An Assessment of Stochastic Variability and Convergence Characteristics in Travel Microsimulation Models

by

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ABSTRACT

In the middle of the 20th century in the United States, transportation and infrastructure development became a priority on the national agenda, instigating the development of mathematical models that would predict transportation network performance. Approximately 40 years later, transportation planning models again became a national priority, this time instigating the development of highly disaggregate activity-based traffic models called microsimulations. These models predict the travel on a network at the level of the individual decision-maker, but do so with a large computational complexity and processing time requirement. The vast resources and steep learning curve required to integrate microsimulation models into the general transportation plan have deterred planning agencies from incorporating these tools. By researching the stochastic variability in the results of a microsimulation model with varying random number seeds, this paper evaluates the number of simulation trials necessary, and therefore the computational effort, for a planning agency to reach stable model outcomes.

The microsimulation tool used to complete this research is the Transportation Analysis and Simulation System (TRANSIMS). The requirements for initiating a TRANSIMS simulation are described in the paper. Two analysis corridors are chosen in the Metropolitan Phoenix Area, and the roadway performance characteristics volume, vehicle-miles of travel, and vehicle-hours of travel are examined in each corridor under both congested and uncongested conditions. Both congested and uncongested simulations are completed in twenty trials, each with a unique random number seed. Performance measures are averaged for each trial, providing a distribution of average performance measures with which to test the stability of the system.

The results of this research show that the variability in outcomes increases with increasing congestion. Although twenty trials are sufficient to achieve stable solutions for the uncongested state, convergence in the congested state is not achieved. These results indicate that a highly congested urban environment requires more than twenty simulation runs for each tested scenario before reaching a solution that can be assumed to be stable. The computational effort needed for this type of analysis is something that transportation planning agencies should take into consideration before beginning a traffic microsimulation program.

Dedicated to Alex:
Thank you for your support, your humor, and your guidance.

And to my parents:
Thank you for knowing when to let me go and when to hold me tight.

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INTRODUCTION

Since the birth of the transportation planning field in the mid-1900’s, the priorities of transportation planners have shifted from simply building efficient roadways to a greater concern for transportation equity, environmental impact, safety, sustainability, and other important societal demands. In order to seriously examine the emerging policy scenarios that are being deployed to achieve these goals, such as ramp metering, congestion pricing, high-occupancy vehicle lanes, etc., the planning community must move towards a method that reveals travel at the level of the individual decision maker. In recent years, this disaggregate method of planning has taken the form of the microsimulation modeling approach. Although microsimulation has made huge advances in the past two decades, these models do still have challenges that must be overcome in order to ensure their widespread acceptance in the modeling community. One such challenge is the fact that model results vary to a certain degree with every simulation when random number seeds are variable. The extent of this variability and how it can be overcome by practitioners will be examined closely in this paper.

From the Trip-Based to the Activity-Based Approach

Currently, the most widely used and trusted method of urban transportation planning is the 4-step method. This procedure involves four individual models that are integrated to ultimately predict traffic characteristics on individual roadways. The first step of the model is trip generation. In this step, trips ends are estimated in the form of attractions to and productions from individual traffic analysis zones (TAZ's). The second step of the model is trip distribution, which matches the productions with attractions and creates fully-formed trips with origin and destination information. Next, the mode choice procedure determines the travel mode – such as personal auto, rail, walking, etc. – by which the trip will be completed. Finally, the route choice procedure assigns a specific route by which travelers will reach their destinations. (*1*)

Microsimulation is a general term that can be applied to any number of dynamic systems. A system in which individual decision-making entities can be aggregated to achieve a higher-level group behavior is a system in which microsimulation can be applied. A vast body of literature exists describing the various microsimulation projects related to transportation and the urban form. Activity-based travel demand models use microsimulation to predict the characteristics of trips made by individuals as a function of the activities in which they choose to participate. (*2, 3*) Time-dependent traffic patterns, such as peak-hour congestion, have been modeled using microsimulation techniques, (*4*) and even the evolution of land use over time can be microsimulated (*5*). The relative success of these microsimulation models all contribute to the planning community's increasing confidence in the field of microsimulation, resulting in a build of momentum toward the use of microsimulation in the planning field.

Although the four-step model is a highly valuable tool for urban transportation planning, it does fall short of an ideal planning tool in many ways. For quite some time it has generally been accepted in the transportation field that travel is a derived demand. It is derived from the desire of individuals to participate in certain activities. The 4-step model is a trip-based approach, treating travel as a demand in and of itself. Microsimulation models, on the other hand, treat travel demand as an activity-based phenomenon. Because the 4-step model results in traffic characteristics at an aggregate level, it is often not possible to detect the details in daily travel using this method. Details that can be modeled with microsimulations that are not capabilities of the 4-step model include everything from the number of vehicles waiting in a left-turn queue to the route a transit rider takes when walking from the park-and-ride lot to the train station.

By transitioning to a microsimulation activity-based approach, planners are able to harness the power of individual decision making behavior and use these individual decisions to observe group behavior in a very detailed fashion. (*6, 7, 8, 9*) This disaggregate approach makes it possible to avoid aggregation bias by utilizing probabilistic choice-making behavior. Because of this focus on the individual, microsimulations have profound potential for evaluating and even visualizing the effects of policy changes and modal investment projects. (*10*) These results can potentially help bridge the gap between technical professionals and policy makers. However, as is discussed below, a microsimulation's reliance on the probabilistic choice-making behavior of its agents can be both a benefit and a hindrance.

Challenges Facing the Microsimulation Model

As with any infant innovation, the microsimulation modeling community must overcome certain challenges before its models can be widely accepted and implemented in practice. One such challenge is the complexity and computational intensity of the models. Because a microsimulation must follow the decision maker at every step in the model and track its progress through the system, extremely large data sets are often required. In the case of transportation system simulation, the microsimulator must know at every second during the modeling time frame where to find each vehicle, traveler, or household and what that entity's next step will be in the following second. Given that the model holds such vast quantities of information, a microsimulation can become quite complex, and model run times and storage requirements are often underestimated by practitioners.

Another serious impediment to the adoption of microsimulation models in the transportation planning community is their stochastic variability. Each decision made by an individual in a simulation is the result of a probabilistic choice that must rely on a random number. When the random number seed is changed, identical results in subsequent model runs can no longer be guaranteed. Analysts are accustomed to the reliability of producing identical results in identical model runs using the 4-step method, and the stochastic variation in results of microsimulators raises suspicion as to the validity of the results. Each model run represents a single day and no transportation system in the "real world" can have identical characteristics from one day to the next. Many therefore view this stochastic variation in results as a reflection of observable variation in surface travel. No matter how one chooses to view it, the stochastic variation in a simulation can mask the true impacts of policy and modal investment scenarios: it becomes difficult to decipher what is truly a result of policy change and what is simply a reflection of the stochastic variation.

Running a microsimulation model system multiple times offers the ability to obtain stable and robust model outputs that facilitate comparisons across scenarios. In running a model just once for multiple scenarios, the critical question that arises is to what extent each of these sources of variability contributes to differences in outputs. Unless one can be sure that sufficient runs of the model have been performed, such that a comparison of stable output values can be made across scenarios, it is not possible to conduct accurate scenario analysis. Planning agencies that are under tight schedules to produce long range transportation plans and policy studies in response to local and federal regulations, and numerous requests from policy makers, cannot afford the luxury of making multiple runs. Too few runs could result in reporting results that have not yet reached a stable and reliable set of values, while too many model runs could result in computational inefficiency and unnecessary expense. In this context, the potentially long run times, and the desire to know how many times a stochastic microsimulation model system needs to be run to obtain stable averages, constitutes the issue motivating this research.

Review of Related Literature

The issues addressed in this paper are not new; there is a body of literature that has examined stochastic variability in microsimulation modeling contexts and proposed approaches to address it. The intent here is to further add to the body of knowledge on this topic so that practitioners can be more informed on ways to handle stochastic variability in outcomes of microsimulation models. The literature that speaks to the issues of stochastic variability in microsimulation modeling is constantly growing.

Gibb and Bowman (*11*) consider the notion of simulation error, i.e., the Monte Carlo simulation error arising from the discretization of choice behaviors in microsimulation model systems of activity-travel demand. They term simulation error as the random noise problem, and describe techniques to establish convergence in these models. They report that minor adjustments in the method of successive averaging, where outcomes from multiple runs are successively averaged to convergence, can substantially improve computational efficiency. Walker (*12*) proposed a microsimulation modeling environment to make such approaches more accessible to planners. She notes that the simulation error is actually an appealing feature of microsimulation models in that it allows one to estimate the size of the error associated with point forecasts and generate confidence intervals based on the distribution of outcomes from multiple runs. Vovsha et al (*13*) also describe some practical approaches to achieve equilibrium in activity-based microsimulation models. In addition to successive averaging of outcomes over multiple runs, they suggest enforcement techniques such as reusing random number seeds and gradual freezing of travel choice dimensions once they exhibit stability in outcomes.

A more detailed study was undertaken by Castiglione et al (*14*) who investigated the amount of stochastic variation arising from random simulation error in the San Francisco County Transportation Authority (SFCTA) activity-based travel demand model. Their experiments were also aimed at determining the number of runs required to obtain stable and reliable results. They ran the SFCTA model 100 times; each time the model was run, only the sequence of random numbers used to simulate individual choices in the model system was changed. The variability in the output was quantified based on two factors – the type of sub model (i.e., tour generation, destination choice, and so on); and the geographic resolution (such as zone or county level) at which the variability in outcomes is measured. For each combination of the two factors, the percent difference between the successive average of a particular output and the final mean (after 100 simulation runs) was computed and plotted after each simulation run. They found that all model components demonstrated a high level of stability even at the highest geographic resolution (zone level). The variability at lower geographic resolutions (county and neighborhood levels) was relatively lower, suggesting that aggregation over space reduces (masks) variability in outcomes. They also found that a relatively small number of runs was sufficient for the outputs to converge to a stable value. However, they do note the potential pitfall associated with running a microsimulation model only once. The outputs from individual model runs could vary as much as 10 to 25 percent from the successive average computed after 100 simulation runs. The authors also indicate that the number of simulation runs required to achieve stability in model outcomes is dependent on the model system and the particular planning application. Finally, they note that their findings apply in the context of the SFCTA activity-based model and it would be useful to conduct similar analysis (such as the one in this paper) for other model systems.

Lawe et al (*15*) implemented TRANSIMS for Chittenden County in Vermont. They conducted various sensitivity tests, including tests to assess the sensitivity of model results to changes in the random number seed. Five model runs, each with a different random number seed, were performed and the variation in results (traffic volumes and average speeds) for 10 links in the network was examined carefully. The coefficient of variation (CV) was computed for every hour of the day for each of the 10 links, and the average CV value was computed for a full 24 hour period. It was found that there was very little variation in the average daily CV among the five different runs for both traffic volumes and average speeds. Overall, it was concluded that, for medium-sized areas with little or no congestion, microsimulation models may not be that sensitive to variations in the random number seed.

Similar results were also reported by Veldhuisen et al (*16*), where the effects of simulation error on travel demand estimates were found to be negligibly small. They found a very high correlation across outcomes from successive runs of the model system and also note, similar to Castiglione et al (*14*), that the Monte Carlo error is higher at higher geographic resolutions. Overall, while there has been some evidence on variability due to repeated runs of a microsimulation model system with different random number seeds, additional tests are needed to accumulate a larger body of knowledge on this issue, especially in highly congested metropolitan areas.

The TRANSIMS Model

Although the experiment reported here may be undertaken using any microsimulation model, the model components used in this study are those specifically embedded in the TRANSIMS (Transportation Analysis and Simulation) model system. This state-of-the-art program is an agent-based cellular automata model used for approximating activity-based travel demand. Not only does the program individually monitor any number of drivers in their activity participation decisions for the course of a simulation and track the routes each driver takes on the network, it also simulates the actual act of driving by allowing drivers to progress through a series of cells. A driver cannot progress into the next cell if it is already occupied by a vehicle, which means that bottle-necks and congestion can be accurately re-created on the network.

The generalized steps for running a TRANSIMS implementation are as follows: build a highway network, overlay the highway network with transit services, convert demand from existing origin-destination trip tables or derive demand from a synthetic population with generated activity lists, route the trips on the network, microsimulate the completion of all trips over the 24-hour period, and finally stabilize travel characteristics by iteratively re-routing and microsimulating trips. For this particular experiment, demand is presented in the form of existing origin-destination tables rather than being generated based on activity lists.

The stochastic variation of results is measured in this experiment by changing random number seeds in the router module of TRANSIMS. Repeated runs of the router and microsimulator are performed using different random number seeds driving the simulation of choice behaviors and vehicular movements in this one model component. The resulting stochastic variability, and the extent to which stability in results is achieved at the end of a certain number of runs, are evaluated and reported.

The chapters that follow will include an overview of the TRANSIMS highway and transit networks that have been created to reflect conditions in the Phoenix Metropolitan area and an overview of the router and microsimulation stabilization processes. A detailed description of the experiment will be followed by the results, showing the extent to which random number seed variation in each module creates a variation in results. Finally, the results of the experiment and the future work on this issue will be discussed.

THE HIGHWAY AND TRANSIT NETWORKS

As with any other comprehensive travel demand modeling process, the first step is to create a highway and a transit network. By building the network, the microsimulation modeler is creating a detailed virtual city. The network creation requires an intense effort and is possibly the most time-consuming element of the modeling process. In TRANSIMS, the network contains links, representing roadways, nodes, points where two or more links intersect, signals and their timings, signs, pocket (turning) lanes, activity locations, parking lots, transit stops, lane connectivity parameters, process links, and other elements. Entering a table or list of data for all these entities would be time constraining. To minimize this type of tedious work, the only required inputs to the TRANSIMS network-building executable are the node, link, and zone files. TRANSIMS has the ability to use these required inputs and deductive logical coding to generate the remaining parameters of the network. The required input data have been gathered from the existing 4-step model provided by the Maricopa Association of Governments (MAG).

Developing the Highway Network

The network that is developed for a 4-step model implementation must accommodate trips being made from one traffic analysis zone to another traffic analysis zone (TAZ). For this reason, 4-step model networks are built with zone centroids, which represent the point in that zone from which all trips originate or to which they are destined. A centroid connector is added in these networks that link the zone centroid to the roadway network. These zone centroids and centroid connectors are only theoretical network elements that do not exist in the "real world." The TRANSIMS network does not contain zone centroids or centroid connectors. Rather, the software constructs activity locations, parking locations, and process links along either side of any roadway. The xy-coordinates of TAZ centroids are used to assign each activity location to a zone by matching the location to the same zone as the nearest centroid in terms of Euclidean distance. These activity locations become the new points of origin or of destination. A process link connects each activity location to a parking location, where travelers leave their vehicles for the duration of their activity. Figure 1 shows the MAG network and the TRANSIMS network. One will notice that the short diagonal links located throughout the MAG network are not included in the TRANSIMS network. These are the centroid connectors and are not applicable to the TRANSIMS network. In this activity-based microsimulation network, the activity location becomes similar to the zone centroid and the process link, connecting the activity location to the highway network, is comparable to the centroid connector.

From the Trip-Based to the Activity-Based Network

The network data that is made available from MAG provided the essential start-up information needed to complete this research. However, details needed to be added to this essential data in order to ensure that vehicles move smoothly through the network during a microsimulation. TRANSIMS requires that the user input a node file, link file, and a zone file. The node file contains xy-coordinates for each node identified on the network. The MAG network, because it contains centroid connectors that have a centroid at one end, included nodes that were

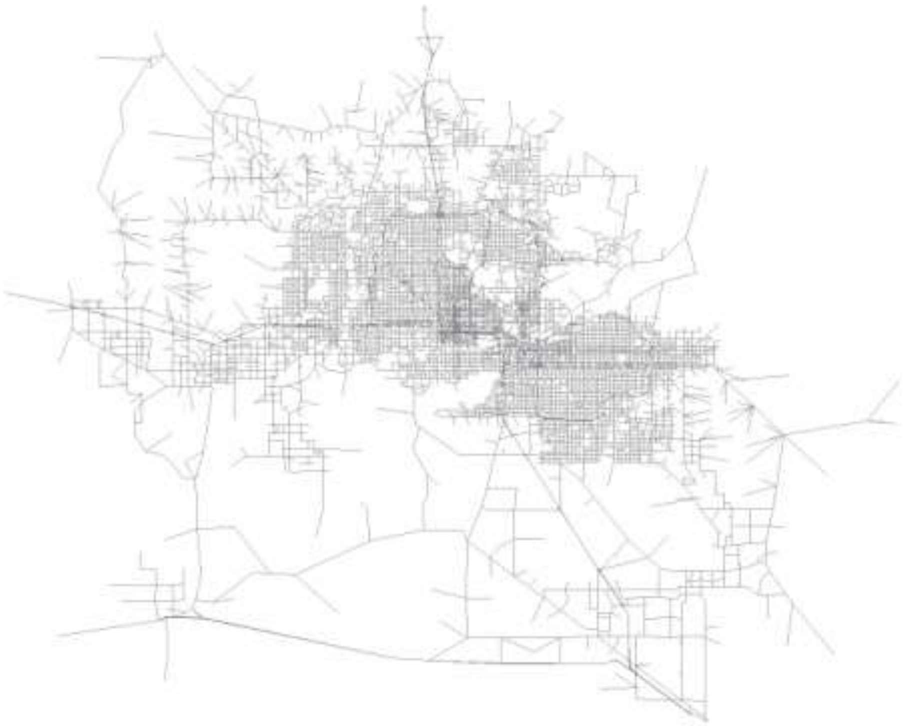

FIGURE 1a Phoenix Metropolitan Area Network Provided by MAG.

FIGURE 1b Phoenix Metropolitan Area Network Created for TRANSIMS.

actually zone centroids. These centroids are only theoretical places and are not identifiable in the physical network, therefore the nodes that were also centroids were deleted in the TRANSIMS network. The exception to this rule was the centroids of external zones, at which nodes were not removed. The zone file contains xy-coordinates of the zone centroids and an area type description. Area types ranged from rural to suburban to urban and allowed TRANSIMS to create categories in which to place each network element. Each area type has different criteria for placing traffic control signals and default timing assignments for those signals. The Phoenix Metropolitan network contains 1,995 internal TAZs and 11 external TAZs. The external zone centroids represent gathering points for trips that take place partially outside the metropolitan planning area. Finally, the input link file contains specific characteristics of all the roadways on the network. This includes the node identification number of the node at either end of the link, the number of lanes in each direction, the speed in each direction, capacity of the roadway, and the length of the link. This link file also contains a description of the mode(s) of travel that is (are) allowed to use that link and the facility type of the roadway – freeway, entrance/exit ramp, major arterial, etc. Some changes to MAG link information needed to be made in order to make the network more detailed and more compatible with TRANSIMS requirements. For example, no link in the TRANSIMS network should be given artificially high speeds or capacities. This technique is sometimes used in a trip-based model network in order to allow a large number of vehicles to travel a certain path without causing a link failure.

In order to create the network objects that do not come from one of the three input data files, TRANSIMS contains several modular executable scripts that automate the generation of network elements with repeatable patters. The executable file *TransimsNet.exe* uses the three input data files described above and several user-defined parameters to generate activity locations, process links, parking locations, lane connectivity, turning lanes or “pocket” lanes, and warrants for traffic control signals and signs. Using the *TransimsNet.exe* user-defined parameters, a researcher can control which intersections are identified as needing a signal or sign control. For each area type, the user identifies the two lowest level facility types for which a signal is warranted at their intersection; TRANSIMS identifies sign warrants independently. For this research, the signal control warrants are shown in Table 1. Also by using the parameters available in this executable, the turning lanes are set to 75 meters in length, u-turn capability is added to all dead-end links, and three is designated as the maximum number of activity locations that can be placed along either side of a link.

TABLE 1 Traffic Signal Warrants for each Area Type in the Network

Area Type	Description	Facility Type 1	Facility Type 2
1	Urban	Collector	Collector
2	Urban – Suburban	Major Arterial	Collector
3	Suburban	Major Arterial	Collector
4	Suburban – Rural	Major Arterial	Major Arterial
5	Rural	Major Arterial	Major Arterial

Once the network elements have all been created, the *IntControl.exe* executable is used to create traffic control signals and signs at each intersection where control is deemed necessary. The program uses the signal warrants and sign warrants created in the previous executable. In this step of network creation, each signal is given a phasing plan and a timing plan. The software decides what phases the signal should have – for example, a northbound/southbound left turn only phase followed by an eastbound/westbound all directions phase – and then assigns a timing plan for each of those phases. These phasing and timing plans are created based on some logical assignment within the software's code. The user has the ability at any point to enter the timing and phasing plan files to make changes or adjustments to the plan. For this research, no changes were made to the TRANSIMS default assignment algorithm results.

Enhancing the TRANSIMS Network

The majority of the elements created in TRANSIMS are done so using the software's default algorithms. This will inevitably result in some elements being created with characteristics not compatible with the real world network. The modeler has the ability to enter the data files created for each network element and make enhancements in order to align the TRANSIMS network as close as possible with the actual physical network. In several instances, the Phoenix TRANSIMS network required an adjustment to lane connectivity characteristics. Figure 2 shows an example of a typical 4-way intersection and the connectivity between the links. The links themselves are shown in grey while the connections are shown in red and the turning lanes are shown in green. Minor adjustments such as this are a continuous occurrence in the development of the TRANSIMS model. Even after simulations have begun, the researcher must check to see where unreasonable traffic congestion is found and make adjustments to the network in an attempt to alleviate that congestion.

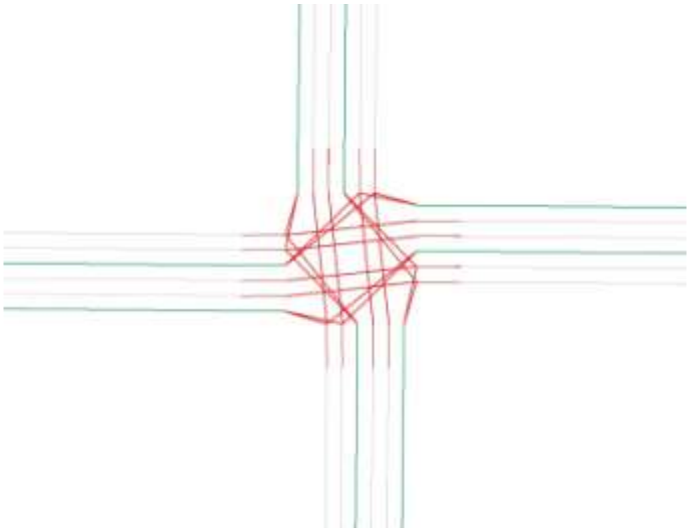

FIGURE 2 Typical 4-Way Intersection with Connections.

Another serious consideration to be made with the Phoenix network in particular was the assignment of activity locations to traffic analysis zones. When trips are loaded onto the network in this research, they are done so in the form of zone-to-zone origin-destination files. Each trip must have a beginning and an end point. In TRANSIMS, those points are activity locations. Therefore, in order to assign a beginning and end point to each trip, each activity location must be matched with a zone. This matching is done by finding the zone centroid to which each activity location is closest. In the Phoenix network, large areas exist around certain zone centroids, especially in the low density, less developed neighborhoods and near mountain and desert preserves, where there are no major roadways and therefore no activity locations. Figure 3 shows the activity locations and zone centroids on the network. The activity locations are dark blue while the zone centroids are shown in red. One will notice the large areas of land that are lacking in major roadway development. This resulted in a large number of TAZ's to which no activity locations were assigned, therefore causing a failure to load any trips with origins or destinations in these zones. For this problem, a simple program was created to re-assign activity locations to zones after the TRANSIMS assignment. The program script first looks for any zones to which no activity locations were assigned, then finds the two closest activity locations by Euclidean distance to that zone's centroid. It checks to make sure the activity location had not been previously re-assigned, and then re-assigns those two activity locations to the zone.

Developing the Transit Network

In the past, the presence of public transit service was often overlooked when planning for new roadways and infrastructure investments. The ISTEA legislation places a heavy emphasis on planning for public transit services. TRANSIMS accommodates that goal by offering detailed transit planning mechanisms and making microsimulation of public transit possible. However, the transit network must first be created using TRANSIMS executables and input network data.

Integration with the Highway Network

The transit network is integrated with the highway network and relies heavily on the linkages there that already exist. Therefore it is imperative to create a fairly comprehensive highway network before attempting to create a transit network. Transit modes that use the highway network, like local bus, express bus, and paratransit, must travel along its travel path using links and nodes that have already been created and can be identified by number. For transit modes that use a dedicated right of way, such as a light rail line, links and nodes must be created while creating the highway network.

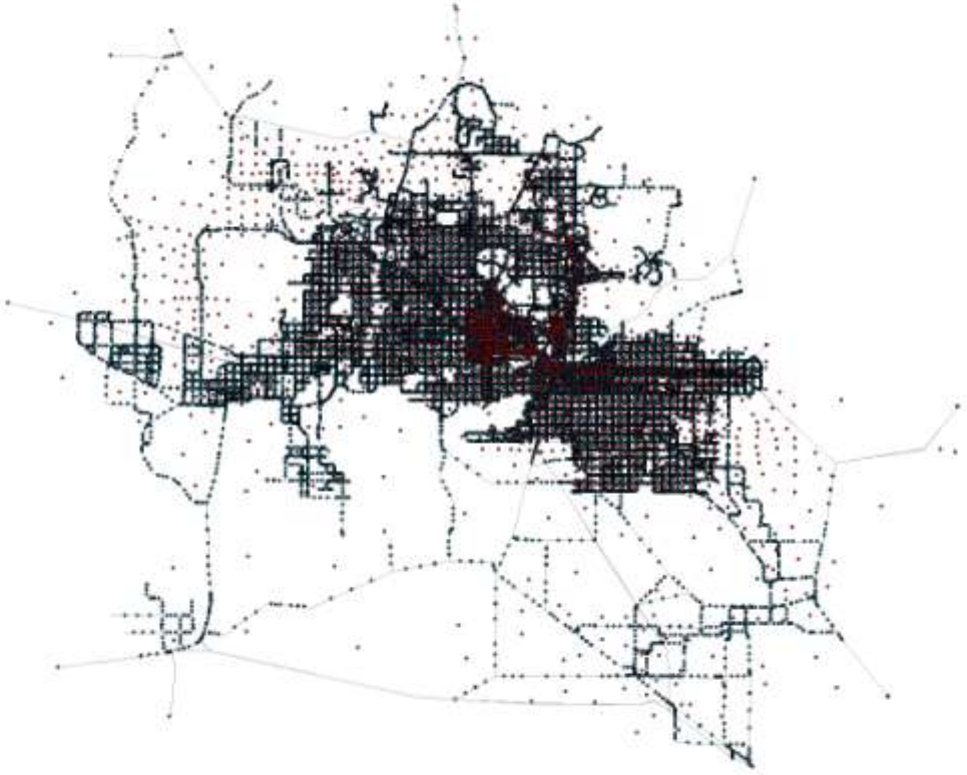

FIGURE 3 Zone Centroids Compared to Activity Locations.

When creating the highway network that will eventually support transit, one must take into consideration any transit modes that run on a dedicated right of way, or a link that allows only that mode of travel. For example, a light rail line that runs along a dedicated track cannot be placed on a network in which to rail tracks exist. Rail transit links are treated just like any other link during highway network creation. The links on a light rail line must be connected at either end to nodes and must be given a capacity, length, free flow speed, and number of lanes in each direction. In the case of these links, however, the facility type and allowable modes are both coded as simply “lightrail.” The researcher has the choice of connecting these links using nodes that are dedicated to the transit system alone or using nodes that are also used on the highway network. If a node is shared between a highway link and a rail link, then that rail will have to interact with auto traffic at an intersection with some complex phasing and timing plans. If the rail node is unique to the rail links, it is assumed that the rail is either above or below the highway grade and that the transit and auto modes do not interact. In this implementation, light rail links were coded separately from highway links. There are some instances where the light rail nodes are shared and some where they are unique to light rail links. Short links were also created near the location of each light rail station that allow only the walk mode, so that travelers can transition from the highway network to the light rail network.

Developing Transit Routes

The TRANSIMS executable which creates data files of transit elements, TransitNet.exe, requires two input files on which it bases all other transit elements. One input file, called the “transit nodes” file lists the nodes in the highway network where transit routes stop to collect passengers. These nodes, when listed in order, guide the transit vehicle along its path. The user can force a transit vehicle to take a certain route by placing a negative sign in front of the node ID number. This will force the transit vehicle to pass by that node, but will not allow the vehicle to stop. This method of transit routing is particularly helpful when coding express bus routes, which generally use the freeway system and travel for long distances without stopping to load or drop off passengers. The other data file that is required for transit network coding is the “route header” file. This data file lists the characteristics of each transit route, in particular the route’s headway during each service time period. A service time period is a continuous segment of time over which transit vehicles have the same schedule characteristics. For example, transit vehicles do not run at all in the Phoenix area between midnight and 4:00 AM. Between 6:00 and 9:00 AM and again between 4:00 and 7:00 PM service is increased to meet peak travel time demand. The headway of a transit route is the time between each transit vehicle on that route. A passenger that remains stationary at a single stop and measures the time between one transit vehicle and the next transit vehicle on the same route is measuring the headway. Each transit time period can have a different headway assigned to each transit route. A time period in which a particular route does not run will have a headway of zero for that route.

Using the transit route and transit header data files, the TRANSIMS executable can create a transit system that includes the schedule of each route, the location of consecutive stops along that route, and the schedule of the drivers that operate each route. Using this information, a transit user will decide which route(s) to take to reach his or her destination. Figure 4 displays the transit network in the Phoenix Metropolitan Area. Figure 5 shows individually the routes for each type of transit offered: local bus, express bus, and light rail.

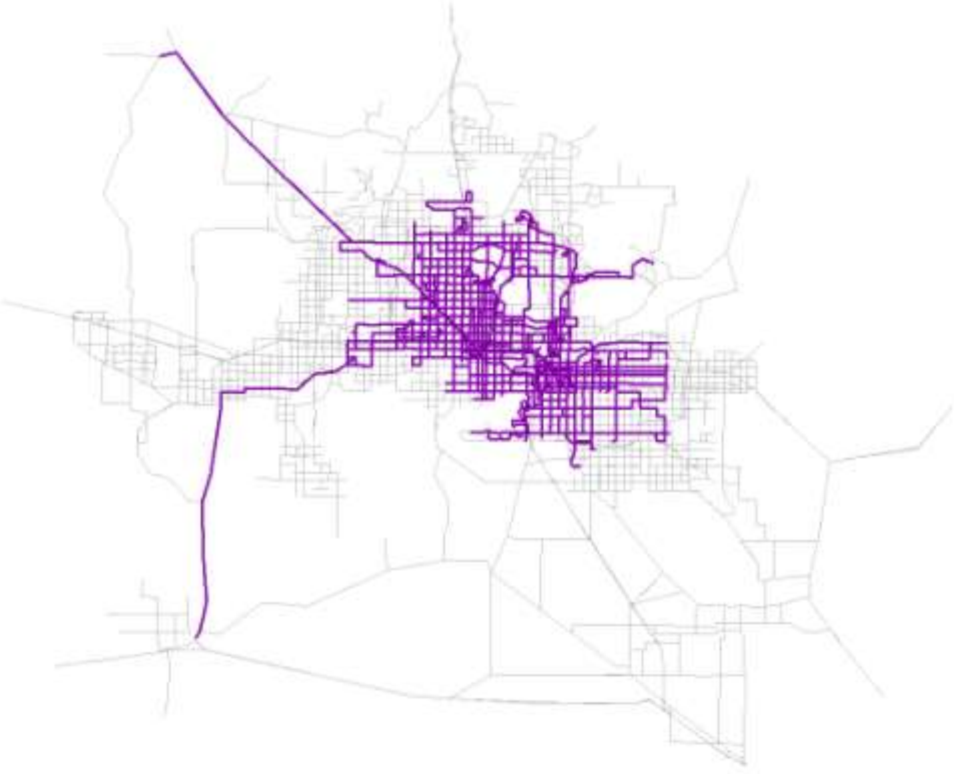

FIGURE 4 Phoenix Area Transit Network.

FIGURE 5a Phoenix Area Local Bus Network.

FIGURE 5b Phoenix Area Express Bus Network.

FIGURE 5c Phoenix Area Light Rail Network.

Subareas

Microsimulation, as discussed, is an extremely time consuming endeavor. The greater the area over which trips are simulated, the more time and computational effort is required. Therefore, in many planning areas, it is desirable to simulate vehicles only over a subarea of the full region. The creation of a subarea is made relatively simple using the TRANSIMS executables. The executable called SubareaNet.exe uses all of the previously generated highway and transit network data files and a shape file polygon provided by the user that corresponds with the desired subarea boundaries to create subarea network files.

Research in the Phoenix area is performed with the use of a subarea boundary. Though trips are routed for the entire region, only those trips within the subarea or passing through it are microsimulated. Because this research loads trips based on zone-to-zone origin-destination tables, it was decided that the subarea should not split any existing traffic analysis zone. Much of the research taking place in the area is centered on the 20-mile-long light rail service that connects Phoenix to Tempe and Mesa. Therefore, the subarea boundary was chosen by constructing a five-mile buffer around the light rail line. The five-mile buffer was then extended to reach the boundary of any TAZ that fell partially within the initial buffer. Figure 6 illustrates the portion of the TRANSIMS network that is included in the subarea boundary.

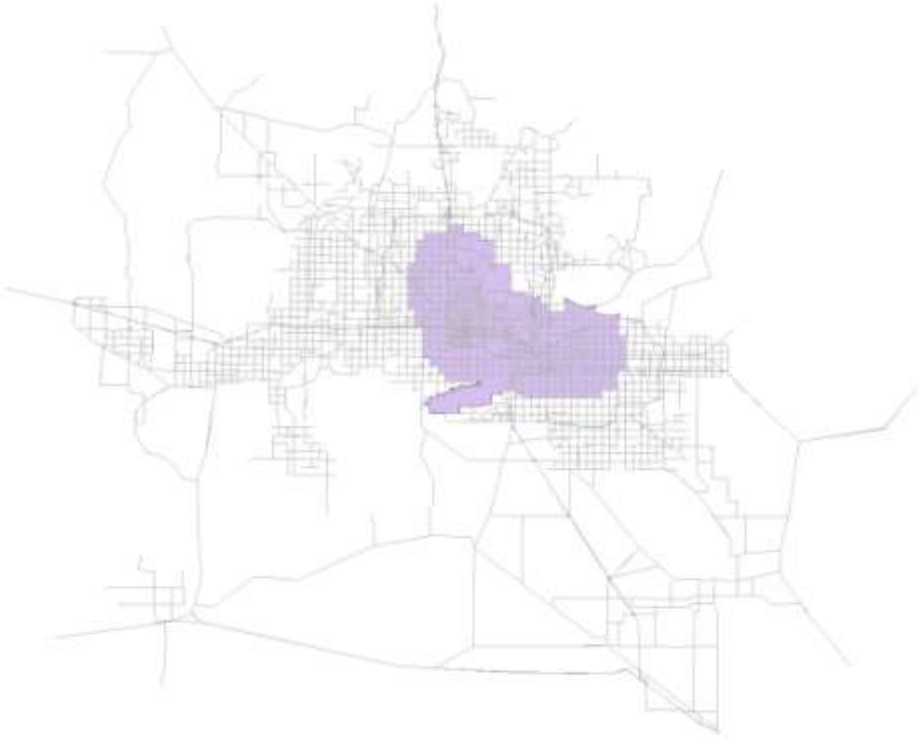

FIGURE 6 Subarea Network.

SIMULATING TRAFFIC USING TRANSIMS

The ability to travel from one location to another in order to fulfill a desire for activity participation is a service that is demanded by residents of a metropolitan planning organization. Just like any other service, travel is engaged in a supply and demand relationship that fluctuates over time. The supply is represented by the available roadways and travel services while the demand changes daily and is a derivative of activity participation. Simulation of traffic in the TRANSIMS network evolves much like a person’s travel behavior takes place. When a traveler wants to engage in an activity, he or she must first decide that they are going to make a trip using a certain mode of transportation. The traveler must then decide by which route they will reach the destination. Finally, the traveler must navigate the transportation system, making decisions along the way that will aid them in reaching their destination. If the route the traveler chose was congested or in some other way undesirable, he or she will most likely take a new route the next time they make the same trip. Following this same procedure, a TRANSIMS modeler must first enter the trips along with their origins, destinations, and mode of choice into the system. TRANSIMS must then route the trips and then microsimulate the trips by re-creating the driving behavior as each vehicle navigates the system. Finally, if any link is highly congested or any traveler experienced an unacceptable travel time, TRANSIMS will try again to route the trips in a more efficient manner. This chapter describes the TRANSIMS simulation process and the steps that must be taken to approximate travel characteristics.

Converting Daily Trips

The first step in simulation is to convert the trips from zone-to-zone origin-destination tables to actual travel plans for each traveler. Origin-destination trip tables for this research were made available from MAG by purpose and mode. For this particular research, though a transit network is available, demand and therefore converted trips has been limited to those utilizing the personal automobile alone. An origin-destination table for a particular purpose and mode of travel simply contains the origin zone in one column, the destination zone in another column, and the number of trips made from the origin to the destination in a 24-hour time period. Table 2 shows the number of trips being made on the network for each purpose and mode of travel in the Phoenix Area simulation.

The home-based ASU purpose includes any trip with home as either the origin or destination and Arizona State University as the other trip end. Home-based university is similar, but the trip end can be any of the region's other institutes of higher education. The total number of auto trips being executed in a 24-hour period comes to 14, 910, 781 or approximately 15 million trips. The question arises then, how does TRANSIMS know at what times during the day these trips take place?

The answer to the above question is diurnal distributions. Using the 2009 National Household Travel Survey (NHTS) data specific to the Phoenix Metropolitan Area, time of day distributions for each trip purpose and mode of travel above were constructed. The number of trips taken for each purpose and mode were aggregated into 15-minute time bins. The percentage of total trips that makes up each time bin becomes the diurnal distribution of travel. These percentages can be applied to the trips on the TRANSIMS network.

TABLE 2 Daily Trips by Mode and Purpose

Purpose	Mode		
	Single-Occupancy Vehicle (SOV)	High-Occupancy Vehicle (HOV)	Large Trucks
Home-Based ASU (ASU)	137132	369	n/a
Home-Based University (HBU)	170193	576	n/a
Home-Based Work (HBW)	2614715	10710	n/a
Home-Based Other (HBO)	4605270	60512	n/a
Non-Home-Based Work (NHW)	1990578	3369	n/a
Non-Home-Based Other (NHO)	1953720	21291	n/a
All Large Truck	n/a	n/a	3342346

When answering questionnaires, survey participants tend to round trip start and end times to the nearest 15-minute mark. This causes large spikes in the data on those 15-minute marks. In reality, trip start and end times are continuous measurements. Because the diurnal distribution described above is gathered from survey results, the data tend to be discontinuous, displaying large spikes at the 15-minute marks. For this reason, a distribution smoothing procedure is built in to TRANSIMS and is used in this study. The smoothing procedure rounds out the distributions to a more continuous data set. Figure 7 shows the original diurnal distribution for the single occupancy vehicle home-based other trips and the same data after the smoothing procedure has been applied. Because trips are made for different purposes at different times of day, the diurnal distribution for each trip purpose has a unique shape. Figure 8 shows the smoothed diurnal distributions for the six single-occupancy vehicle (SOV) trip purposes and the heavy truck trips. Note that heavy truck time-of-day data is not gathered from the NHTS but from the MAG-provided trip tables for various times of day. Diurnal distributions for high-occupancy vehicle (HOV) trips are similar to the distributions for SOV trips of the same purpose. One can see that travel to Arizona State University and other institutes of higher education has four peak periods, presumably related to travel to classes at different times of day: early morning classes, mid-day classes, evening classes, and night classes. Home-based work trips, as expected, have peak trip percentages during the morning and evening rush hour time periods.

Router Stabilization

As discussed, traffic microsimulation is an iterative process in which trips must be routed and travel time calculated many times before a stable solution is reached. Travel times and congestion levels can be calculated using the microsimulator, but microsimulation is extremely time intensive. Therefore, it is standard practice in TRANSIMS implementations to reach stabilization in the router before utilizing the microsimulator. The procedure for stabilizing the router without utilizing the microsimulator is described below

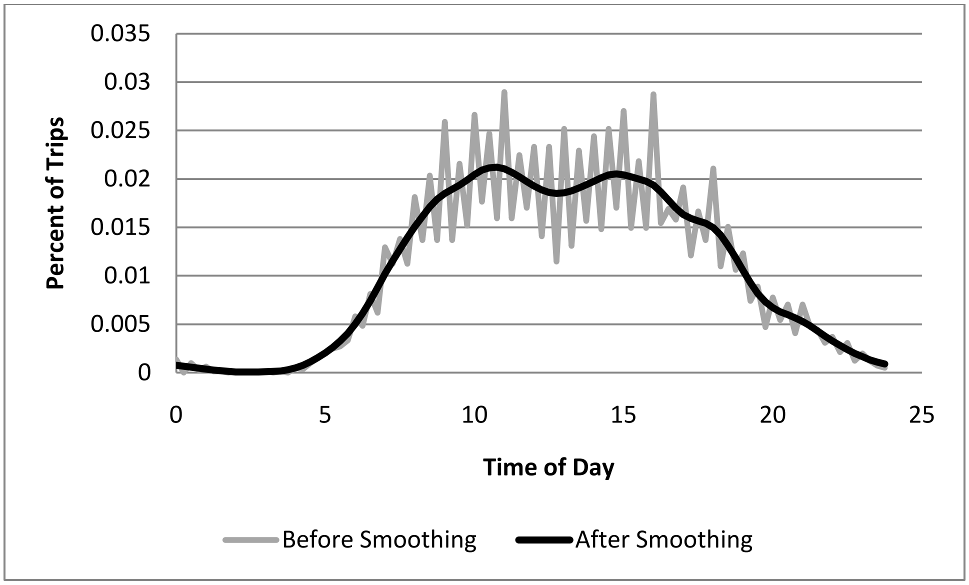

FIGURE 7 Time of Day Distribution for SOV HBO Trips.

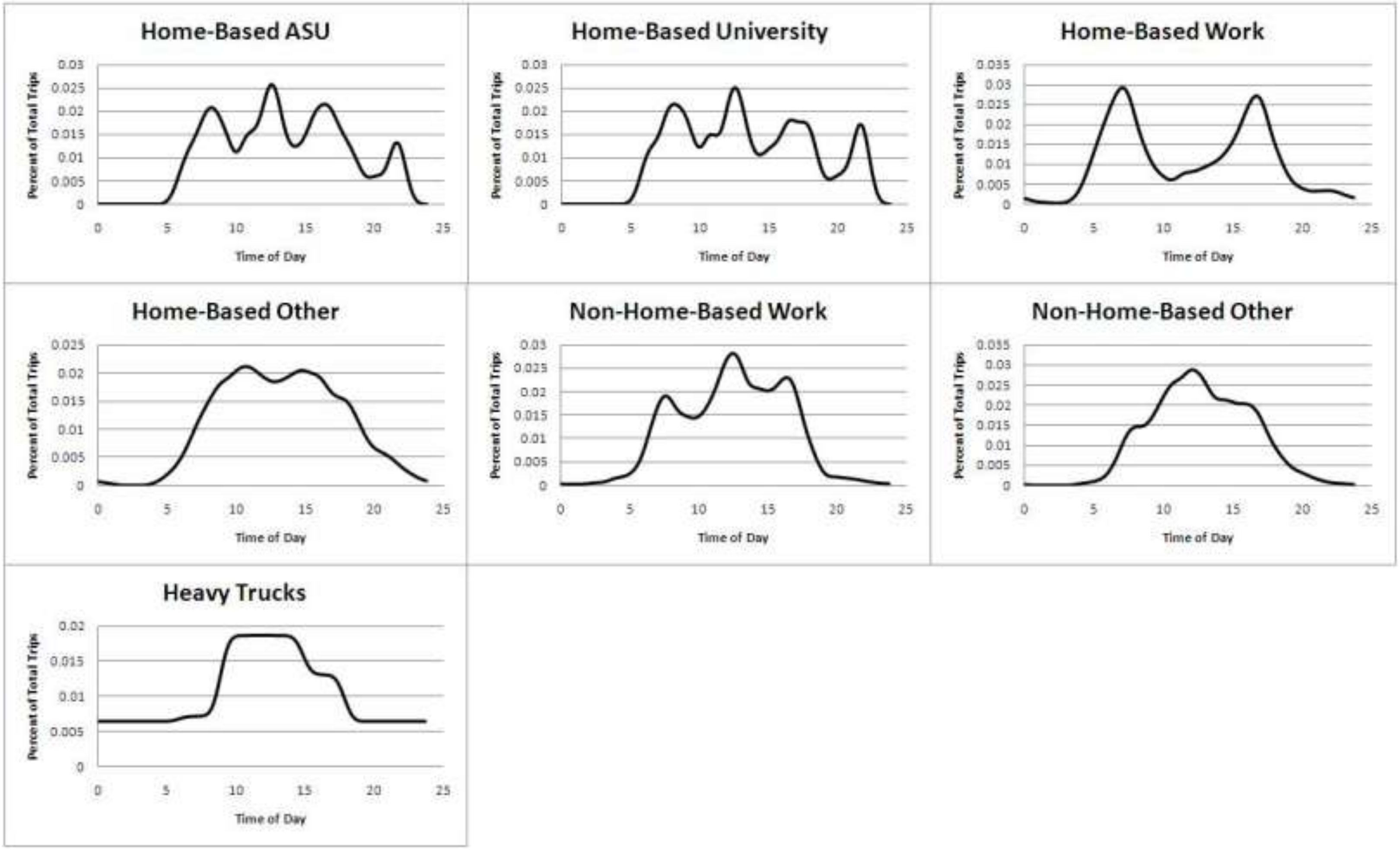

FIGURE 8 Smoothed Diurnal Distributions for Single Occupancy Vehicles and Heavy Trucks.

Stabilization Process

The router stabilization process is one that is generally standard across all TRANSIMS implementations. Many executable modules are available in the TRANSIMS system, each with a unique function. The order in which executables are run dictates the way in which a process is completed. In the stabilization process used in this research, the output from each executable constitutes a portion of the input to the following executable. The router stabilization process is shown in detail in Figure 9. Executables are shown in blue while data files are shown in orange.

Router stabilization begins with the trip file created during trip conversion. This file describes the start time and predicted end time as well as the origin and destination activity locations of each trip. The initial router assigns a travel route to every trip in the input trip file. The executable PlanSum.exe is often thought of as a “mini-microsimulator.” Just like the microsimulator, the plan sum executable calculates volumes on each link and travel times for each vehicle. However, plan sum accomplishes this using simple speed and congestion approximating equations. Unlike the microsimulator, plan sum does not simulate each vehicle in a second-by-second time step and does not follow movements of individual travelers on the network. The initial link delay file that is produced by PlanSum.exe can be used to initiate the iterative stabilization process.

Each executable in the router stabilization process has an assigned task that produces data useful for all the executables that follow. The first step is to create a list of households that experience at least one trip selected for re-routing.

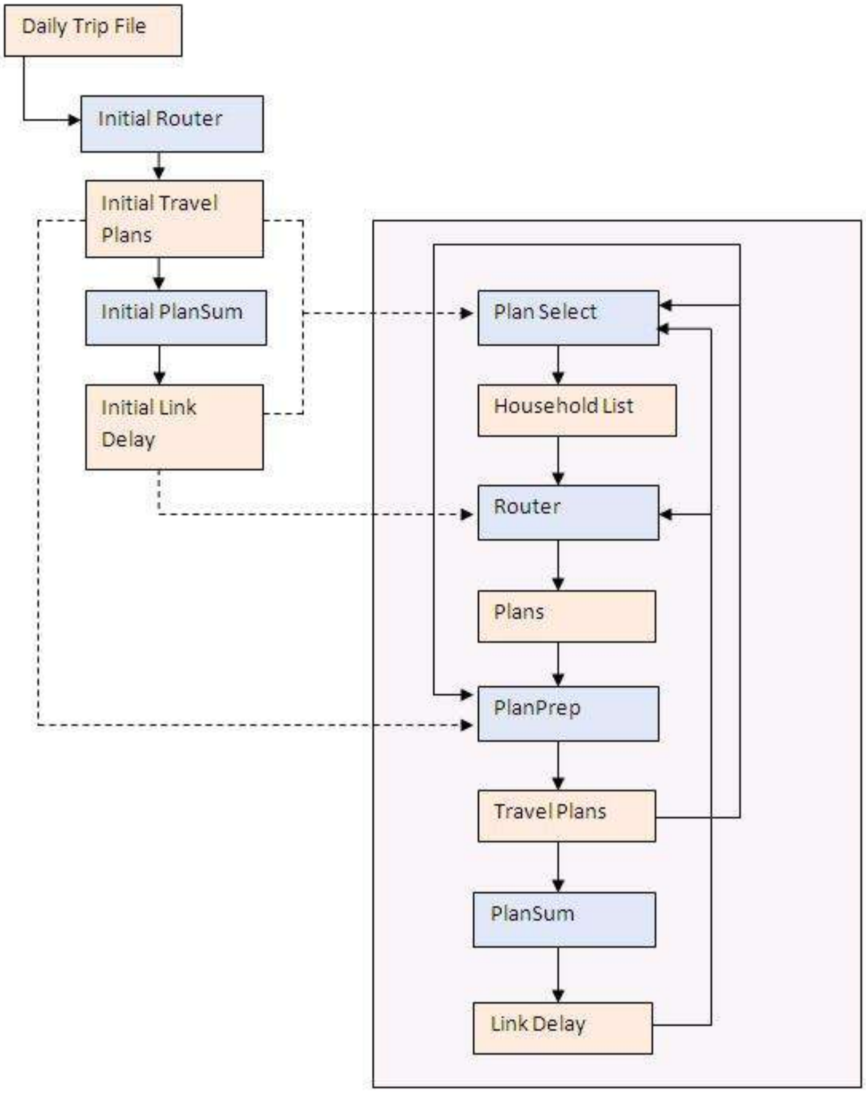

FIGURE 9 Router Stabilization Process.

The selection criteria is designated by the user and can be a random selection, a function of the level of congestion the vehicle encounters, or a function of the travel time required for a trip. The households that were selected are then re-routed using the previously generated link delay file to account for congestion due to all trips that are not being re-routed. Travel plans are then prepared by combining the plans for re-routed trips and plans for all the trips not selected for re-routing. Finally, the plan sum executable is utilized again to calculate new link delays using the newly designated travel plans.

The router stabilization process continues until it reaches convergence. Convergence is generally indicated by the number of households that are selected for re-routing. As the routed trips begin to reach a stable solution, one in which changing the routes of some vehicles cannot significantly decrease congestion or travel times, the number of trips being selected for re-routing will also decrease. The following section describes convergence criteria for the router stabilization process in this research.

Router Convergence Criteria

In this research, router convergence was measured using two separate household selection criteria. The first selection criterion implemented was one relating to the level of congestion on each network link. The link delay file is examined and all links that experience a volume-to-capacity ratio (V/C) greater than 1.25 are identified. When the V/C ratio is greater than one, it indicates a situation where the volume on the link is more than the capacity, heralding a congested state. A V/C ratio of 1.25 indicates volume that is 25% greater than the capacity. Any trip that was planned to travel on one of the indicated links with V/C ratio of 1.25 or greater is selected for re-routing.

The second household selection criterion used in this research was travel time. If a traveler can decrease his or her travel time by 5.0% or more by choosing a different route, then the household to which that traveler belongs is chosen for re-routing. The maximum allowable travel time change is 180 minutes (3 hours) and the minimum allowable change is one minute.

With each successive iteration, the percentage of households selected for re-routing should decrease some small amount. With a greater number of iterations, the amount of decrease in the number of households selected will itself decrease, until a point is reached in which continuing the iterative process will not continue to decrease the percent of households selected. This point is considered the point of convergence. This research begins by selecting households based on V/C ratio, and when that criterion reaches convergence, the travel time criterion is applied. Figure 10 shows the percent of households selected for re-routing in each iteration. Iterations one through five use the V/C ratio criterion while iterations six through twelve use the travel time criterion. One can see that in iteration six, the point where selection criteria are changed, the largest number of households is selected for re-routing. By iteration twelve, the percentage of households requiring a new route plan is reduced to less than one.

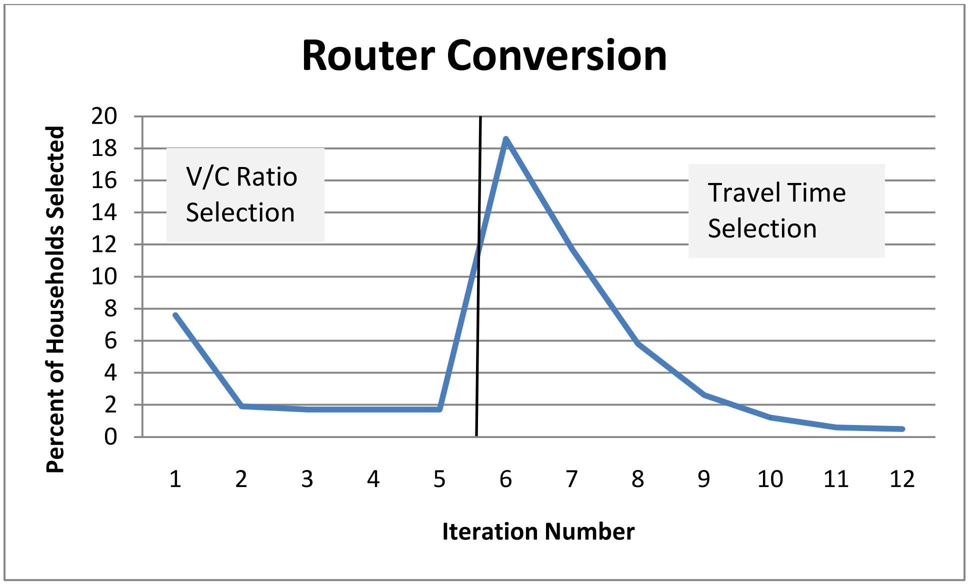

FIGURE 10 Percent of Households Selected for Re-Routing in Each Router Iteration.

Microsimulator Stabilization

Just like the router, the microsimulator requires than an iterative process be implemented before the results can reach a stable conclusion. Though the routing of trips is completed across the entire region, trip microsimulation in this research is performed only over a subarea of the region. For this reason, the TRANSIMS executables must be combined in such a way that the plan sum executable calculates approximate link delays over the entire region while the microsimulator calculates link delays on the subarea. The two link delay files are then combined by replacing link delays calculated with the plan sum executable with link delays calculated by the microsimulator for network elements in the subarea.

The microsimulation stabilizing process is outlined in Figure 11 and described in detail below. As in Figure 9, executable files are highlighted in blue while data files are shown with an orange background.

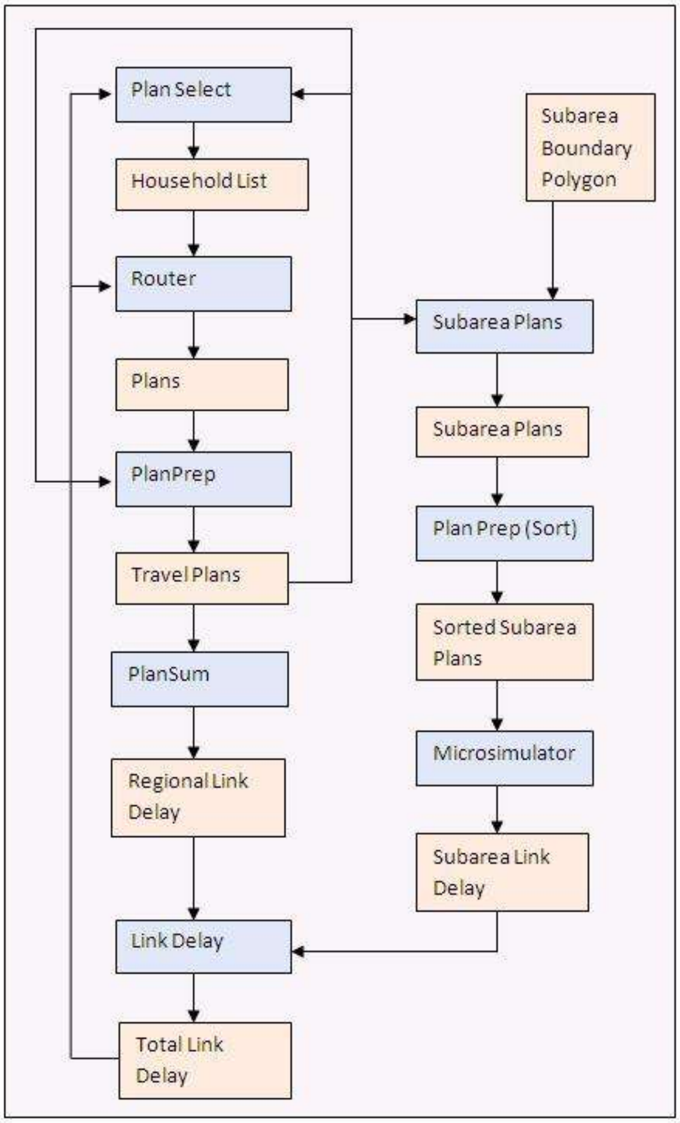

FIGURE 11 Microsimulation Stabilization Process.

The stabilization process begins by selecting households to be re-routed based on the most recent link delay file. The router stabilization process can flow easily into the microsimulator stabilization process simply by using the link delay file produced in the last iteration of router stabilization as an input file to the plan selection executable in the first iteration of microsimulation stabilizing. For this reason, the first iteration of microsimulator stabilization will have very few households selected for re-routing. Unlike the router stabilization, the microsimulator stabilization uses only the travel time change criterion to select households for new travel routes. The selected households are re-routed, new plans combined with old plans, and the new link delay files for the region are calculated using PlanSum.exe. The first four executables in this process are identical to the four executables in the router stabilization process.

The router and microsimulator stabilization processes diverge in their methods when it comes to the microsimulation of trips. TRANSIMS uses the most recent total travel plans data and the subarea boundary polygon shape file to create a list of subarea plans. Subarea plans are routed paths that lie at least partially within the subarea boundary. This could mean a trip with its origin, destination, or both inside the subarea boundary or a trip that travels through the subarea, even though both its origin and destination lie outside the boundary. Once subarea plans are selected, they are sorted by time to meet the requirement for microsimulation input data. Finally, the subarea trips are microsimulated on the network. The link delay file that is calculated from the microsimulator is much more detailed that the link delay file calculated for the entire region. Therefore, the regional and subarea link delay files are combined using the link delay executable. Information for links within the subarea is gathered from subarea link delay file while information for all other links is gathered from the regional link delay file.

The convergence criterion used for microsimulation stabilization is similar to that applied to router stabilization: when the number of households selected from one iteration to the next ceases to decrease, the simulation has reached a point of convergence. In the router stabilization, the percent of households selected for re-routing eventually reached a relatively constant state with little change from one iteration to the next. This constant was also a very small percentage of households. In microsimulation stabilization, because small network errors cause large bottlenecks and the network for this research is still being modified, the percent of households selected will reach a constant state but it will not be a low percentage. The convergence analysis for this microsimulation stabilization is shown in Figure 12. One will note that even when the number of households selected for re-routing reaches a constant state, approximately 15% of all households are still being re-routed in each successive iteration.

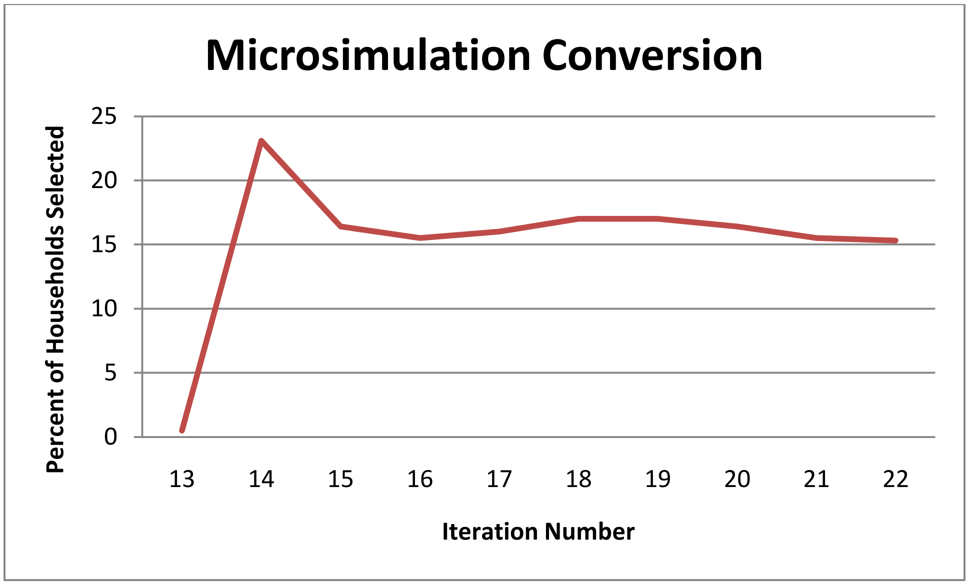

FIGURE 12 Percent of Households Selected for Re-Routing in Each Microsimulator Iteration.

EXPERIMENTAL DESIGN

The purpose of this research is to examine the extent to which results of a traffic microsimulation model differ when a random number seed is varied as well as to explore a method of overcoming that variation. One common approach to overcoming differential results in the same simulation is to run the simulation several times, each time using a different random number seed, and average the results. Because traffic microsimulations are extremely time-consuming and computationally expensive, it is desirable to determine the number of times that a simulation should be run in order to achieve a stable solution. Considering the needs of various types of congested and uncongested states of a traffic network, the research was conducted using diverse traffic congestion levels. This experiment was designed in such a way that stochastic difference due to random number seed variation could be examined in both a congested and uncongested regime.

Effect of Random Number Seed on TRANSIMS Simulations

The random number seed in TRANSIMS is a user-defined value by which the program generates random numbers to be used in probabilistic choice-making agent behaviors. Each traveler in a TRANSIMS simulation, called an “agent,” is assumed to represent a real-world traveler on the system. When traveling through a transportation network in order to reach a destination or activity, a person will always be faced with several choices both before the trip is made, when the travel route is being determined, and while the trip is in progress and the user is navigating the network. When a traveling agent in TRANSIMS is faced with more than one choice of behavior, the software uses probabilistic choice to make that decision. Programmers who build agent-based behavior software like TRANSIMS must also be modelers of real-world choices. They use real-world statistics from travelers that make a specific choice to describe the probability of an agent choosing a certain course of action. Probabilistic choice in the model allows an agent to pursue a decision based on that real-world probability. As opposed to a live person who makes decisions based on information gathered and personal perception, a software agent bases its choice on a random number.

The random numbers generated in the TRANSIMS router affect the way in which a traveler perceives impedance on a specific route. Impedance is a term used to describe the generalized cost associated with choosing a certain travel path. This is not just the monetary cost to the user, but the combined cost of travel time, waiting time, tolls, parking fares, gasoline usage, etc. The impedance calculation is simply a linear combination of costs, each multiplied by a weighting factor that reflects general preferences of the system users. Each human user of the real-world highway and transit networks has his or her own definition of impedance. For example, one user may consider the cost to the environment when choosing a route path while another user who does not consider the environment may instead consider the relative safety of vehicle passengers if the vehicle were to break down in a dangerous area. The TRANSIMS router calculates impedance based on an objective equation that includes only the quantitative characteristics of network elements along the planned route. The router then allows an agent's perception of that calculated impedance to vary based on random probabilistic choice. In this research, the random impedance is set to 20%, indicating that a traveler may perceive the impedance to be up to 10% greater or 10% less than the calculated objective impedance value. This will have a substantial effect on the route that is chosen for that traveler.

The random numbers generated in the TRANSIMS microsimulator affect the way drivers make choices as they navigate the highway network. While navigating through a real-world highway network a driver asks him or herself many, many questions and makes many decisions, even though some of these decisions may be unconscious ones. A driver must decide how soon to give a turning signal, when to accelerate or decelerate and at what rate, when to change lanes, how long to wait at a stop sign, whether there will be a wide enough gap in traffic to turn left, etc. These decisions all have an impact on the flow of traffic and, when combined, the overall state of the network. In the TRANSIMS microsimulator, many of these same choices must be made by an agent and are done so using probability and random numbers. One of the more common choices an agent in the microsimulator is faced with is base on the slow down probability, which determines whether that agent will slow to allow another driver to change into its lane. Another important choice made by agents is based on the lane in which an agent must be located in order to turn into its assigned parking area. Probabilistic choice determines the distance between an agent and its parking lot that exists when an agent begins to navigate into the necessary lane.

Random numbers can change the choice of drivers from one simulation to the next. One driver making one differing choice during his or her travel will not have an observable effect on the state of the network. However, when combined, the differentiating behaviors of all drivers can have a substantial impact on the results of the simulation. For this research, the focus has been placed on random number changes in the TRANSIMS router.

The Simulation Process

In this experiment, an entire process of simulation is completed, including a number of iterations of router stabilization and several iterations of microsimulator stabilization, all the while using the same random number seed in the router and microsimulator. This process is referred to as a "trial." The process is then repeated again using a random number seed for the router that is different that the random number seed used in the router in the previous trial. Each trial maintains the same random number seed in the router throughout its many iterations, but this random number seed is different in each trial. The results of each trial are extracted from the data files and compared with results of all other trials in order to identify the extent of stochastic variation. Twenty trials were completed using an uncongested situation and twenty more using a congested state. Two trials were also performed with the same random number seed throughout all model iterations. This was done to examine the possibility of isolating the stochastic difference in favor of evaluated only the true variability caused by network and demand changes.

Analysis Corridors

The Greater Phoenix Metropolitan Region in Arizona has a population of more than 4 million people, making it the twelfth most populated metropolitan region in the country. The city is surrounded by the Sonoran Desert, which contributes little in the way of obstacles to urban sprawl. The urbanized area is therefore spread vastly across land that extends great distances from the central city. This is a similar situation in other major metropolitan areas, and, like in those other areas, the Phoenix area highway network experiences severe congestion during morning and evening peak travel times. These characteristics make Phoenix a prime candidate location for studying activity-based transportation models and therefore relevant to this study.

Two distinct corridors were chosen for this experiment so that characteristics of one freeway segment would not skew the results of the experiment. The first of the two corridors is a segment of roadway along the US 60, an east-west freeway that connects the cities in the southeast of the region to the central downtown. In one direction, the corridor is approximately six miles long and contains an average of six lanes of traffic, one of which is reserved for high-occupancy vehicles (HOV) of two or more people during peak hour travel.

The second analysis corridor is similar to the first in all but location and capacity. The second corridor is a segment of State Route (SR) 51, a north-south freeway that joins the central downtown to the communities in northern Phoenix. In one direction the corridor is approximately five miles long and averages four lanes of traffic, again with one HOV lane. This segment, as compared to the US 60 corridor, services some higher end retail locations and provides easy access to tertiary and quaternary employment opportunities.

The two corridors were chosen such that they are comparable in the analysis. Both segments are generally heavily congested in the morning and evening peak hours, though rarely in the traffic jam state. Short segments were chosen as an attempt to avoid heterogeneity in the segments. Each corridor consists of 40 TRANSIMS links – 20 links in each direction – and none of the links are entrance or exit links. Figure 13 shows the two segments highlighted.

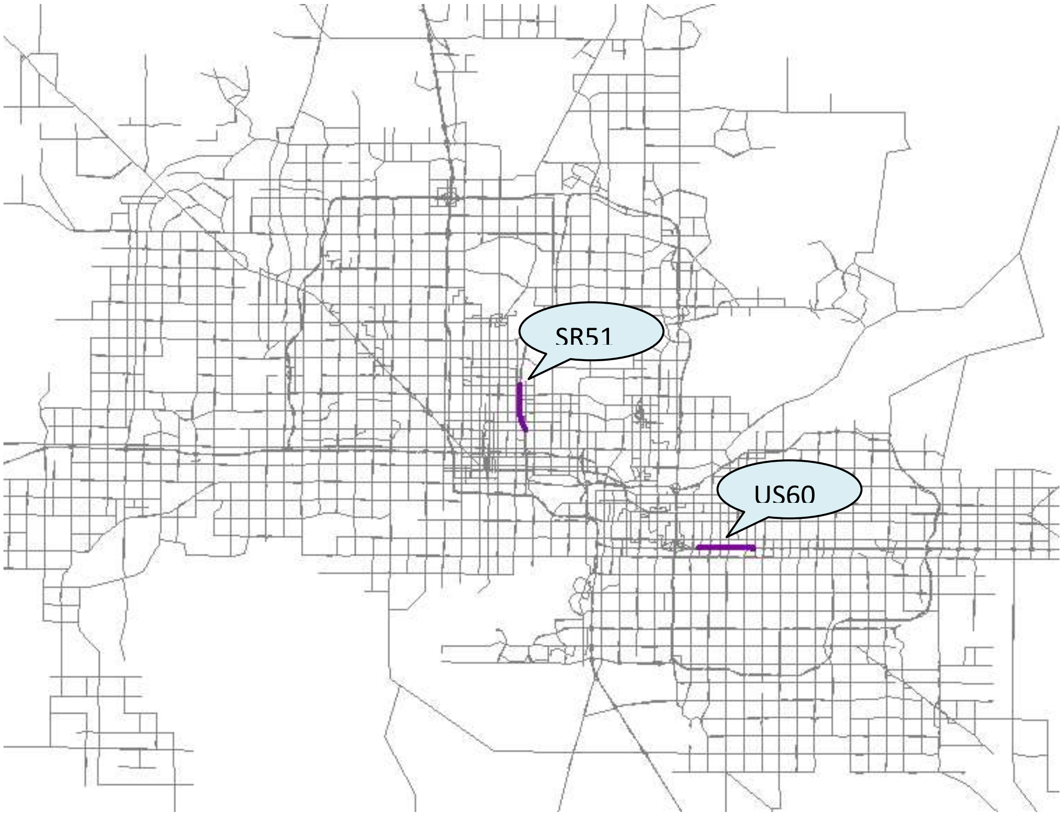

FIGURE 13 Analysis Corridors on the Network.

In order to examine the difference in variability caused by a change in geographic scale, total summed roadway characteristics for the entire subarea of analysis were also collected in the congested state. According to Castiglione et al (*14*) a greater geographical area should contain less variability than the meso-level analysis of the US 60 and SR 51 corridors.

Uncongested and Congested Simulation Details

As discussed, 20 trials were completed for both the congested and uncongested regime research. These 20 trials each consisted of several iterations of the router and microsimulator stabilization. Therefore, the entire effort is quite computationally cumbersome. In order to alleviate some of the processing time and data storage requirements, the simulation was completed for only one hour's worth of routed trips. In both experiments, the router was run the entire region, but only routed those trips scheduled to start between 6:00 and 7:00 AM. These trips were only made using the personal automobile, either driving alone or carpooling, and commercial freight vehicles. Once the trips were routed between 6:00 and 7:00 AM, the microsimulation was run for the entire day. This ensured that any trips that began at 6:59 AM would still have the ability to be completed. The characteristics of the analysis segments were gathered from data created during microsimulation. For the uncongested experiment, this data was gathered between 7:00 and 8:00 AM, when the majority of trips being simulated had reached their destinations. The data gathered for the congested experiment was gathered between 6:30 and 7:30 AM, a time during which trips were still starting and the network was sure to have a heavy flow. As a measure to ensure that the uncongested experiment was indeed uncongested, only a subset of the trips routed were microsimulated.

In both the uncongested and congested experiments, the number of router and microsimulator stabilization process iterations was chosen so that a stable solution was reached. In both experiments, 12 iterations of the router stabilizer were required in order to reach convergence. This number is expected to be the same in either experiment, since the inputs to the routing process did not vary. The inputs to the microsimulation process, however, did vary: only a subset of the routed trips was used in the uncongested experiment. Hence, as expected, the microsimulation stabilization process in the uncongested experiment required only 8 iterations while the same process in the congested regime required 10. Each trial in the congested regime required slightly more computational time.

Measurement of Stochastic Difference

The methods used to evaluate stochastic difference in the results of this research were chosen such that the degree of difference could be examined quantitatively while at the same time describing the extent to which a stable solution was achieved. The three roadway characteristics that were chosen to represent the stochastic difference are volume, vehicle-miles of travel (VMT), and vehicle-hours of travel (VHT). The volume describes the average number of vehicles on each link for the one-hour analysis time between 7:00 and 8:00 AM for the uncongested state and between 6:30 and 7:30 AM for the congested state. VMT measures the total distance traveled by all vehicles on the corridor combined during the analysis time. VHT is similar to VMT, but it measures time of travel rather than distance. A greater value for VHT will indicate that traffic moved more slowly through the corridor.

The stochastic variation in outcomes over the 20 simulation runs is measured using traditional statistical indicators such as range, standard deviation, and coefficient of variation. In order to determine whether the average roadway characteristics reached stability after 20 simulation runs, the successive average was computed after each run and plotted to see if the degree of oscillation virtually vanishes by the time all runs are completed. The cumulative average at the end of the nth trial is a simple arithmetic mean of all outcomes obtained up to and including the nth trial run:

$$\bar{X}_n = \frac{(X_0 + X_1 + \cdots + X_n)}{n}$$

where $\bar{X}_n$ is the cumulative average after the nth trial and $X_0, X_1, \ldots, X_n$ are the corridor characteristics of interest at the end of each trial run. In addition, consistent with the computations in Castiglione et al (#), a second measure of stability was calculated as the percent difference between the cumulative average up to a certain trial number and the final cumulative average obtained after all 20 trials were completed. Essentially, the percent difference is measured as:

$$\%Diff = \frac{\bar{X}_n - \bar{X}_{20}}{\bar{X}_{20}} \times 100$$

where $\bar{X}_{20}$ is the cumulative average at the end of the 20th trial run (i.e., the last one).

Examining the cumulative average and percent difference from the final average after each trial will show whether the number of trials is appropriate for reaching a stable solution. If the number of trials is sufficient to reach a stable conclusion, a plot of the cumulative average will eventually converge on a value that approximates the true characteristic value, and a plot of the percent difference from the final average will converge on zero.

RESULTS AND DISCUSSION

The research presented here has been focused on determining stochastic difference in a traffic microsimulation model and comparing results from a congested network state to an uncongested state. The results can be used by practitioners of transport modeling as they develop microsimulations of their own to predict network performance. If a practitioner is aware of the roadway congestion levels on a particular corridor he or she will be better equipped using these results to predict the number of trials that will need to be run, therefore the time and computational effort required.

Results of Router Random Number Seed Trials

The first test completed is a duplication test, where two trials are run with the same random number seed in throughout. The results of this test are shown briefly in Table 3. One can see that the microsimulation results were duplicated exactly, indicating that the results from the tests to follow are indeed studying the variability due to random number stochasticity alone.

TABLE 3 Duplication Test on Router Random Number Seed

Trial		Volume	VMT	VHT
US 60	Base	60460	18310	630
	Duplicate	60460	18310	630
SR 51	Base	60349	16676	565
	Duplicate	60349	16676	565
Total Subarea	Base	4048274	1161820	41469
	Duplicate	4048274	1161820	41469

The results for the variation in random number seed in the router are presented below. Standard statistical descriptions of the data are provided, including mean, minimum and maximum, median, standard deviation, range, and coefficient of variation. The range is calculated as the maximum minus the minimum. The coefficient of variation is the standard deviation divided by the mean.

The volume that is displayed in Tables 3, 4, and 5 is a calculation total sum of volume entering each link during the one hour analysis period. This translates to the total number of vehicles handled by the program. In a free-flow state, the addition of vehicles to the roadway will not greatly affect the travel time on the corridor. This is reflected in the results of the analysis, indicating that vehicle-hours of travel remains constant throughout all trials in the free-flow state. In both congested and uncongested states, the US 60 has greater VMT and VHT than SR 51, supported by the fact that the US 60 has more lanes of traffic – and therefore a higher total volume – and is slightly longer in each direction than SR 51.

The coefficient of variation aids in describing the degree to which the results of the trials vary: a greater coefficient of variation indicates a greater dispersion of the roadway characteristic outcomes in the twenty simulation trials. The dispersion in either corridor is greatest when the roadways are congested. This result is compatible with the intuitive hypothesis that a greater number of vehicles will result in a greater variation of outcomes.

TABLE 4 Results of Simulation Trials in Analysis Corridors

Measure	US 60			SR 51		
	Volume (veh)	VMT (miles)	VHT (hours)	Volume (veh)	VMT (miles)	VHT (hours)
			Uncongested Regime			
Mean	1738.95	537.38	6.00	821.19	214.71	2.00
Minimum	1669.00	516.00	6.00	793.00	208.00	2.00
Maximum	1803.00	558.00	6.00	847.00	230.00	2.00
Median	1742.00	539.00	6.00	820.00	214.00	2.00
Std. Deviation	30.22	9.43	0.00	14.01	4.84	0.00
Range	134.00	42.00	0.00	54.00	22.00	0.00
CV	0.02	0.02	0.00	0.02	0.02	0.00
			Congested Regime			
Mean	61568.14	19289.86	788.10	47967.29	12843.38	236.14
Minimum	45327.00	13709.00	288.00	24874.00	6785.00	85.00
Maximum	80790.00	26299.00	1663.00	62494.00	17255.00	624.00
Median	62080.00	19688.00	782.00	49180.00	13365.00	176.00
Std. Deviation	8530.94	3078.64	361.18	9644.59	2853.15	152.49
Range	35463.00	12590.00	1375.00	37620.00	10470.00	539.00
CV	0.14	0.16	0.46	0.20	0.22	0.65

Table 5 lists the results of volume, VMT, and VHT aggregated over the entire subarea of analysis in the congested state. According to the coefficient of variation, the individual corridors do indeed show a greater variability than the aggregated subarea characteristics. This coincides with the results of Castiglione et al. (*14*)

TABLE 5 Results of Simulation Trials in Entire Subarea during Congestion

Measure	Volume (veh)	VMT (miles)	VHT (hours)
Mean	4028036.57	1172874.62	41528.62
Minimum	3812011.00	1107295.00	37460.00
Maximum	4132503.00	1207139.00	44377.00
Median	4038948.00	1171265.00	41664.00
Std. Deviation	81482.26	26960.76	1803.38
Range	320492.00	99844.00	6917.00
CV	0.02	0.02	0.04

Roadway Characteristic Convergence

When measuring the convergence of the roadway characteristics, all congestion measures were taken into account as well as both the cumulative average and the percent difference between the cumulative average and final average. Figures 14 through 17 display the cumulative average plots for volume, VMT, and VHT in both the congested and uncongested states.

The figures suggest that both traffic analysis corridors reach a stable solution in the twenty iterations performed for all three characteristics measurements in the uncongested state. This can be seen as the reduction in slope for the last several trials. This result bodes well for metropolitan planning organizations with uncongested corridors. If a practitioner can remain relatively confident that a set of values has converged within twenty iterations, there is not further need to spend time or other resources in performing more trials. Figures 16 and 17, however, show that the congested state is not as close to convergence as the uncongested measures. With the exception of the VHT on the US 60, there is little evidence that any of the roadway performance measures have converged or will converge in immediate additional trials. The analysis on SR 51 shows that all three characteristics measured are continuously decreasing. Though the slope is shallow in these functions, there is little sign that slope is becoming more shallow near the terminal trials. The absence of this slope reduction suggests that the values do not reach convergence in the twenty iterations presented here.

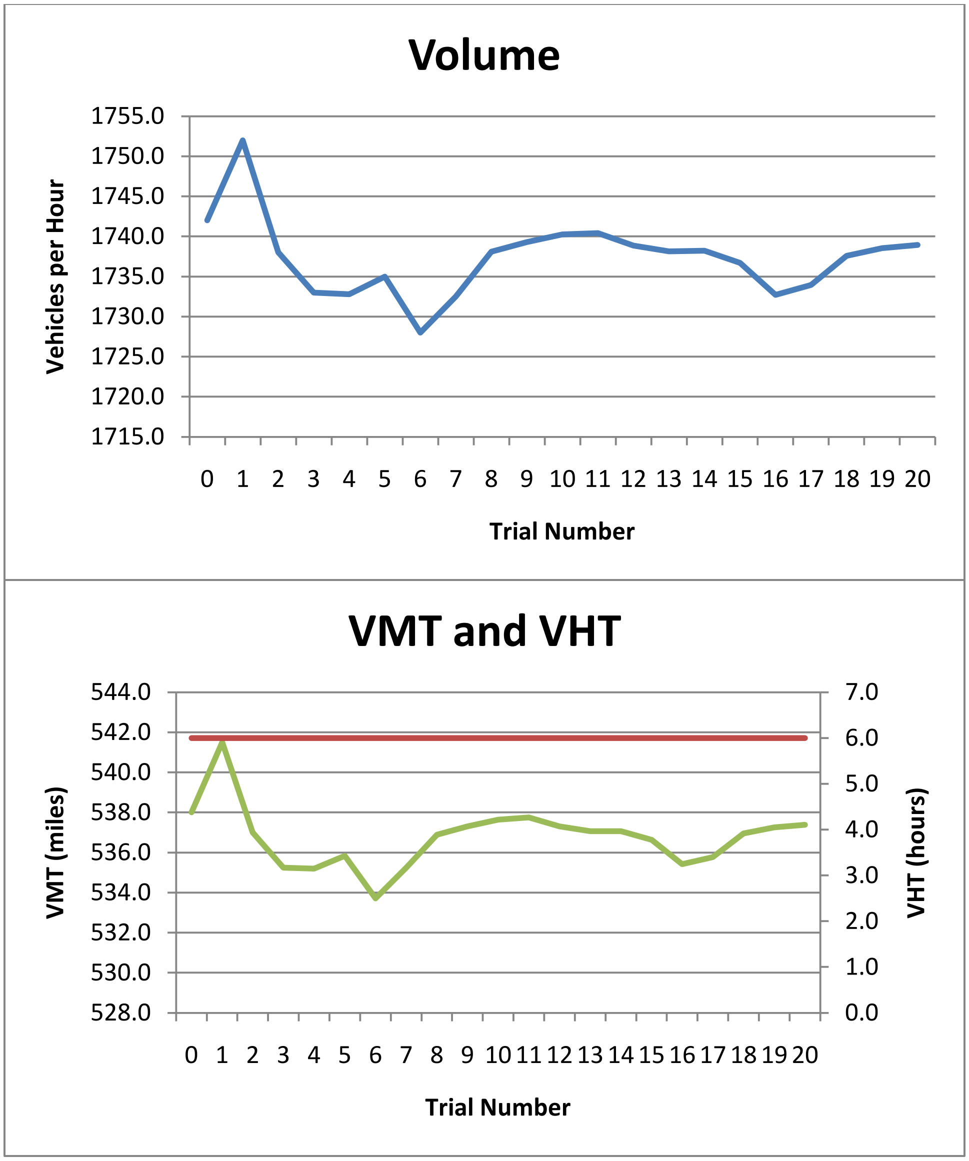

FIGURE 14 Cumulative Average on US 60 in Uncongested Traffic.

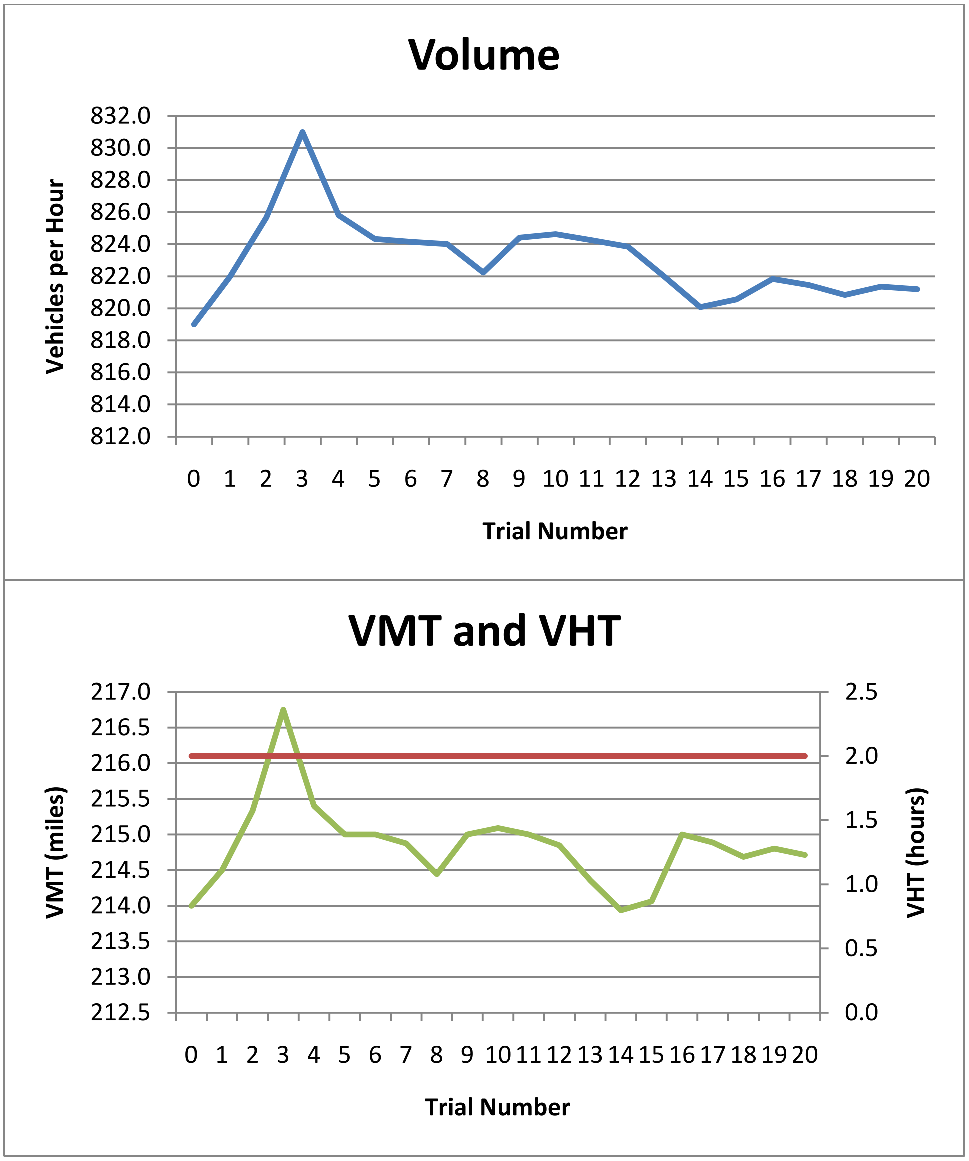

FIGURE 15 Cumulative Average on SR 51 in Uncongested Traffic.

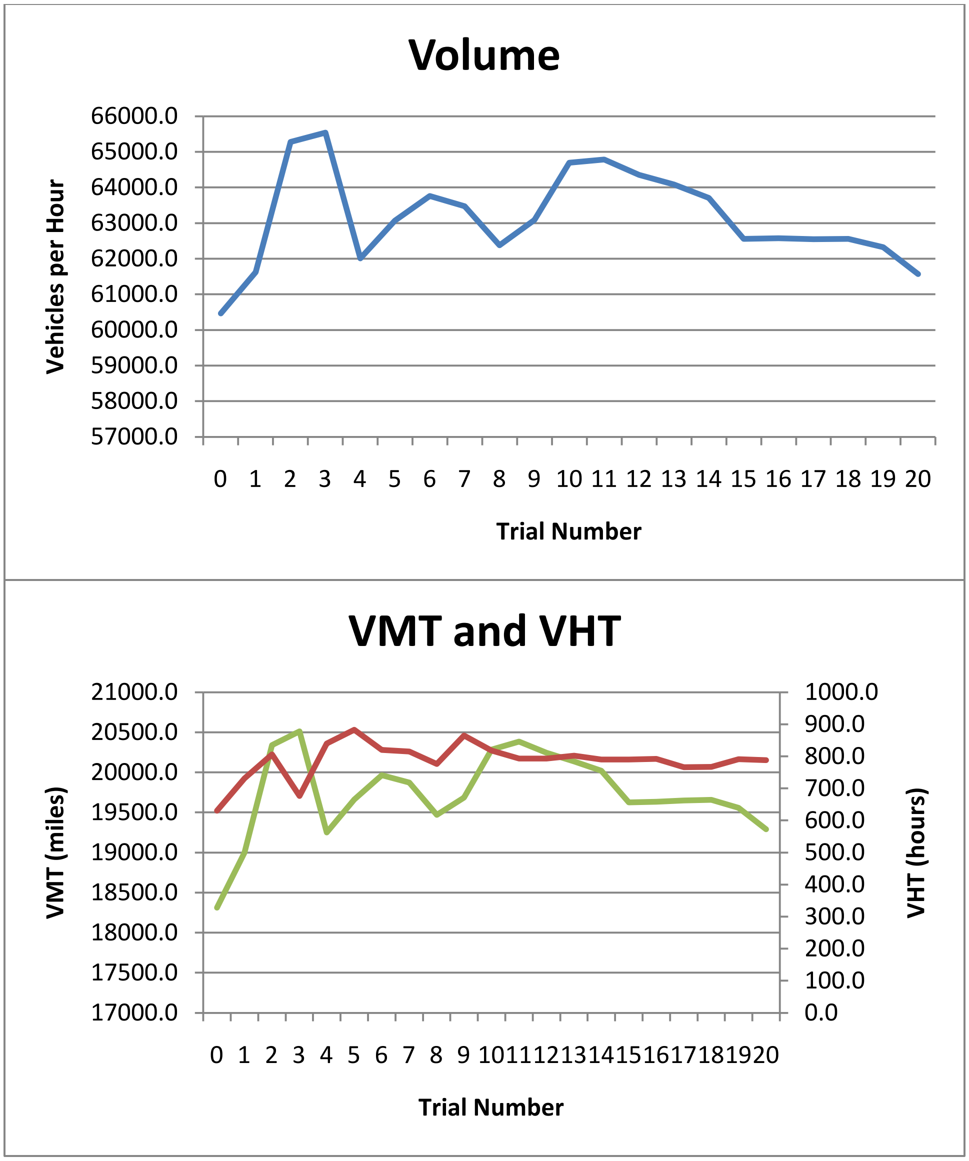

FIGURE 16 Cumulative Average on US 60 in Congested Traffic.

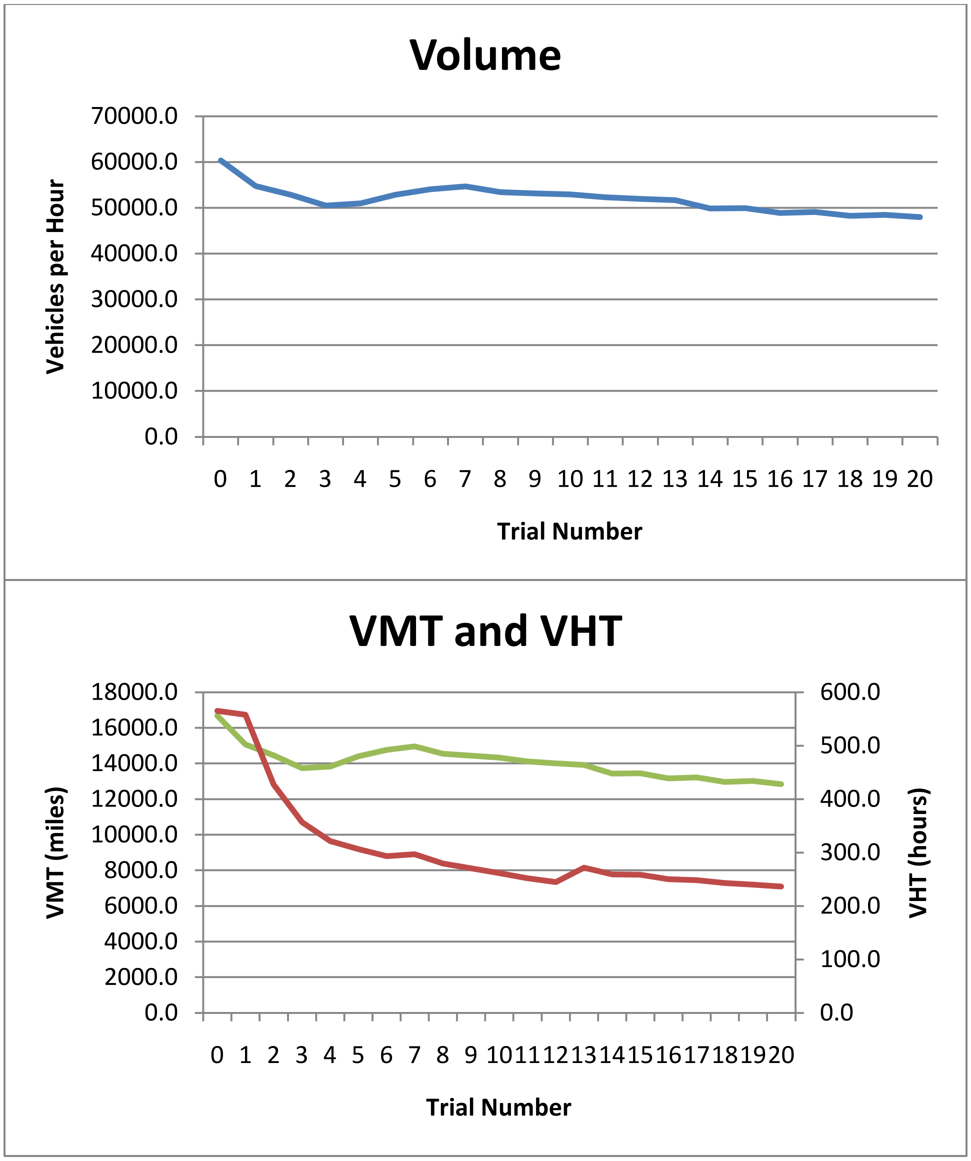

FIGURE 17 Cumulative Average on SR 51 in Congested Traffic.

The convergence measurement of cumulative averages has a very similar result to that showing percent difference of the cumulative average to the final average. Figures 18 and 19 show the cumulative percent difference for congested and uncongested volumes on the US 60 and on SR 51, respectively. While the last data point on these graphs must be equal to zero simply by the formula definition, one can see that the graphs representing uncongested traffic clearly converge around the zero percent line: the plots come very close to zero several trials before the last. This is not so in the graphs representing congested traffic, where the plot merely touches the zero percent mark at the very last trial and not before. Again, one can see that the volume on SR 51 appears to be approaching the zero percent difference goal, however the telling reduction in slope is again absent in this graph.

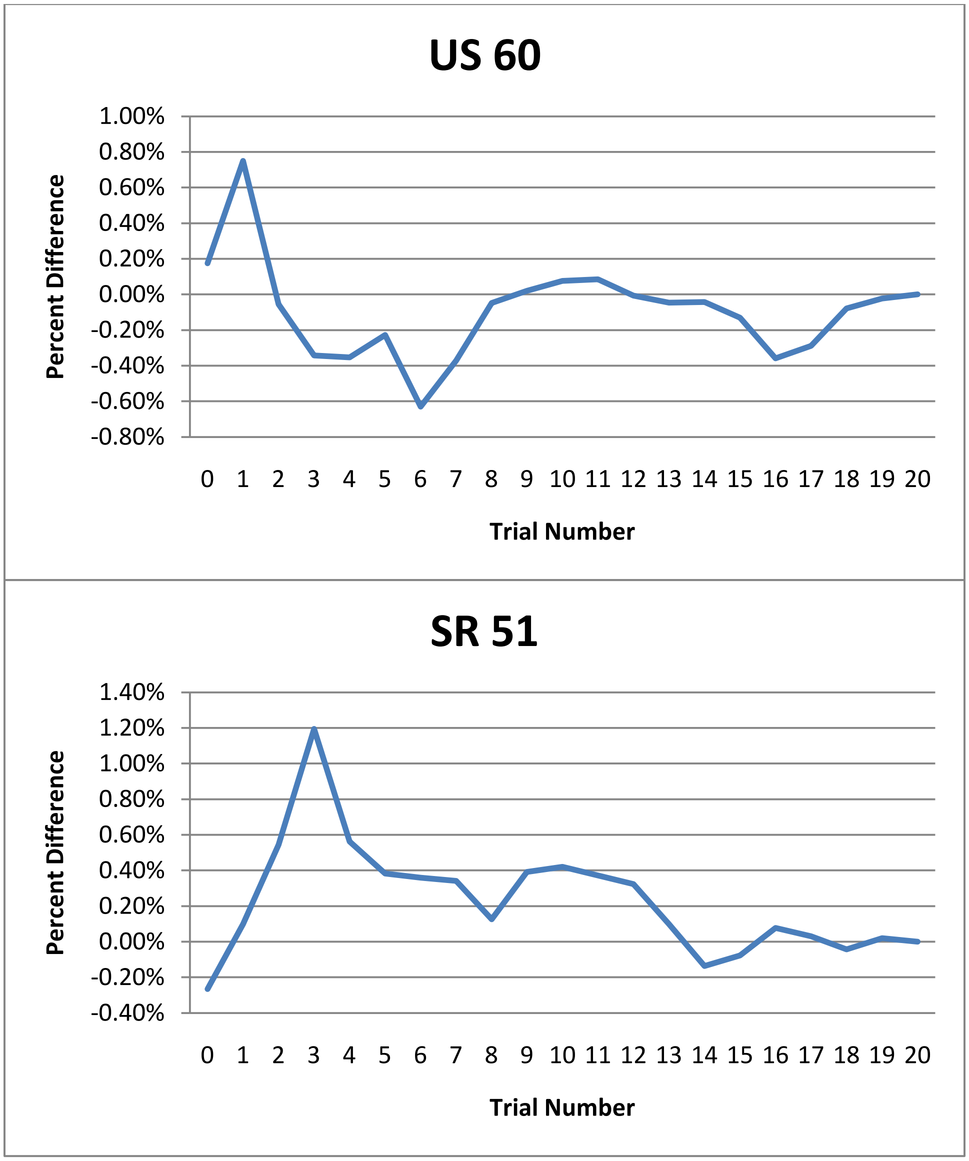

FIGURE 18 Cumulative Percent Difference in Volumes in Uncongested Traffic.

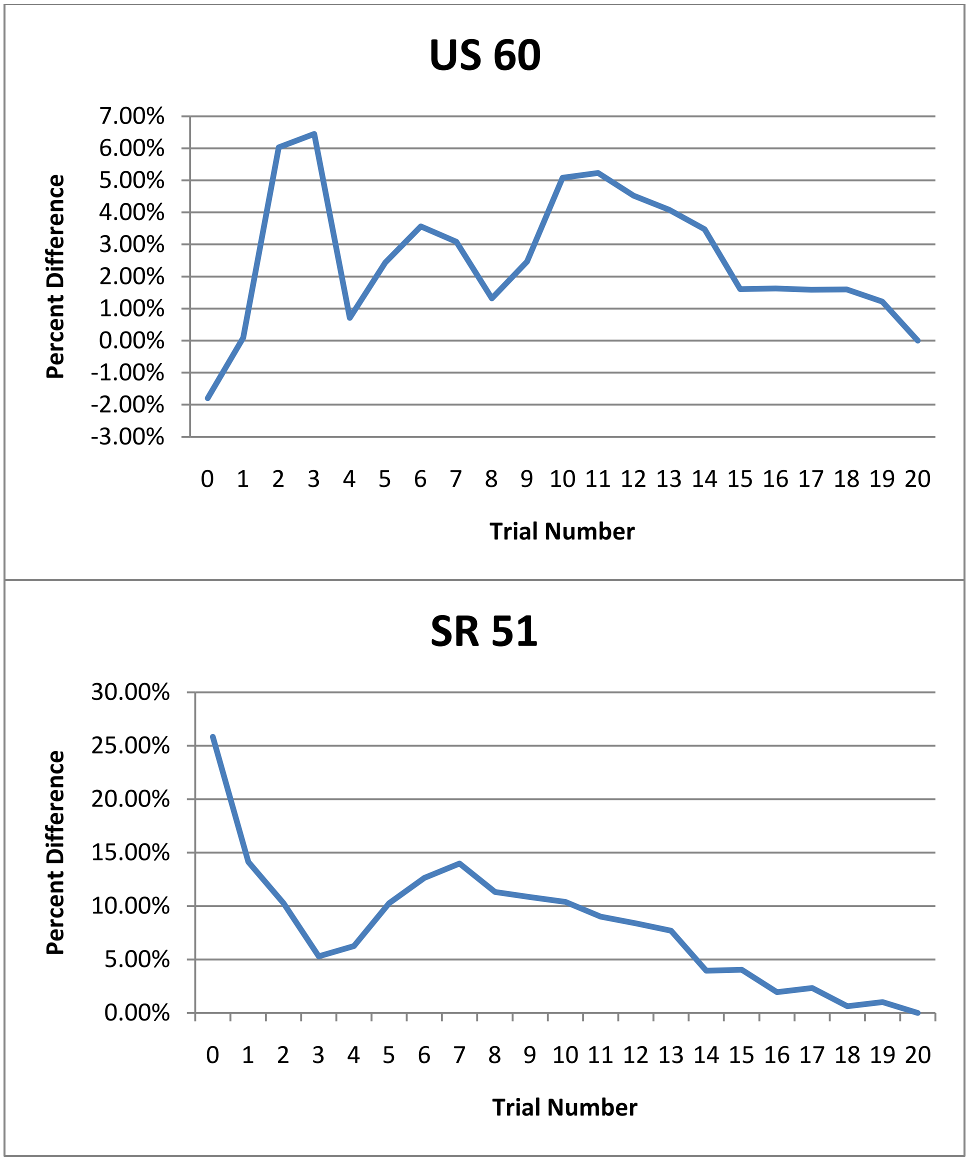

FIGURE 19 Cumulative Percent Difference in Volumes in Congested Traffic.

Sample Size Calculation

The analysis above begs the question, how many trial runs will it take to reach a stable solution? The answer to this question can be found approximately using sample size calculation procedures. In order to generate an estimate of roadway characteristic that is within 10% of the actual roadway conditions, a bound is set on the error of estimation such that:

$$\bar{x} - d < \mu < \bar{x} + d$$

where $\bar{x}$ is the mean roadway characteristic, μ is the actual value of that characteristic, and *d* is the precision. Assuming the worst case of the acceptable scenarios, $\bar{x}$ is 10% greater than μ, or

$$\bar{x} = 1.10\mu$$

and therefore

$$\bar{x} - d = \frac{\bar{x}}{1.10} \rightarrow d = 0.091\bar{x}.$$

The equation for calculating required sample size is as follows:

$$n = \frac{\left(z_{\alpha/2}^2\right)(s^2)}{d^2}$$

where *n* is the required sample size, *s* is the sample standard deviation, and $z_{\alpha/2}$ reflects the confidence level of the calculation. With a confidence level of 95%, this value is equal to 1.96. Finally, putting together all the information into one equation, one finds that:

$$n = \frac{3.8416s^2}{0.008281\bar{x}^2}.$$

The required sample size calculated will be different depending on the data set from which it is calculated. Table 6 shows approximate sample size calculations from each of the trial data sets calculated for the congested state.

TABLE 6 Sample Size Calculations from Congested Trial Data

Data Set		Mean	St. Dev.	Sample Size
US 60	Volume	61568.14	8530.94	9
	VMT	19289.86	3078.64	12
	VHT	788.10	361.18	98
SR 51	Volume	47967.29	9644.59	19
	VMT	12843.38	2853.15	23
	VHT	236.14	152.49	194
Total Subarea	Volume	4028036.57	81482.26	1
	VMT	1172874.62	26960.76	1
	VHT	41528.62	1803.38	1

Discussion of Results

In a real-world situation, it is often the case that a greater number of vehicles will lead to a greater variability in travel time. When one is sure that the roadways on one's travel path will be uncongested, one can easily estimate the travel time. However, travel time estimation, as with estimation of all other roadway performance characteristics, becomes more difficult to estimate when the factors of many additional drivers are taken into account. This is obvious in this research in the way that the congested experiment produces a greater variation in results than the uncongested experiment.

The implications of these findings translate to the computational effort required to perform microsimulations of traffic in a large urban environment. In general, transportation planners built predictive models for the most congested time of day. As has been seen in this research, the most congested time periods translate to the greatest variability in roadway performance characteristics. Under these congested conditions, a single simulation run for a specific scenario will not result in a reliable solution. If a planner works toward the goal of finding a stable solution to roadway performance characteristics, he or she must be prepared to perform a simulation of each single network scenario more than twenty times. In this research, each simulation run required approximately seven hours to complete, depending on the availability of processing power in the machine being utilized. Therefore, more than twenty simulation runs will require quite a great deal of resources to complete.

Practitioners must also take caution when selecting the geographic level of analysis: a higher level analysis produces less variability in the results. This, however, could simply mean that the true quantity of stochastic variability in a larger geographic framework is being masked by the averaging or aggregation of total vehicles in the area of analysis. A stable solution in a larger area analysis will not necessarily translate to a stable solution at the corridor level.

Six sample data sets were calculated for the congested state: volume, VMT, and VHT on the US 60, SR 51, and over the total subarea. Each of these sample sets was used to perform a calculation of the approximate number of trials needed to reach a solution that is within 10% of the actual solution. Surprisingly, only three of the data sets indicated that more than twenty trials need to be completed. Not surprisingly, however, is that the three data sets that did require more trials were also the three data with the greatest coefficient of variation. The calculations based on total subarea analysis data points claim to need only one trial in order to reach 10% of the actual solution. This supports the claim made above that aggregation over a larger geographic region could mask the true stochastic variability of the analysis. It is possible that with the specific roadway characteristics for which calculated sample size was less than twenty, even though a “converged” value was not achieved, the estimations did reach within 10% of the true value. In this case, however, because this implementation of TRANSIMS is not necessarily calibrated exactly to the region, the “true” value may not represent the actually real-world values of the road, but rather a theoretical “final answer” that is a product of the parameters to which the TRANSIMS modules are set.

Planners in areas with large numbers of uncongested roadways, however, may find the results found in this research extremely uplifting. In less than twenty iterations, a stable solution was found for three separate roadway performance measurements on two completely separate corridors. This finding indicates that small urban areas may find themselves in a better position to implement microsimulation traffic models into their existing transportation planning procedures than large metropolitan environments. This is not to say, however, than the adoption of microsimulation in a large urban environment is not possible or desirable. Today’s available technologies could allow a planning agency to access super computers across the country with large quantities of processing power. In this experiment, for example, the researcher utilized up to 16 processors at one time located on a super computer in Santa Barbara, California, completing the simulation in a small fraction of the time it would have taken on a standard personal computer. Planning agencies should be aware, however, before beginning a microsimulation modeling project, of the computational expense and time that will be necessary to complete the simulations and should plan for this large computational expense.

Summary and Conclusions

The transportation modeling process is a decision support system for which one cannot begin to estimate the value in terms of urban metropolitan future efficiency, equality of opportunity, environmental impact, and economic prosperity. Since the middle of the 20th century, metropolitan planners and engineers have rigorously searched for ways in which more efficient transportation network planning models could be achieved that provided the most accurate predictions of roadway conditions. With the evolution of new technologies that allow faster computations with greater processing power, transportation planners have turned toward the agent-based model, which allows microsimulation of behaviors at the level of the individual decision maker. TRANSIMS is one such microsimulation modeling tool that is used for traffic modeling. To date, only a select few Metropolitan Planning Organizations (MPOs) across the country use microsimulation tools in their day-to-day operations. The majority of MPOs are wary of turning to a tool that requires vast amounts of computing power and steep learning curves for practitioners. The research presented here hopes to shed some light on the workings of the microsimulation models while at the same time evaluating their ability to return stable network performance characteristics.

Random number seeds that are used for probabilistic choice in TRANSIMS, as in other agent-based simulations, have an effect on the outcome of the model. When a random number is changed – or in the case of TRANSIMS, a random number seed – the results vary stochastically from one simulation trial to the next. One way to overcome this variation is to repeat the simulation multiple times with different random numbers and average the results. This practice is computationally intense and it is desirable to have an idea of how many times a simulation must be run to reach a stable average solution.

In this research, it is determined that an uncongested roadway network has much less variability than a congested network and therefore reaches a stable solution more quickly. A roadway network that is congested contains a greater number of decision making agents, each contributing to stochastic variability in the model with its individual decisions. It was seen that twenty iterations of a router stabilization and microsimulation stabilization were sufficient to find a stable solution in an uncongested network. However, for a congested regime, more than twenty trial runs would be necessary.

The opportunities for future work related to this research are manifold. It will be desirable in the future to determine approximately how many trial runs would be sufficient to reach a stable solution in the congested regime. To that end, future research may determine a method by which the number of trial runs required can be predicted using known traffic volumes during highly congested periods. TRANSIMS is by no means the only agent-based traffic microsimulation tool being employed by researchers. Future research could focus on the stochastic variability in other modeling tools to determine if the required trial runs are similar across all tools or if each should come with its own estimates for convergence. In the broader spectrum of research applications, research in the technology fields could yield a more efficient way to carry out microsimulation that reduces the processing, data storage, and time requirements.

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