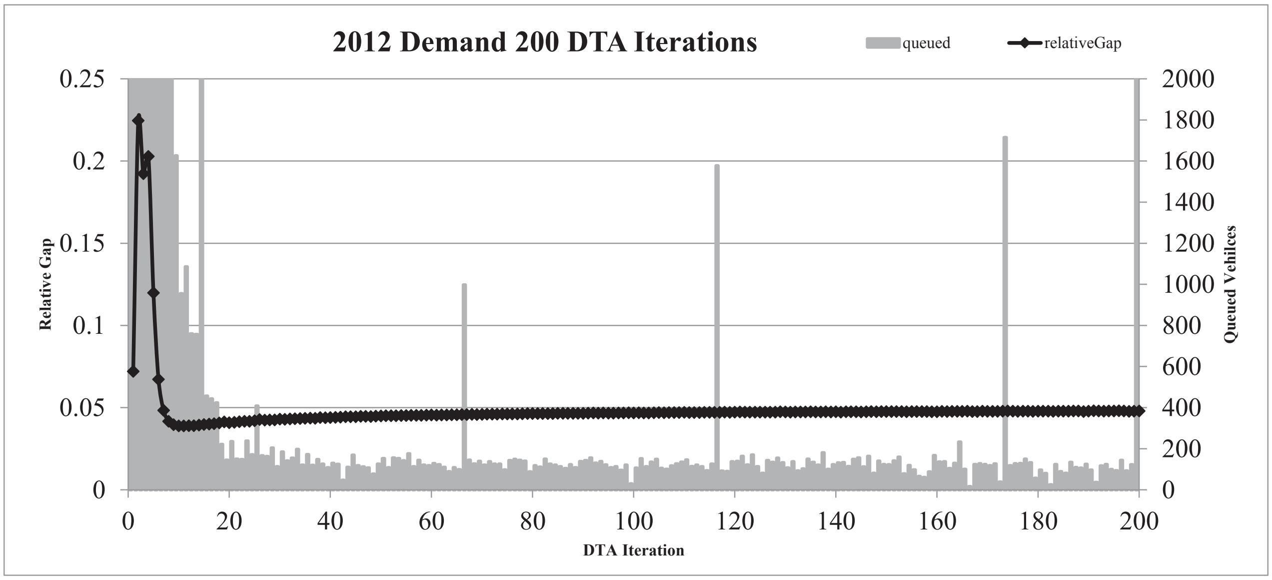

Figure 2: 2012 demand 200 DTA iterations.

slightly different than the prior charts with the relative gap values appearing to be higher during periods of less congestion. In general, the relative gap decreased until the MSA was reset then it decreased even further. The last two sets of 50 (90% and 100% demand) produced a result similar to the prior charts where the relative gap increased after a very large dip. The final relative gap value stabilized just over 0.04. The queued vehicles appear much more chaotic in this plot. This is due to the queued vehicles forming in the single simulation runs that use the path files for that iteration but with 100% of the demand. So, the earlier paths were allocated based on the DTA′s "knowledge" of a fraction of the demand which is reflected in the relative gap, but the queued vehicles use the path information with all the vehicles. The queued vehicles chart shows a decreasing behavior over the process of the scripted DTA and the final 50 iterations shows a normal plot of queued vehicles, which would be expected because the paths were allocated using 100% demand at that point.

The 2034 scenario consisted of more demand and a greater amount of congestion and its results are shown in Figure 4. Because of this, in general the simulation would take longer to run per iteration. The added congestion is reflected in the queued vehicles value. Relative gap, however, converges to a value of roughly 0.03 then slightly increases to just under 0.05 as shown in prior charts. The relative gap is higher while the network is uncongested with reduced demand. As the congestion decreases, the system achieves a smaller relative gap. The queued vehicle values are very high early in this chart because they are results from the single simulation runs using the path results from the DTA with a fraction of the total demand. The queued vehicles fluctuate throughout the DTA with a slight amount of reduction towards the end, but still with some large peaks. For the most part, DTA values trend towards a level line from 50 to 200 iterations with average values around 6,000 queued vehicles.

The final test was the 2034 scripted DTA test shown in Figure 5. Similar to the 2012 scripted DTA run, the relative gap peaks were smaller in the lower demand levels than they were for the higher demand levels. The overall relative gap values decreased throughout the process, but increased slightly for each set of 50 iterations starting around the 60% demand level rather than the very end for the 90% and 100% demand levels. Just as was seen with the scripted DTA in the 2012 scenario, the relative gap values are higher during the uncongested iterations of the DTA process. Final relative gap values were approximately 0.025. The queued vehicles chart decreased over time with large peaks occurring when the MSA resets. The final 50 iterations showed a greatly reduced number of queued vehicles showing a more stable system.

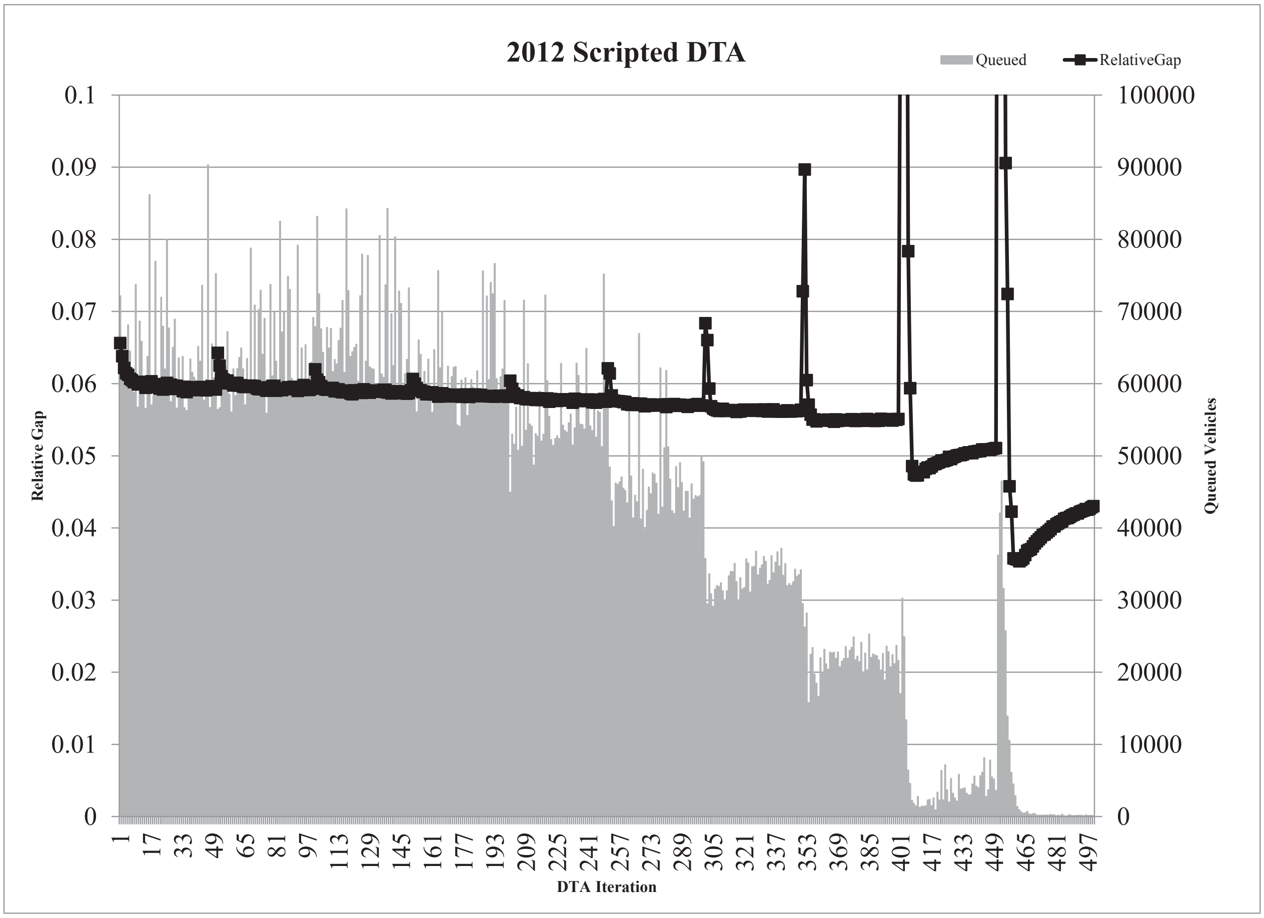

Figure 3: 2012 scripted DTA.

5 RESULTS COMPARISON

All of the results indicated behaviors of convergence. In all cases relative gap reduced and queued vehicles reduced. Relative gap increased in all tests after an initial significant decrease indicating that the smaller relative gap value (at approximately iteration 10) in all of these charts might not be the point of convergence and that another measure is needed. In this case, a measure of the queued vehicles is supplemented with the measure of change in relative gap over time. The queued vehicles plots indicated that instability maybe present even at the end of all the DTA iterations or there is just more demand than can be loaded on the capacity of the network. In the case of scripted DTA with MSA resets, the queued vehicles appeared to become more stable over DTA iterations.

Because the simulation was stochastic, where vehicles departed based on distributions and the car following algorithm provided variation between each vehicle, a single simulation run would not provide sufficient information on the value of the DTA process. Thirty simulations were processed for each scenarios final DTA result. Summary trip statistics were gathered in order to view from a system wide perspective how well the DTA process performed. Table 1 and 2 show average values of each trip statistic measure for the 30 simulations of each scenario. The rows show average values for aggregate measures of trip statistic values recorded from the simulations. These measures include completed trips, incomplete trips (trips that have entered the network but could not reach their destination by the end of the simulation), queued trips (trips that were intended to enter the network but could not because of queued entry links), vehicle miles traveled

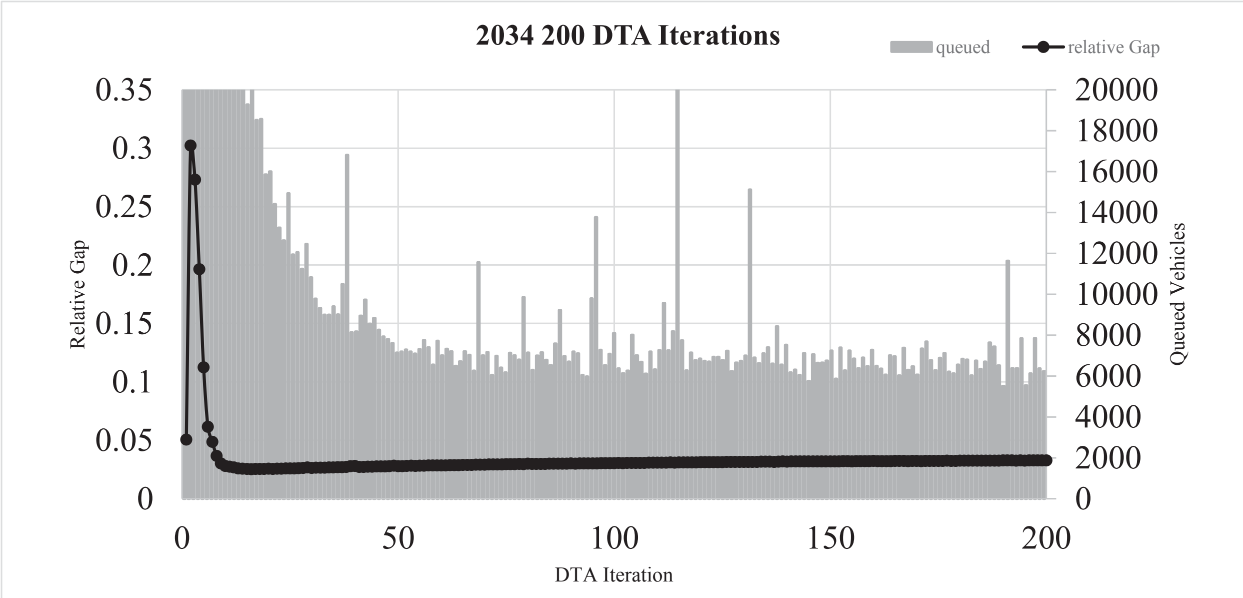

Figure 4: 2034 200 DTA iterations.

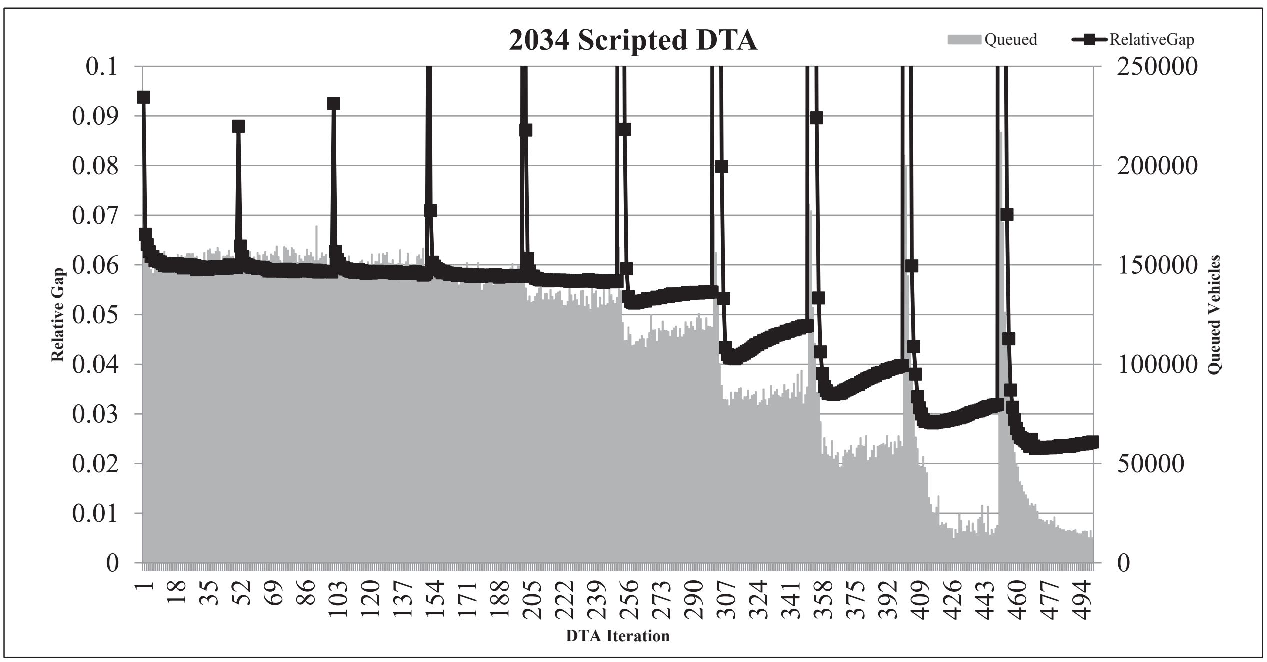

Figure 5: 2034 scripted DTA.

(VMT), total stopped time (totStopped), total number stops (totStops), total travel time of all trips (totTT). The last five measures are average of average values from all the simulation runs.

Table 1 shows the average trip statistic values of 30 simulation runs using the final DTA iteration results of trips in the 2012 scenarios. In this table, the number of completed trips increases from the 200 iteration run to the scripted DTA run by 1 trip. These results indicate very little change in system performance between the normal DTA process and the scripted DTA process for the base year model.

Table 1: 2012 average trip statistics for 30 simulation runs of final DTA iteration results. Note: Time is in minutes, delay in seconds, and speed in miles per hour.

	200_DTA	Scripted_DTA	Difference
Completed	543,369.83	543,370.30	0.47
Incomplete	14,877.80	14,919.60	41.80
Queued	187.00	144.97	-42.03
VMT	3,307,523.32	3,299,395.73	-8,127.58
totStopped	1,471,840.54	1,486,696.61	14,856.07
totStops	3,047,961.43	3,029,925.00	-18,036.43
totTT	6,317,161.03	6,308,022.73	-9,138.30
avgSpd	31.42	31.38	-0.03
totDelay	2,755,446.21	2,753,776.78	-1,669.43
avgDelay	1.10	1.10	0.00
avgStopped	0.68	0.68	0.00
avgStops	1.23	1.22	0.00

Table 2: 2034 average trip statistics for 30 simulation runs of final DTA iteration results. Note: Time is in minutes, delay in seconds, and speed in miles per hour.

	200Iter_DTA	Scripted_DTA	Difference
Completed	630,140.40	624,742.63	-5,397.77
Incomplete	43,681.13	44,687.73	1,006.60
Queued	12,232.03	16,615.57	4,383.53
VMT	3,632,948.97	3,619,218.28	-13,730.69
totStopped	3,715,526.11	4,031,072.64	315,546.53
totStops	6,938,018.97	7,869,662.83	931,643.87
totTT	10,920,303.32	11,558,290.69	637,987.37
avgSpd	19.96	18.79	-1.18
totDelay	6,949,189.84	7,583,225.42	634,035.58
avgDelay	3.86	3.99	0.14
avgStopped	1.53	1.61	0.08
avgStops	2.33	2.50	0.17

Table 2 shows the final results of the DTA for completed trips in the 2034 scenarios. This was the more congested scenario and the scripted DTA was expected to outperform the other. These results however show that the 200 iteration run was able to produce paths that yielded more completed trips, faster speeds, and less delay. The MSA resets produced a system that was a little more congested the lowest average speed, highest delay and most stops.

6 CONCLUSION

The goal of dynamic traffic assignment is to find a stable point where the vehicles choose paths based on prior knowledge of the congested road network for a specified time period. Based on the literature, DTA in calibration should still be run at the same time the other parameters in the simulation are being calibrated. This study focused on the unique calibration issue with forecasted models where calibration data is not available and the process of user equilibrium is the goal for calibration. This paper compares DTA results from an already calibrated base year model and a more congested future year model.

This paper formally supports the concern that there are issues with DTA processes on large scale congested networks. Overall the data shows that the DTA process needs to be improved in order to support a DTA application of forecasted or congested demand. This paper documented results from the large scale model and simulation for DTA in two different ways, one where DTA was run as normal and one where it is restarted with the demand increasing over the iterative process. Literature and past results have shown that there might be an improvement to the DTA performance by loading partial demand throughout the DTA process slowly increasing demand to 100% allowing for trips to determine best paths without over congesting to gridlock.

Contrary to past results and the literature, this project achieved no improvement using a partial demand loading technique. In the case of the 2012 scenario, there was practically no difference in relative gap values and trip performance. The 2034 scenarios were more congested but showed very small differences with the scripted DTA scenario actually performing slightly worse in being able to get all the vehicle trips on the network and finding paths that are more efficient.

More questions must be answered regarding the results of the congested forecasted DTA runs. Although the relative gap shows that the model converged, it is possible that the DTA needs to run even more iterations than what was tested in time for this paper. The amount of queued trips was very high, meaning the DTA is having a difficult time working with the number of vehicles that are being added. The main cause of the challenges with DTA from the evidence presented in this paper appear to be related to the queued vehicles count inhibiting the system from being able to best distribute trips to best paths. Though the DTA is converging as shown through the relative gap values, the trip times and queued trips are still high. In order to get more trips onto the network further research could be done utilizing signal timing optimization along with DTA of forecasted models.

This paper investigates strategies that can be used to find convergence with simulation based DTA in forecasted models. Examples provided show that relative gap should not be the only measure of convergence for dynamic traffic assignment and that other quantitative measures are needed to indicate when a model has reached a point of acceptable stability and equilibrium. The relative gap approach to understanding when a model converges is used successfully with static traffic assignment as the measure of convergence, but new problems arise when only using this measure in the same way with dynamic traffic assignment. If the large-scale microscopic models grow in interest and use, modelers will need to further the research in how to best utilize the existing DTA applications or work to build new applications that are better suited for these challenges.

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