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SOUTHERN CALIFORNIA ASSOCIATION of GOVERNMENTS

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Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT) in Southern California

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1. Introduction

The State of California has recently embarked on an aggressive movement towards reducing greenhouse gas emissions that contribute to global climate change, promoting sustainability, and better managing vehicular travel demand. The recent California State Senate Bill 375 explicitly calls for major metropolitan areas in California to meet ambitious greenhouse gas (GHG) emission reduction targets within the next several years. Metropolitan areas are considering a range of policies to meet the emission reduction targets including land use strategies, pricing mechanisms, managed lanes, telecommuting and flexible work hours, enhancement of transit and pedestrian/bicycle modes, and use of technology to better utilize existing capacity. The analysis of these policies, and responding to the mandates of legislative actions such as Senate Bill 375 in California, calls for the adoption of model systems that are able to accurately represent activity-travel patterns in a fine-resolution time-space continuum. Moreover, these model systems are expected to provide a platform for simulating integrated land use and transportation plans that are better able to represent gains in emission control in the medium (5-10 years) and the longer term (10-25 years) horizons.

The Southern California Association of Governments (SCAG), the metropolitan planning agency for the Southern California region (includes the counties of Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura), is moving forward with the development of a comprehensive activity-based microsimulation model system of travel demand to enhance its ability to estimate the impacts of a range of policy measures in response to Senate Bill 375 (http://www.scag.ca.gov/sb375/index.htm). SCAG is also required to develop a "Sustainable Community Strategy" through integration of land use and transportation planning and demonstrate its ability to meet the GHG emissions reduction targets by 2020 (8% GHG per capita per day reduction) and 2035 (13% GHG per capita per day tentatively). These are challenging targets for such a vast region, which includes a population of approximately 18.6 million people in 2008 (expected to grow to 23 million by 2035) and offers an extremely complex multimodal and diverse planning context with multiple actors in different jurisdictions. The new activity-based microsimulation model system is developed to address exactly this diversity among persons and contexts, it is expected to be used as one of the modeling tools in the 2016 Regional Transportation Plan (RTP), and is described in this report.

This model system is the outcome of the second phase of research and development as well as application of the Simulator of Activities, Greenhouse Emissions, Networks, and Travel (SimAGENT), which is tailored to the Southern California region and is compared to the four step model system used in the SCAG 2008 Regional Transportation Plan.

2. SIMAGENT

The overall model structure is presented in Figure 1 in a schematic cascading form. The set of blocks on the left hand side represents groups of models that are designed for the first year (baseline) of the simulation that for this application is the year 2003 to align with the four-step model of SCAG developed for the 2008 Regional Transportation Plan. Each block of the figure represents a group of techniques and statistical models many of which are developed to address policy actions aiming at replicating the resident population activity and travel decision making. In essence this first set of models on the left side of Figure 1 recreates the resident population and attributes to each person a daily schedule and ultimately assigns traffic to the network and computes emissions. The middle four blocks evolve the region's economic and demographic landscape over time. This computerized evolution is done using a land use model based on the spatial input-output growth forecast model called PECAS (Production, Exchange and Consumption Allocation System - http://www.scag.ca.gov/modeling/mtf/index.htm). This is paralleled by a set of algorithms and negotiated-with-local-jurisdictions forecasts of residential development, industrial location, and demographic land use-regional economy evolution at aggregate levels (cities and subareas within cities). In the middle of the growth forecast and land-use regional economy components is the household evolution module, which microscopically considers every resident household (and its members) and gives it transitions and changes in time and space. It also converts travel times and the spatial distribution of economic activity and residential locations into accessibility indicators that are used to also drive travel behavior. The right side set of blocks is a repetition of the daily activity and travel patterns models but at the next and all subsequent years of the simulation.

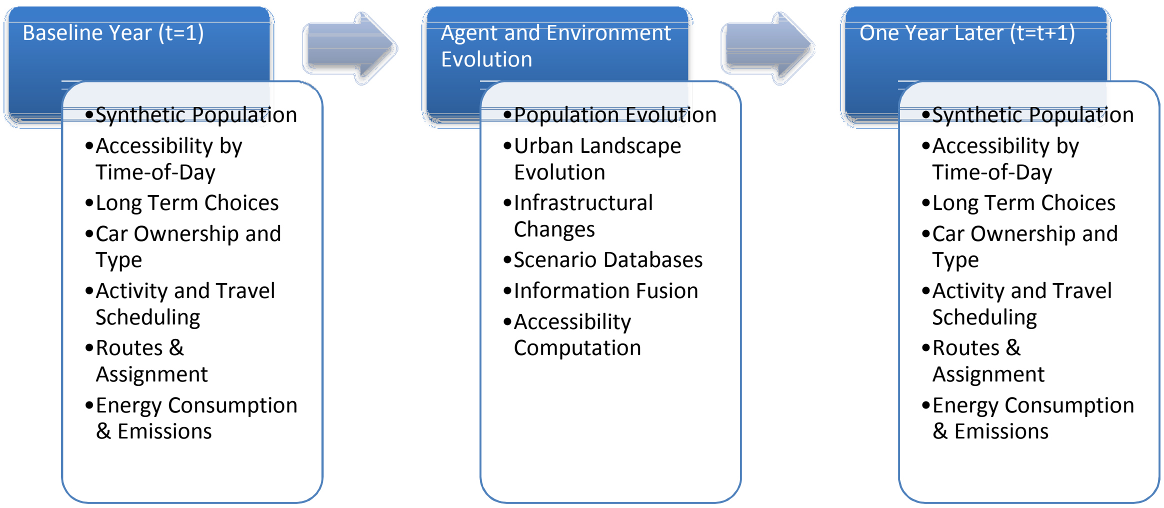


Figure 1 Schematic Representation of SimAGENT Blocks

In this way land use policies of increased density and land use mix can be reflected in shifts in spatial distribution of economic activity, location decisions, car ownership and use, and activity participation and destination choices (including decisions to participate in activities and to travel alone or with others). In building policy scenarios, we start with an assembly of data on the entire roadway network and its characteristics (roadway types, intersections and ramps, number of lanes, and speed limits), and the public transportation network (type of service, routes, and schedules). In parallel, we assemble data on the resident population at different levels of geographical aggregation with core data at the zonal level of the pre-existing four-step model to enable use of existing forecasts and comparisons with simpler model systems. We also assemble external information about demographics, social and economic conditions of the study area, as well as any forecasts available. In this report we focus on the first set of modeling blocks for which a finalized version was completed during the second phase (model version of March 2011, December 2012, and March 2012) of the SimAGENT project for

SCAG and offer a few schematic and numerical examples of output that help us explain some of the findings, issues, and next steps. The SimAGENT model development continues to December 2012 and is expected to use networks and zonal systems of the model used in RTP 2012 but not included in this report. In addition, we are developing in parallel a household evolution method that will progress the resident population from one year to the next.

2.1 PopGen (Population Synthesis)

In SimAGENT, the process starts with an application of PopGen in which the entire resident population is synthetically generated/recreated person-by-person and household-by-household based on the method described in Ye et al., 2009, and further enhanced and improved for more recent applications (see http://urbanmodel.asu.edu/popgen.html) and for SimAGENT developed further (see Pednyala eta al., 2011). The input to this software and block of methods is the spatial organization of the simulated area in the form of zone-specific univariate distributions of resident person and household characteristics provided by the US Census and SCAG for the baseline year (in this case 2003). As the population is recreated on a person-by-person and household-by-household basis, these distributions are used as the control totals for each spatial unit of analysis (approximately 4,000 Traffic Analysis Zones in this version of the model system) in an iterative algorithm that starts from a multivariate set of relationships (in essence a cross-tabulation) among the person and household variables used as seed information. For future years, these distributions are SCAG forecasts based on procedures of the growth forecast block in Figure 1 for 2020 and 2035 corresponding to the GHG target years. The multivariate set of relationships can be kept constant (assuming a steady state of demographic relationships) or can be changed to capture the impact of changing population composition and associated relationships including but not limited to age, birth rates, and household size.

2.2 Accessibility by Time of Day

To represent employment opportunities and the spatio-temporal distribution of activity participation opportunities, we also developed opportunity-based accessibility indicators at the level of the US Census block (203,191 US Census blocks cover the entire study area). In this way, we represent the ease (or difficulty) of reaching 15 different types of industries (representing the opportunities for activity participation) from each of these blocks within 10, 20, and 50 minutes of roadway travel buffers from each of the 203,000 pegs (Chen et al, 2011). The types of industries included in this version are: (a) Agriculture, forestry, fishing and hunting and mining; (b) Construction; (c) Manufacturing; (d) Wholesale trade; (e) Retail trade; (f) Transportation and warehousing and utilities; (g) Information; (h) Finance, insurance, real estate and rental and leasing; (i) Professional, scientific, management, administrative, and waste management services; (j) Educational; (k) Health; (i) Arts, entertainment, recreation, accommodation and food services; (m) Armed forces; (o) Public administration; and (p) Other services (except public administration). Different accessibility values are obtained for the morning peak period (6 to 9 AM), midday (9 AM to 3 PM), evening peak period (3 to 7 PM), and at night (7 PM to 6 AM) capturing not only the different roadway conditions, but also the patterns of opening and closing of businesses during the day by allowing within each period above to also have different opening and closing hours of each industry type. Figure 2 provides an example of this spatial distribution by time of day. The top left hand quadrant also shows the percent of persons arriving and staying at the workplace (in this example banks and related institutions). As expected after 7:00 pm accessibility to these services is dramatically lower because the striking majority of these businesses are closed. The resident population with its detailed characteristics and a selection of indicators of the accessibility they enjoy are the inputs for the next block. Accessibility indicators are used in many of the behavioral models of the baseline year. Then, for subsequent simulation years they are modified based on the middle blocks of Figure 1 when the spatial distribution of economic activities change, and they are also modified based on travel times that may change based on network flow.

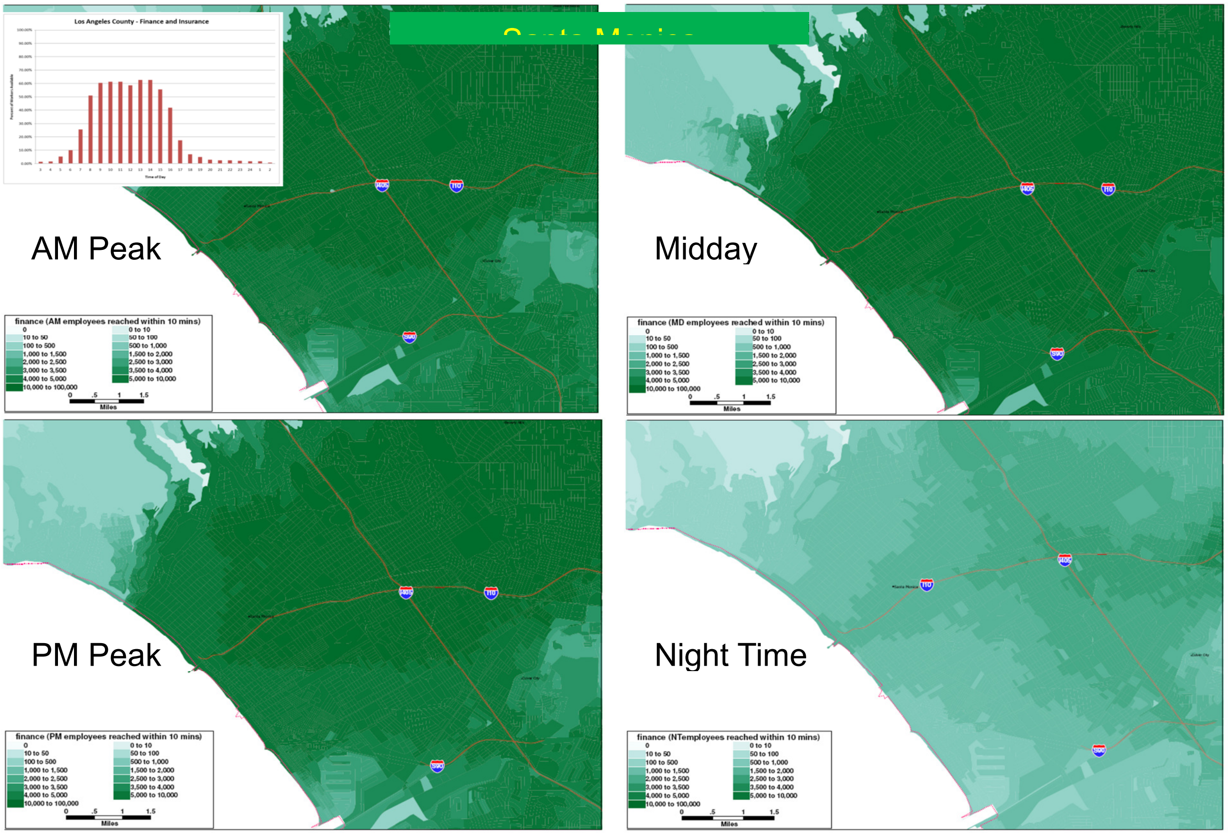


Figure 2 Time of Day Accessibility Map Example in Santa Monica, CA

2.3. Long Term Choices (CEMSELTS)

This block of models was first developed as part of a larger model system (Eluru et al., 2008) and was modified and tailored to the SCAG region using local data. In CEMSELTS (Comprehensive Econometric Microsimulator of Socio-Economics, Land use and Transportation Systems), each person and household created in PopGen, and located in each zone of the study region, is given additional characteristics.

For example, when we examine persons in college a model is used to assign a college location, which is also a hierarchical function of accessibility. Workers are identified using a labor force participation model that is a function of age, gender, education, and presence of children in the household. Employed persons are then assigned (in a probabilistic way) to their type of industry, work location (which is also a function of accessibility), weekly work duration, and work flexibility. Each individual is also assigned a driver's license depending on age, gender, and race. Using these characteristics, household income is computed as a function of race, presence of elderly individuals, education level of members of households, and employment industry of workers in the household. This is followed by a residential tenure model (own or rent) and a housing type model to assign each household to a single-family detached, single-family attached, apartment, and mobile home or trailer type of residence.

An important model in this simulation system is car ownership and type. This type of model in essence determines the predicted non-commercial regional vehicle fleet mix that is used as input to the emission estimation software. This is also particularly important for California because of the expected market penetration of electric cars and the incentive programs created at the state and federal levels in the US to promote this type of technology. A model system like this can be used to assess different incentive structures promoting environmentally friendly technologies in cars. One of the inhibitors in building car ownership, car type and make models is the existence of many possible alternatives in this choice setting that includes many combinations of available alternatives. The solution here is to use Bhat's (2005) random utility model Multiple Discrete-Continues Extreme Value (MDCEV) model, which is capable of modeling multiple vehicle holdings, body types, fuel types, age, and use (miles) simultaneously. This model includes 55 alternatives for body type/vintage (9 body types – Subcompact Sedan, Compact Sedan, Mid-size Sedan, Large Sedan, Coupe, Cross-utility car, SUV, Van, Pickup) and 5 vintage categories (New to 1 year, 2-3 years, 4-5 years, 6-9 years, 10-12 years, >12 years), 47 alternatives for vehicle make (Ford, Chevrolet, Toyota, Honda, etc.), and several hundreds of models across the many body type/make combination categories. Both groups of models include as explanatory variables household composition indicators and residential accessibility reviewed above (Vyas et al., 2011). The model is currently being enhanced to incorporate the additional dimension of fuel type used. It also has the potential of expanding the pool of options to include commercial vehicle fleets. After this step, each of the household vehicles is allocated to a driver in each household based on a probabilistic model using as predictor (explanatory) variables such as gender, education, and employment.

At this point of the simulation cascade on the left side of Figure 1, the model system produces the spatial distribution of all the residents by different social and demographic levels (including race) as well as employment and school locations assigned to each person. In addition, each household is assigned to a housing type. This resembles a complete Census of the resident population and can be done at any level of spatial aggregation. One could also draw samples from this population or proceed to the next step using 100% of the simulated residents. This is particularly convenient and useful in testing different policy scenarios to select a few to study in more detail. It is also possible to focus on a specific subarea (e.g., a city) and perform more detailed analysis and modeling while keeping the rest of the region as an evolving background. The next set of models simulates the life of persons in a day.

2.4 Daily Schedules and Choices (CEMDAP)

For each synthetically generated household and person within each household, daily activity and travel patterns are created in this block of models. To do so, a new modified version of the Comprehensive Econometric Microsimulator of Daily Activity-travel Patterns (CEMDAP http://www.ce.utexas.edu/prof/bhat/CEMDAP.htm) is used as the modeling engine that simulates activity-travel patterns of all individuals in the region for a 24 hour period along a continuous time axis. This model block creates synthetic schedules in two steps: (a) **the generation step** in which work and school activity participation and timing decisions are created, children's travel needs are estimated and an allocation of escort responsibilities to parents takes place, and independent and joint activity participation decisions are modeled; and (b) application of **the scheduling of activities** that produces the sequence of activities, with the departure and arrival times, activity duration(s), mode for each trip, and determination of the location of each activity. The models in this way create a complete description of the activities at locations and movements among locations of each individual over space and time that is congruent with the movements of the rest of the household in which each person belongs. In this way, for each person, we have information about the type of activity, when, where, how long, with whom, in what sequence, and interrelationships with other persons and locations in the engagement pattern.

In the generation step, working and student adults are first passed through models that predict if they will work or go to school in the simulated day. Then, they are given start and end times for their work and school activity. Conditional on this a household level MDCEV model is then used to simulate combinations of joint and solo activities for all persons. This provides an intra-household consistent schedule of activities and makes the entire simulation feasible because its formulation decreases the number of alternatives to simulate. Joint and solo activity durations are predicted for shopping, maintenance, social, entertainment, visit, active recreation, eat out, and other. In addition, durations for work-related and other serving passengers are also modeled. Activities are then arranged in tours (complete sequence of stops and trips starting and ending at the same location) and the modes used are predicted accordingly. The majority of these behavioral facets are modeled using econometric models (discrete choice models, hazard models, regression equations, etc.) that use as explanatory variables household composition and characteristics (e.g., household size, number of children, number of vehicles owned), individual characteristics (e.g., gender, age, race/ethnicity, job type), location characteristics (e.g., opportunity-based accessibility indicators, infrastructure available, transit availability, population density) , and tour/mode/stops alternative attributes (e.g., in-vehicle travel time, distances to destinations. In addition to the typical tour regression models in the tour-based activity models (Vovsha et al., 2005, Bradley et al. 2010), SimAGENT also includes added detail about activity types (e.g., entertainment, eat out, recreation, serve passengers, and so forth) and duration of activities at each location (including at home, work, and school). The model system also includes tour modes that are drive alone, drive with passenger, shared ride, transit, and walk. The end result resembles Figure 3 in which we have two adults that go to work and a child going to school independently. In the evening they all go out for dinner. The trips, stops, activity types, activity start and ends times, modes are all determined by the simulation that includes 17,317,284 Persons in 5,721,914 Households. Simulation of a policy causes changes in destinations, activities alone and with others, durations, and modes creating "realistic" behavioral changes. For additional detail of this SimAGENT aspect see Bhat et al., 2011.

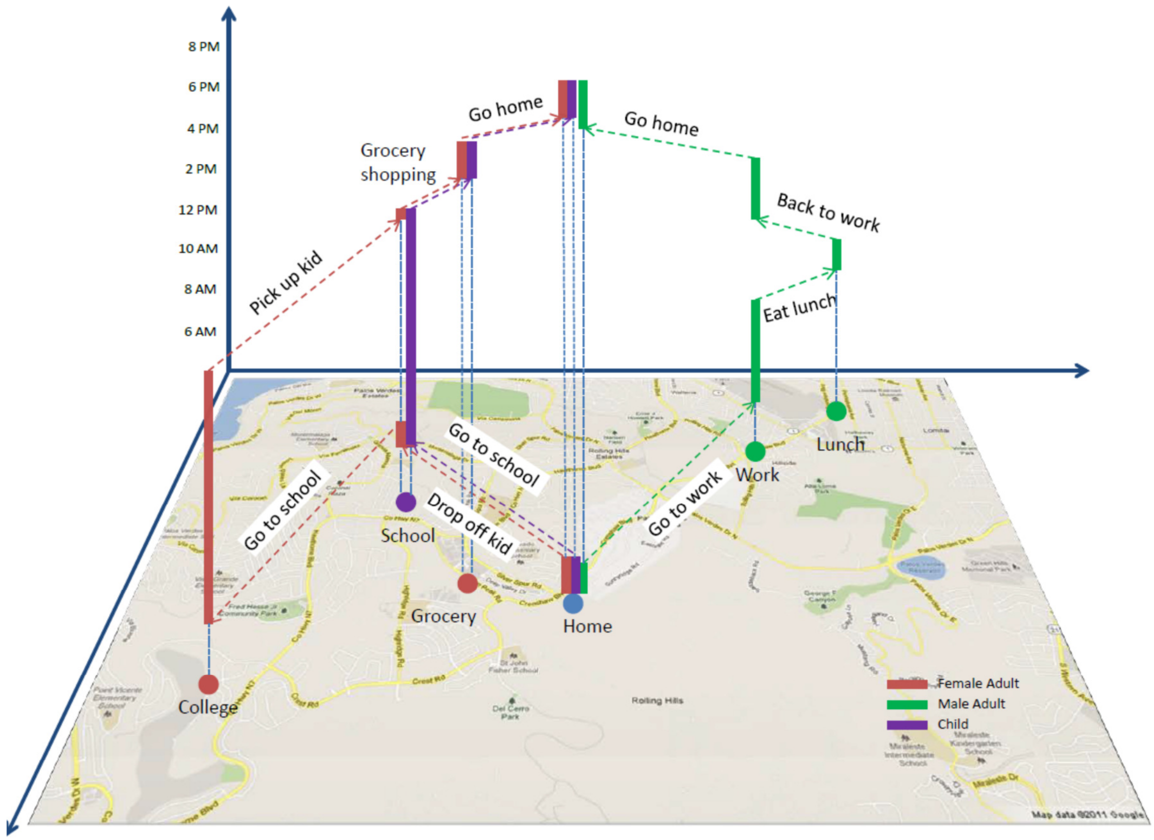


Figure 3 Example of a Daily Three-Person Household Schedule

Table 1, provides a brief description of a few key behavioral indicators from the entire population synthesized by SimAGENT (with heading SimAGENT in Table 1), the survey based on which behavioral equations were estimated and included in the simulation code, and weighted survey averages using the sampling weights provided by NUSTATS, 2003. Table 1 also reports the number of observations that had at least one trip (or one minute of activity for the durations) with activities measured in hours per day. The worktrips include trips to work and back from work. Schooltrips include trips to school and back from school. The shopping trips include trips to shopping (or equivalently the stops with shopping as the activity at the stop). Also, "Activity Duration" in Table 1 is the time between the departure time of the first trip from home and the arrival time of the last trip at home. Overall there is a general agreement between survey data and simulated population by SimAGENT. The standard deviations reported in Table 1 also show a general agreement with similar magnitude between simulated population and survey data with exception the school trips for which all school age children have exactly two trips per day. The output of the model system contains more complete data than an activity survey diary database because it recreates the entire population of the SCAG region and does not have any missing data for each person within each household. This is an important consideration for verification and validation because the simulation produces more information than is currently available from other sources to use as the gold standard or benchmark. At this point, the output from CEMDAP can be used in many different ways. For example, we have developed and pilot tested policy scenarios and studied their impact in timing decisions of individuals (e.g., advancing or postponing the starting of trips). We also coupled this output with the more traditional four-step model routines to perform traffic assignment and emission estimation. Moreover, we are also advancing along the path of using detailed routing algorithms (TRANSIMS router and MATSIM) that can track the simulation of individual vehicles and eventually compute emissions at finer spatial and temporal resolutions moving us along the model development path of TASHA in Toronto (Hao et al., 2010).

Table 1 SimAGENT Average per Person per Day Characteristics Compared to Survey Data

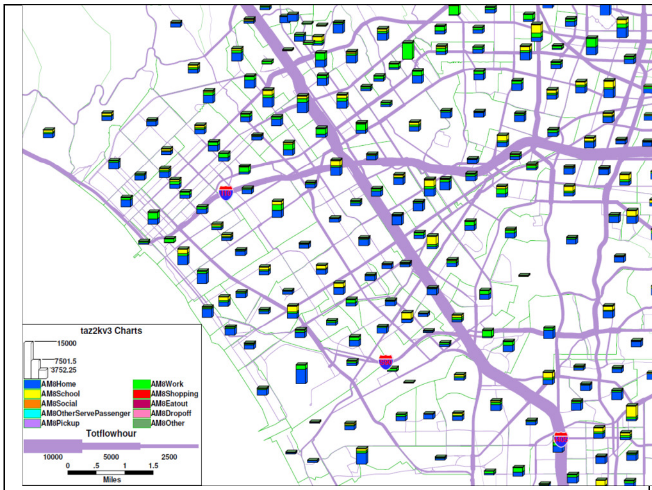
	Survey			Survey Weighted*			SimAgent		
	Mean	**Std.**	**N****	**Mean**	**Std.**	**N****	**Mean**	**Std.**	**N****
Home Based Work	1.77	0.638	8,815	1.76	0.604	9,011	1.71	0.456	4,226,380
Home Based Other	2.81	1.653	22,135	2.83	1.669	26,165	2.70	1.632	11,301,831
Non-Home Based	2.45	1.858	13,164	2.37	1.811	14,204	2.46	1.760	5,304,019
All trips	4.11	2.576	26,754	4.01	2.550	30,962	3.70	2.522	13,728,666
# of work trip	2.37	0.948	9,980	2.32	0.889	10,347	2.58	1.124	4,544,427
# of school trip	2.05	0.343	4,712	2.03	0.280	7,100	2.00	0.001	2,790,932
# of shopping trip	1.47	0.861	6,990	1.42	0.815	7,116	1.84	1.198	2,745,813
# of other trip	3.40	2.388	19,841	3.42	2.425	22,329	3.21	2.411	9,008,573
work duration	8.14	2.675	9,837	8.15	2.633	10,182	8.06	2.184	4,544,427
school duration	6.32	2.092	4,707	6.48	1.983	7,089	5.53	1.563	2,790,932
shopping duration	0.97	0.978	6,990	0.98	1.016	7,116	1.71	1.850	2,745,813
Other activity duration	12.51	3.903	26,690	12.58	3.908	30,898	12.69	5.320	9,008,573
# of go-home trips	1.48	0.784	26,295	1.48	0.798	30,482	1.39	0.742	13,728,666
Activity Duration	8.50	4.454	26,754	8.49	4.339	30,962	7.77	4.681	13,728,666

*sample weights are provided by NUSTATS (2003) to adjust the sample and match known population characteristics. **Number of observations (persons) with at least one trip for trip averages here or one minute of activity for activity durations reported here.

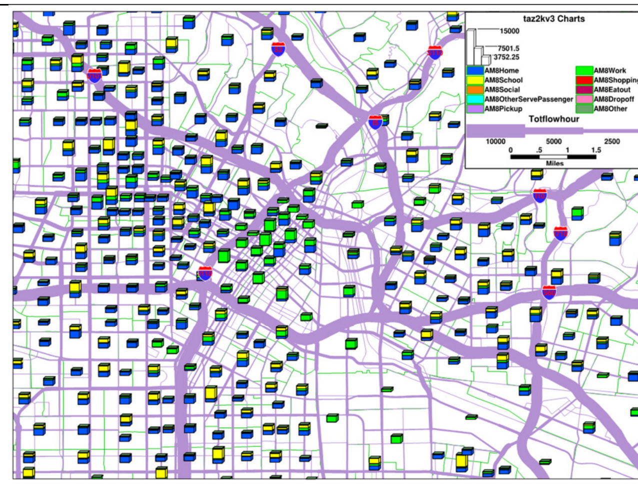
2.5 Routes, Assignment to Networks, and Emissions

The output of CEMDAP in this block is aggregated (i.e., converting person trips to zonal sums of trips) for each of the 4192 zones to create a trip interchange matrix of Origins-Destinations (OD) among the traffic analysis zones at different time periods in a day using the same four periods presented previously for the accessibility indicators. These are combined with similar ODs for heavy vehicles (trucks), and vehicular OD from and to ports and airports, as well as ODs of traffic generated outside the region. These additional OD matrices are the same as the four-step model used by SCAG in its 2008 RTP. Using these trip interchange matrices, traffic assignment (i.e., vehicular origins and destinations are converted into traffic volumes on the highway network based on behavioral and mathematical principles) produces estimates of traffic volumes on the links of the network allowing comparisons among different methods. Figure 4 is the output of traffic assignment during the AM peak, midday, and midnight periods showing vehicle flow per hour. This figure also shows the added output from SimAGENT, which is the number of persons at each location (in this case traffic analysis zone centroids) by each activity type engaged in for that specific hour (7:00 to 8:00 AM and 11:00 AM to 12:00 Noon in Figure 4). During the day the number of persons at work (light green in Figure 4) and school (gold color in Figure 4) are substantial. In the evening hours the maps are dominated by blue color, which is for stay at home activity. In addition, using the typical way of verifying outputs of assignment we examine how close to the observed traffic are traffic volumes estimated by different models. To this end, agencies identify strategic locations forming a ring around major attractors and use them as benchmarks (called screenline and contains 23 locations in this case). Figure 5 shows each of these locations and the relative 'closeness" reproduced by the trip based aggregated four-step model (which is iterated to match these daily traffic counts) and the SimAGENT, which achieves this closeness in one step with no additional adjustments or iterations.

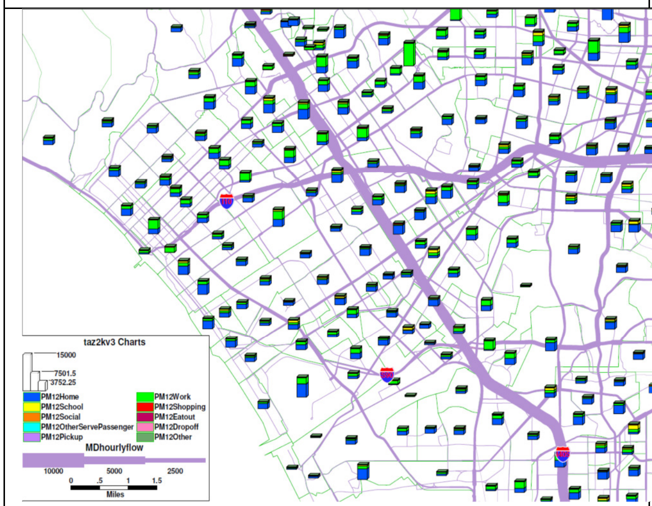
In addition to the screenline comparison, Table 2 presents the assignment statistics for the baseline scenaio. The SimAGENT under baseline scenario generates similar assignment statistics of both light and medium duty and heavy duty vehicles as the four-step model.



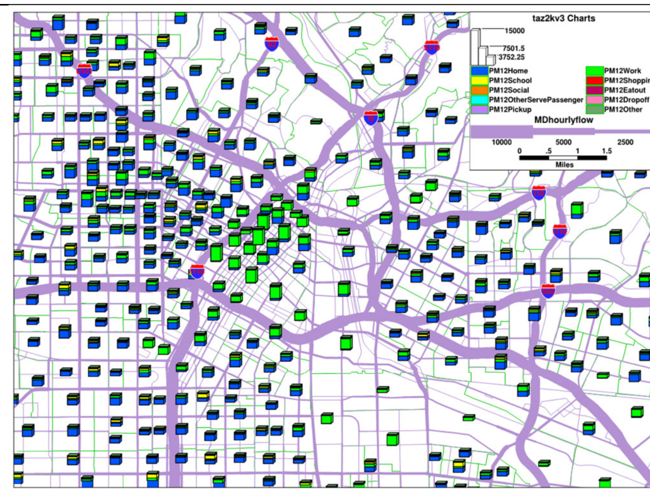
Santa Monica From 7:00 AM to 8:00 AM



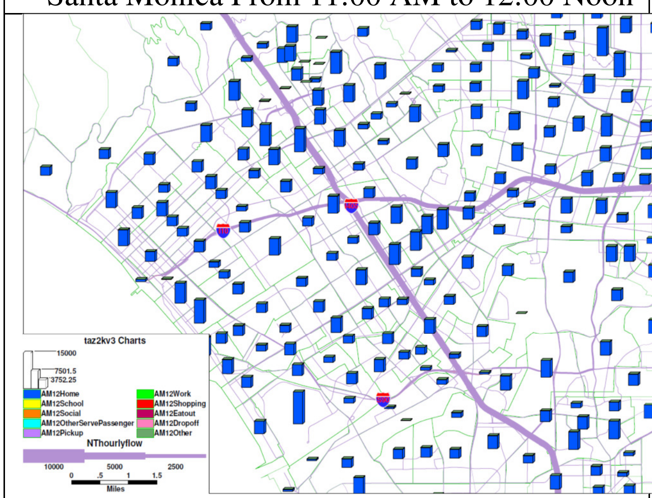
LA Downtown From 11:00 AM to 12:00 Noon



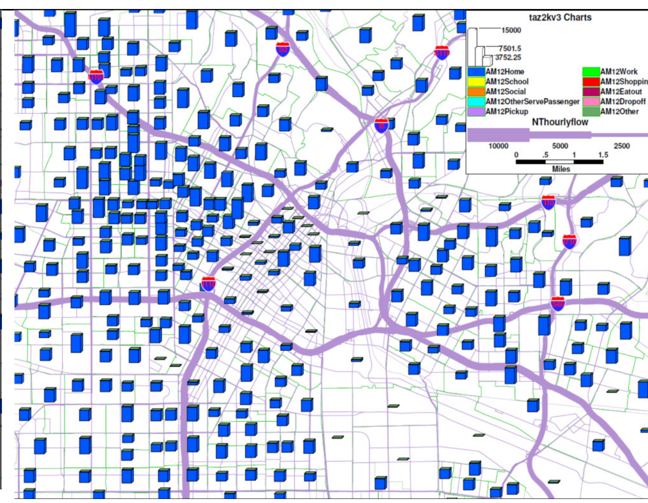
Santa Monica From 11:00 AM to 12:00 Noon



LA Downtown From 11:00 AM to 12:00 Noon



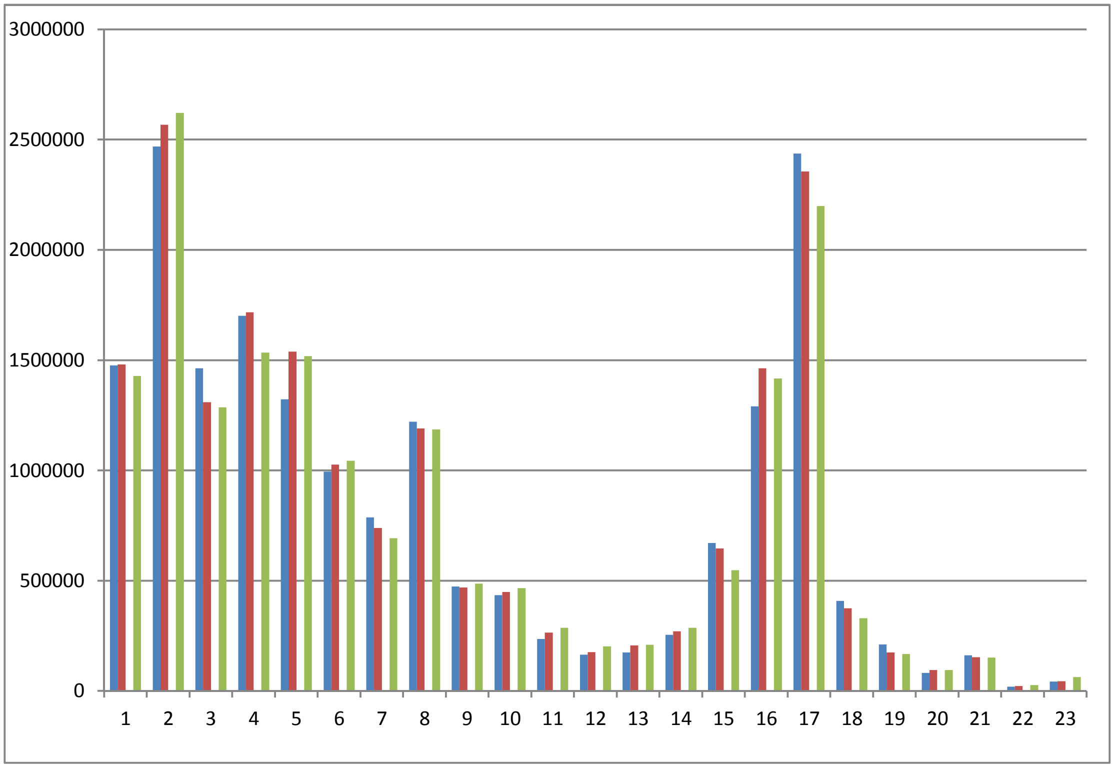
Santa Monica From 11:00 PM to 12:00 AM



LA Downtown From 11:00 PM to 12:00 AM

Figure 4 Assigned Traffic Output in SimAGENT and Number of Persons at Each

Location by Each Activity Type.



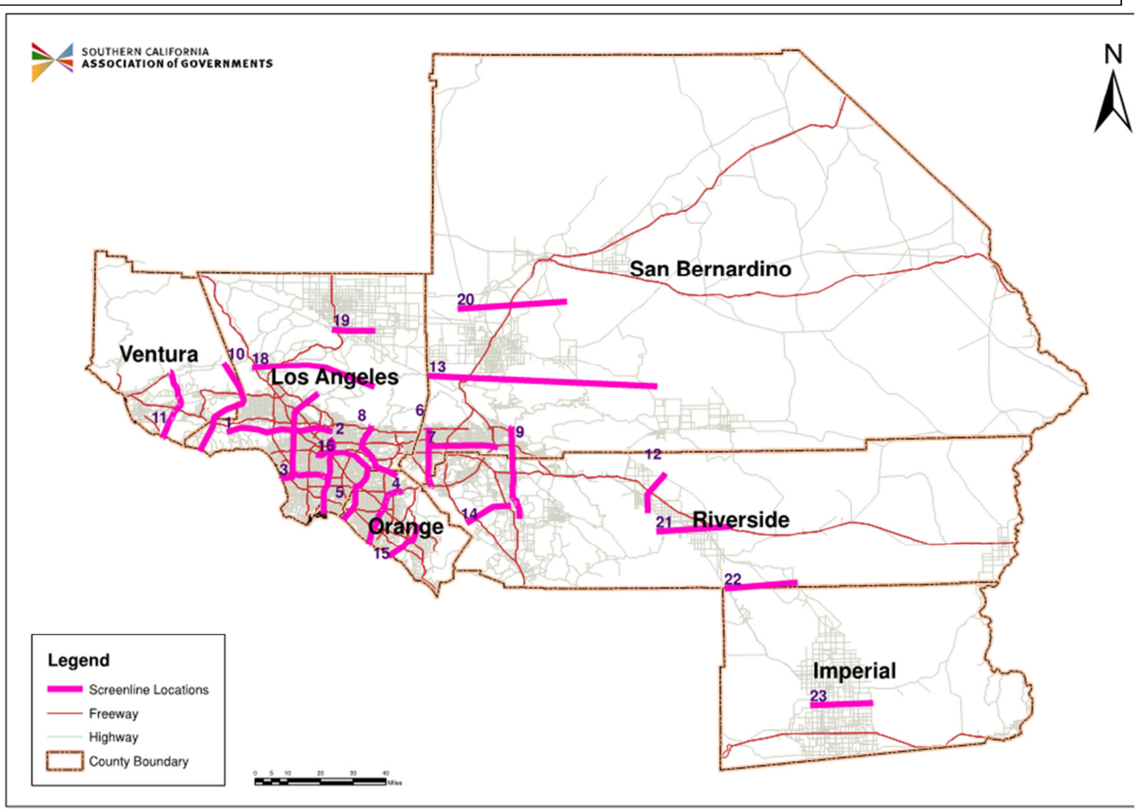


Figure 5 Screenline Daily Traffic Counts Comparisons at 23 different network

locations (red is trip based model, green is SimAGENT, and blue is from observed counts)

Table 2 Traffic Assignment Statistics for four-step model and SimAGENT Baseline Scenario

Vehicle Class	STATISTIC	Trip-based model					SimAGENT baseline				
		AM PK	PM PK	MIDDAY	NIGHT	TOTAL	AM PK	PM PK	MIDDAY	NIGHT	TOTAL
Light & Medium Duty Vehicle	**Average Speed (mph)**	31	26.6	35.3	43.3	31.7	31.8	31.3	36.9	39.8	34.7
	Vehicle Miles Traveled ('000)	76966.3	127676.9	107244	57345.7	369233	68868.2	95893	76705.9	94806.4	336273.5
	Vehicle Hours Traveled ('000)	2486.4	4795.6	3042.1	1323.5	11647.6	2169	3059.9	2077.4	2382.8	9689.1
	Vehicle Hours Delay ('000)	720.4	1779.1	582.9	82.2	3164.6	572.8	813.6	271.2	215.9	1873.5
Heavy Duty Vehicle	**Average Speed (mph)**	35.7	30.9	40.6	52.5	40	37.6	37.3	44.8	50.9	43.5
	Vehicle Miles Traveled ('000)	3850.3	6309.7	10341.7	9120.6	29622.3	3847.5	6290	10347.3	9121.6	29606.5
	Vehicle Hours Traveled ('000)	107.8	204.1	255	173.8	740.6	102.2	168.6	231	179.1	680.9
	Vehicle Hours Delay ('000)	33	80.2	56.2	11.9	181.2	28.1	48.3	35.1	16.7	128.3
All Vehicle	**Average Speed (mph)**	31.2	26.8	35.7	44.4	32.2	32	31.7	37.7	40.6	35.3
	Vehicle Miles Traveled ('000)	80816.5	133986.6	117585.8	66466.3	398855.3	72715.7	102183	87053.2	103928	365880
	Vehicle Hours Traveled ('000)	2594.2	4999.8	3297.1	1497.3	12388.3	2271.2	3228.5	2308.4	2561.8	10370
	Vehicle Hours Delay ('000)	753.4	1859.2	639.1	94.1	3345.8	601	861.9	306.3	232.6	2001.8

Some additional tasks of feasibility testing are also complete during this phase of model development. In fact, many experiments with alternatives to the multi-period static traffic assignment were also completed. One of these experiments uses TRANSIMS along similar lines of development as in Lawe et al., 2010, with an application that aims at recreating the detailed stops along routes that vehicles experience in the simulation using the highway and transit networks. In this application, approximately 64.5 million activity records and 156.5 million travel plans are routed in the network. Table 2 is an example of two households (with household identification numbers 74, and 468). The table also shows the person identification in the household and each activity simulated. Two persons from household 74 did not have out of home activities. Table 3 also shows the duration of each activity, location where it was completed, mode used to arrive to each activity location, and other data about interaction in household of activity and travel, and the vehicle used. The bottom half of the table also shows tracking of vehicle information and the assignment to the main driver within the household. In this way activities are sorted by person in each household and vehicles are connected to each household by the vehicle ID. This output from SimAGENT is restructured to become input for TRANSIMS. This requires adding a home-based activity from the start of the day to the time when the first actual activity begins and other simple conversion of data shown in Table 4. One of the challenges during the process of converting SimAGENT activity records to TRANSIMS activities is the activity location assignment. The original activities are defined as zone-to-zone daily activities. However, TRANSIMS needs the activities and the movements from one activity location to another at finer spatial resolution. For each group of activity locations in each of the 4109 zones we randomly assign to each an activity location within the zone using as seed information observed activity locations. In addition, after all the activities of one household are assigned, we adjust the first and the last activity location of household members to the same location if they have the same zone ID and assume this is the home location of this household (in essence forcing all recorded persons to start and end their day at home and giving them an exact location of home).

Table 3 Example of SimAGENT Activity and Vehicle Data

SimAGENT Activity										
HID	PID	TID	ActType	Duration	ZoneID	ArriveT	Mode	JNTNUM	JNTRVL	VEHID
74	1	1	8	30	101010004	228	7	0	0	1
74	1	1	12	1170	101010000	270	7	0	0	1
74	2	1	2	40	101030002	507	0	0	0	2
74	2	1	12	853	101010000	587	0	0	0	2
74	5	1	7	31	101010003	752	0	0	0	0
74	5	1	12	640	101010000	800	0	0	0	0
468	1	1	11	5	101010001	538	0	0	0	0
468	1	1	3	14	101010002	552	0	0	0	0
468	1	1	12	375	101010001	573	0	0	0	0
468	1	2	3	18	101010001	951	0	0	0	0
468	1	2	12	27	101010001	972	0	0	0	0
468	1	3	9	2	101010003	1008	0	0	0	0
468	1	3	12	121	101010001	1023	0	0	0	0
468	1	4	0	3	101010004	1151	0	0	0	0
468	1	4	12	277	101010001	1163	0	0	0	0
468	2	1	15	243	101010001	295	6	0	0	-1
468	2	0	3	14	101010002	552	4	0	0	-1
468	2	0	12	867	101010001	573	4	0	0	-1
468	3	1	15	290	101010001	282	2	0	0	-1
468	3	0	14	843	101010001	596	2	0	0	-1
468	4	1	15	258	101010001	280	2	0	0	-1
468	4	0	3	14	101010002	552	4	0	0	-1
468	4	0	12	867	101010001	573	4	0	0	-1

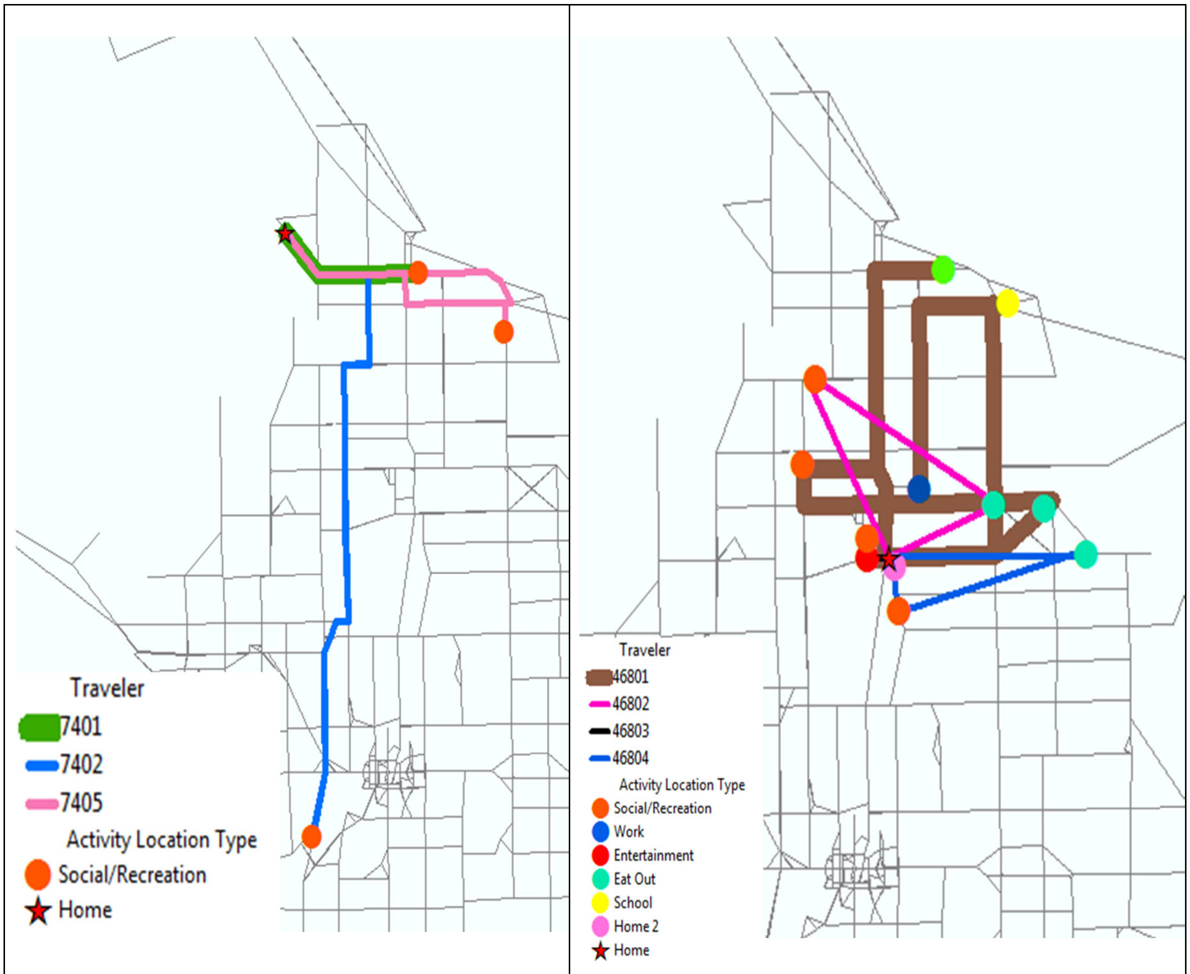
SimAGENT Vehicle							
HID	VID	BODTYP	AGECAT	MAKE	PRIMDRV	ANNMIL	THREAD
74	0	2	2	13	5	45.4288	1
74	1	3	6	2	1	45.4288	1
74	2	1	3	13	2	45.4288	1
468	0	9	6	5	1	13.61	1

Table 4 Example of TRANSIMS Activity and Vehicle Data

HHOLD	PERSON	ACTIVITY	PURPOSE	START	END	DURATION	MODE	VEHICLE	LOCATION	ZONE	PASSENGER
74	1	1	12	0	3.8	3.8	2	741	172838	4013	0
74	1	2	8	3.8	4.3	0.5	2	741	129412	4062	1
74	1	3	12	4.5	24	19.5	2	741	172838	4013	1
74	2	1	12	0	8.45	8.45	2	742	172838	4013	0
74	2	2	2	8.45	9.117	0.667	2	742	172421	4018	0
74	2	3	12	9.783	24	14.217	2	742	172838	4013	0
74	5	1	12	0	12.533	12.533	2	740	172838	4013	0
74	5	2	7	12.533	13.05	0.517	2	740	131714	4086	0
74	5	3	12	13.333	24	10.667	2	740	172838	4013	0
468	1	3	3	9.2	9.433	0.233	2	4680	172959	4088	0
468	1	4	12	9.55	15.8	6.25	2	4680	131311	4064	0
468	1	5	3	15.85	16.15	0.3	2	4680	131304	4064	0
468	1	6	12	16.2	16.65	0.45	2	4680	131304	4064	0
468	1	7	9	16.8	16.833	0.033	2	4680	172967	4086	0
468	1	8	12	17.05	19.067	2.017	2	4680	131079	4064	0
468	1	9	0	19.183	19.233	0.05	2	4680	129347	4062	0
468	1	10	12	19.383	24	4.617	2	4680	131379	4064	0
468	2	1	12	0	4.917	4.917	2	-1	131379	4064	0
468	2	2	15	4.917	8.967	4.05	9	-1	131671	4064	0
468	2	3	3	9.2	9.433	0.233	10	-1	131491	4088	0
468	2	4	12	9.55	24	14.45	10	-1	131379	4064	0
468	3	1	12	0	4.7	4.7	2	-1	131379	4064	0
468	3	2	15	4.7	9.533	4.833	1	-1	131372	4064	0
468	3	3	14	9.933	23.983	14.05	1	-1	131379	4064	0
468	4	1	12	0	4.667	4.667	2	-1	131379	4064	0
468	4	2	15	4.667	8.967	4.3	1	-1	131185	4064	0
468	4	3	3	9.2	9.433	0.233	10	-1	131569	4088	0
468	4	4	12	9.55	24	14.45	10	-1	131379	4064	0

TRANSIMS Vehicle										
VEHICLE	HHOLD	LOCATION	TYPE	SUBTYPE	BODTYP	AGECAT	MAKE	PRIMDRV	ANNMIL	THREAD
740	74	172838	1	0	2	2	13	5	45.4288	1
741	74	172838	1	0	3	6	2	1	45.4288	1
742	74	172838	1	0	1	3	13	2	45.4288	1
4680	468	131379	1	0	9	6	5	1	13.6082	1

Figure 6 shows the daily paths of these two households. Household "74" has 5 persons (with ids 7401, 7402, 7403, 7404, 7405) but the 3rd and 4th persons are not included because they have no travel. The second household "468" has all its four persons (46801, 46802, 46803, and 46804) represented in the tables and paths of Figure 6. The TRANSIMS router uses the SimAGENT input data and generates a series of activity path records which are composed of travel mode, time period of travel, origin-destination locations, turning points on the path, and so forth. This information is stored in an Arcview® polyline file to show the travel path on the network. The entirety of paths for each household is a travel plan and the two travel plans of the households are shown in Figure 6. The household members of the right hand side sketch with ids "46802" and "46804" have trips that did not get routed on the TRANSIMS network and they directly move from an origin to the destination with a travel mode of "Magic Move". This is because the persons traveled by "School Bus" (Mode = "6") and "Driven by Parent (for child)" (Mode = "4") and VEHID = "-1" which could not be routed on the network. This is an example of the type of details that need to be post-processed in addition to a variety of other comparisons among different assignment algorithms and sensitivity analysis that are planned for the next phase in model development.



Household "74" Three persons with some overlap of paths	Household "468" Four persons with unassigned trips

Figure 6: Travel Plans for Households 74 and 468

Testing of emissions estimation was also performed at this stage of model development using the more traditional approach that is also used in conformity studies with the four step model, but this time employing SimAGENT multi-period static traffic assignment. The output of the traffic assignment by different time periods in a day is then used as input to the software EMFAC (a California region-tailored emissions calculating software) that produces estimates of fuel consumed and GHG emissions. Table 5 compares the EMFAC output between the two model systems (4-step and SimAGENT). Both systems use the same truck traffic, special generators (ports and airports), and external to the study area traffic. Due to decreased VMT and delay, SimAGENT generated fewer emissions compared with the four-step model. The model year for regional fleet composition is 2003. We also experimented with different year-by-year fleet compositions in EMFAC2007 and years of simulation showing a dramatic decrease in pollutant emissions but very low sensitivity to CO2 emissions due to the fairly constant fuel efficiency of the technology groups in the software. It should also be noted that in the past few months the California Air Resources Board published EMFAC2011 that includes new vehicle standards (called Pavley) and a module for strategic growth scenarios. This will be used in the project continuation that is expected to end in December 2012.

Table 5 Emissions in Four-step Model and SimAGENT Baseline Scenario (Tons/Day)

Four-step model											
	ROG	CO	NOx	CO2	PM_EX	TIR_W	BRK_W	PM_TOT	SOx	Fl_Gas	Fl_Dsl
L+MDV	326.9	3392.1	343.6	189060.5	6.3	0.8	2.3	9.4	2.0	19834.5	117.8
HDT	61.5	486.8	430.7	40852.1	15.0	0.2	0.3	15.5	2.9	877.5	2968.8
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	392.4	3952.5	802.7	233603.6	21.8	1.0	2.6	25.3	5.1	20845.3	3312.4
SimAGENT Baseline											
L+MDV	293.9	3058.3	312.0	167182.0	5.4	0.8	2.1	8.3	1.7	17542.9	109.6
HDT	59.0	470.6	432.5	40078.4	14.6	0.2	0.3	15.1	2.9	826.8	2941.6
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	356.9	3602.5	773.0	210951.3	20.5	1.0	2.4	23.8	4.8	18503.0	3276.9
Difference											
L+MDV	-10.09%	-9.84%	-9.18%	-11.57%	-13.64%	-8.53%	-8.68%	-11.99%	-11.27%	-11.55%	-6.96%
HDT	-4.10%	-3.33%	0.42%	-1.89%	-2.61%	0.00%	0.00%	-2.55%	-1.04%	-5.78%	-0.92%
Other	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
TOTAL	-9.05%	-8.85%	-3.71%	-9.70%	-5.74%	-7.10%	-7.68%	-5.99%	-4.98%	-11.24%	-1.07%

2.6 Policy scenarios

In this section we provide a few examples of different policy scenarios tested until March 2012. This is an illustration of the potential this new method has and provides an idea of what we should expect in the version with more zones.

2.6.1 Travel time based scenario

SimAGENT allows testing a variety of policy scenarios due to its micro-simulation approach. In addition to the baseline scenario of Figure 4, two additional scenarios were designed to examine the impacts of travel cost increase policies. The two cost increase scenarios are:

- 100% travel cost increase
- 1000% travel cost increase

The daily traffic flows on the screenlines for the two policy scenarios are shown with baseline scenario in Figure 7. Slight decrease in daily traffic volume can be observed in 100% cost increase scenario when compared to baseline scenario. It is reasonable to conclude that doubling the travel cost has some impacts on drivers' travel behavior. When the travel cost increase up to 10 folds of the original cost in base scenario, more significant drops of the traffic flows on the each of the 23 screenlines indicate that the drivers tend to decrease their travel to some extent as the cost significantly increases.

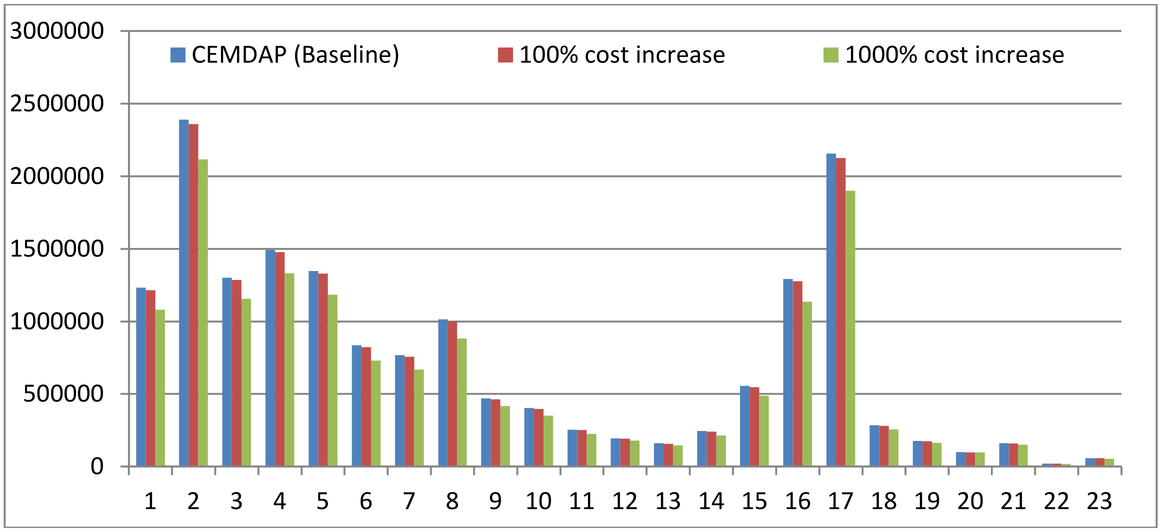


Figure 7 Screenline Daily Traffic Counts Comparisons between Policy Scenarios

In addition to the screenline comparison, Table 6 presents the assignment statistics for different scenarios. As expected, less VMT and higher travel speed were achieved under the two cost increase scenarios compared with the baseline scenario (see Table 2). The VMT decreased by 2% in the 100% cost increase scenario and 16% in the 1000% cost increase scenario. As a result, vehicle hour delay decreased by 6% in the100% cost increase scenario and 36% in the1000% cost increase scenario and the travel speed increased.

Table 7 compares the emissions for the three SimAGENT scenarios. The emission results are consistent with the assignment outputs. With the travel cost increase, fewer emissions were generated in the two cost increase scenarios. By doubling the travel cost, the CO emission decrease slightly for about 1.2% shown in Table 8. More significant decreases (up to 10.0%) of CO emission due to the less traffic on the network can be observed from the 1000% cost increase scenario. The overall conclusion, however, is that SimAGENT s not very sensitive to costs. This is due to the data we use as source of information (from 2001) and the lack of information about sensitivity to costs.

Table 6 Traffic Assignment Statistics for Two Cost Increase Scenarios

Vehicle Class	STATISTIC	SimAGENT 100% cost increase					SimAGENT 1000% cost increase				
		AM PK	PM PK	MIDDAY	NIGHT	TOTAL	AM PK	PM PK	MIDDAY	NIGHT	TOTAL
Light & Medium Duty Vehicle	Average Speed (mph)	32.1	31.6	37	39.6	35.3	34.1	33.4	37.4	39.9	36.5
	VMT ('000)	67338.1	94482	75341.5	127752.5	364914.2	57113.7	82419.9	68548.7	122089.7	330172
	VHT ('000)	2099.2	2992.2	2035.2	3223.4	10350	1674.9	2464.9	1834.4	3060.3	9034.6
	VHD ('000)	539.2	788.3	261.3	438.8	2027.6	361.1	556.9	221.8	396.5	1536.2
Heavy Duty Vehicle	Average Speed (mph)	38.1	37.4	45	47.7	42.9	40.8	39.8	45.5	48.2	44.2
	VMT ('000)	3848.3	6290.9	10348.4	9104.5	29592.1	3855.7	6297.3	10354.2	9109.1	29616.2
	VHT ('000)	101	168.3	230.2	190.9	690.3	94.5	158.1	227.8	189	669.4
	VHD ('000)	27	47.9	34.4	27.5	136.8	21.1	38.8	32.2	25.8	117.9
All Vehicle	Average Speed (mph)	32.4	31.9	37.8	40.1	35.7	34.5	33.8	38.3	40.4	37.1
	VMT ('000)	71186.4	100773	85689.9	136857	394506.3	60969.4	88717.2	78902.8	131198.8	359788.2
	VHT ('000)	2200.2	3160.4	2265.4	3414.2	11040.3	1769.4	2623	2062.2	3249.4	9704
	VHD ('000)	566.2	836.2	295.7	466.3	2164.3	382.2	595.7	254	422.3	1654.1

Note: VMT – Vehicle Miles Traveled
VHT – Vehicle Hours Traveled
VHD – Vehicle Hours Delay

Table 7 Emissions in Four-step Model and Three SimAGENT Scenarios (Tons/Day)

SimAGENT Baseline											
	ROG	CO	NOx	CO2	PM_EX	TIR_W	BRK_W	PM_TOT	SOx	Fl_Gas	Fl_Dsl
L+MDV	293.9	3058.3	312.0	167182.0	5.4	0.8	2.1	8.3	1.7	17542.9	109.6
HDT	59.0	470.6	432.5	40078.4	14.6	0.2	0.3	15.1	2.9	826.8	2941.6
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	356.9	3602.5	773.0	210951.3	20.5	1.0	2.4	23.8	4.8	18503.0	3276.9
SimAGENT 100% cost increase scenario											
L+MDV	289.8	3015.6	307.8	164668.1	5.3	0.8	2.0	8.1	1.7	17279.3	108.3
HDT	58.9	470.0	432.8	40052.7	14.6	0.2	0.3	15.1	2.9	825.2	2940.7
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	352.6	3559.2	769.1	208411.7	20.4	0.9	2.3	23.7	4.8	18237.7	3274.5
SimAGENT 1000% cost increase scenario											
L+MDV	259.3	2702.6	277.0	146451.9	4.7	0.7	1.8	7.2	1.5	15369.0	98.2
HDT	58.3	466.5	435.0	39893.3	14.6	0.2	0.3	15.0	2.8	816.9	2933.1
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	321.5	3242.7	740.5	190036.1	19.7	0.9	2.1	22.7	4.6	16319.2	3256.9

Table 8 Emission Comparison between SimAGENT Three Scenarios

Difference between SimAGENT Baseline and 100% cost increase scenario											
L+MDV	-1.4%	-1.4%	-1.3%	-1.5%	-1.7%	-1.4%	-1.3%	-1.6%	-1.5%	-1.5%	-1.2%
HDT	-0.2%	-0.1%	0.1%	-0.1%	-0.1%	0.0%	0.0%	-0.1%	0.0%	-0.2%	0.0%
Other	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
TOTAL	-1.2%	-1.2%	-0.5%	-1.2%	-0.5%	-1.2%	-1.2%	-0.6%	-0.5%	-1.4%	-0.1%
Difference between SimAGENT Baseline and 1000% cost increase scenario											
L+MDV	-11.8%	-11.6%	-11.2%	-12.4%	-13.5%	-11.4%	-11.3%	-12.8%	-12.2%	-12.4%	-10.4%
HDT	-1.2%	-0.9%	0.6%	-0.5%	-0.6%	0.0%	0.0%	-0.6%	-0.3%	-1.2%	-0.3%
Other	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

TOTAL	-9.9%	-10.0%	-4.2%	-9.9%	-4.0%	-9.2%	-10.0%	-4.8%	-4.6%	-11.8%	-0.6%

2.6.2 Generalized Cost based scenario

To examine the sensitivity of SimAGENT to a function that combines time and cost we developed a Generalized Cost (GC) application with five GC policy scenarios that were designed as follows:

1. Baseline
2. 100% Drive Alone (DA) Cost increase
3. 100% Auto (DA and Shared Ride) Cost Increase
4. 25% DA In-Vehicle-Travle-Time (IVTT) Increase
5. 25% Auto (DA and Shared Ride) IVTT Increase

Different from travel time based scenarios, the GC scenarios used GC based accessibility measures to replace the travel time based measures and further run the GC scenarios. The following sections discuss about the outputs of the assignment and emissions.

The daily traffic flows on the screenlines for the four policy scenarios are shown with the baseline scenario in Figure 7. It can be observed that the increases of drive-alone and share-ride did not impact the number of trips on these screenlines. Reversely, less traffic was reported in the two IVTT increase scenarios. It suggested that the designed cost increase scenarios didn't show the sensitivity of the SimAGENT to the travel cost increase. On the other hand, the decrease in traffic on the screenlines implied that the SimAGENT is sensitive to IVTT changes to some extent.

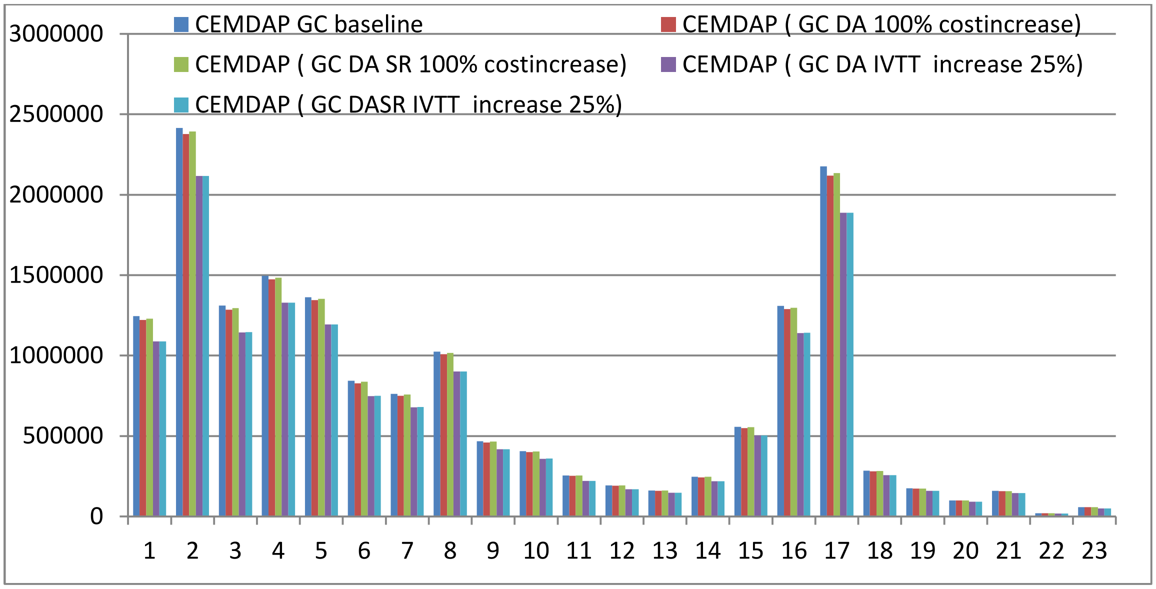


Figure 7 Screenline Daily Traffic Counts Comparisons between Policy Scenarios

Tables 9 and 10 compare the baseline with the travel cost and IVTT increase scenarios, respectively. Slight increases in average speed, and slight decrease in VMT, VHT, and VHD for both light and heavy-duty vehicles are observed when the travel cost increases. Both travel time based and GC based policy scenarios did not show the travel cost impacts on travel behavior due to small changes. In contast, significant decreases in VMT, VHT, and VHD are observed in Table 10. Both 25% IVTT increase scenarios gained about 10% decrease in VMT and 20% decrease in VHD compared with the baseline, which implies that the IVTT variable plays a "heavier" role in traveler's decisions than the travel cost.

The comparison of emission for the five scenarios is shown in Table 11. The emission results are consistent with the assignment outputs. Small decrease in emissions can be observed from the cost increase scenarios compared with baseline scenario. By increasing the IVTT, most of the emissions by passenger cars and light and medium trucks decrease by more than 10% as shown in Table 12.

Table 9 Traffic Assignment Comparison of GC-Based Baseline and Travel Cost Increase Scenarios

Vehicle Class	STATISTIC	CEMDAP (GC based) baseline					CEMDAP (GC based) DA cost increase 100%					CEMDAP (GC based) DASR cost increase 100%				
		AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL	AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL	AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL
Light & Medium Duty Vehicle	Average Speed (mph)	31.8	31.2	37	39.7	34.7	31.9	31.5	37.2	39.8	34.9	31.8	31.4	37.2	39.8	34.8
	VMT ('000)	68828.8	96124.3	76079.8	95754.4	336787.3	67801.9	94171.5	74497.7	94519.9	330990.9	68671.7	95081.7	75054.8	95054.2	333862.4
	VHT ('000)	2167.6	3081	2056.7	2411	9716.2	2124.2	2988.4	2001.8	2374.8	9489.2	2158.7	3025.9	2018.2	2388.2	9591
	VHD ('000)	573.1	837.5	272.6	220.8	1903.9	554.6	794.4	259.9	214.5	1823.4	569.3	811.5	263.9	217.2	1861.8
Heavy Duty Vehicle	Average Speed (mph)	37.7	37	44.7	50.9	43.4	37.9	37.4	44.9	51	43.6	37.7	37.2	44.8	50.9	43.5
	VMT ('000)	3848.1	6290.5	10346.3	9121.4	29606.2	3847	6292.9	10346.8	9121.7	29608.4	3846.1	6289.4	10346	9121.8	29603.4
	VHT ('000)	102.2	170.1	231.2	179.3	682.9	101.6	168.5	230.4	179	679.5	102.1	169.2	230.7	179.2	681.2
	VHD ('000)	28.1	49.5	35.4	16.9	129.9	27.6	47.9	34.6	16.7	126.8	28	48.7	34.9	16.8	128.4
All Vehicle	Average Speed (mph)	32	31.5	37.8	40.5	35.2	32.2	31.8	38	40.6	35.5	32.1	31.7	38	40.6	35.4
	VMT ('000)	72676.9	102414.8	86426.1	104875.8	366393.5	71648.9	100464.4	84844.5	103641.6	360599.3	72517.9	101371.1	85400.9	104175.9	363465.8
	VHT ('000)	2269.8	3251.1	2287.9	2590.3	10399.1	2225.8	3156.8	2232.3	2553.8	10168.7	2260.8	3195.1	2248.9	2567.4	10272.1
	VHD ('000)	601.1	887	307.9	237.8	2033.8	582.2	842.3	294.5	231.2	1950.2	597.3	860.2	298.8	234	1990.2

Note: VMT – Vehicle Miles Traveled
VHT – Vehicle Hours Traveled
VHD – Vehicle Hours Delay

Table 10 Traffic Assignment Comparison of GC-Based Baseline and IVTT Cost Increase Scenarios

Vehicle Class	STATISTIC	CEMDAP (GC based) baseline					CEMDAP (GC based) DA cost increase 100%					CEMDAP (GC based) DASR cost increase 100%				
		AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL	AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL	AM PEAK	PM PEAK	MIDDAY	NIGHT	TOTAL
Light & Medium Duty Vehicle	Average Speed (mph)	31.8	31.2	37	39.7	34.7	32.3	32.7	37.8	40	35.4	32.2	32.7	37.8	40	35.4
	VMT ('000)	68828.8	96124.3	76079.8	95754.4	336787.3	66191.6	86205.9	64660.9	80663.5	297721.9	66291.4	86237.4	64703.6	80707.2	297939.5
	VHT ('000)	2167.6	3081	2056.7	2411	9716.2	2051.4	2636.8	1712.7	2017.7	8418.7	2058.2	2633.9	1713.8	2018.8	8424.6
	VHD ('000)	573.1	837.5	272.6	220.8	1903.9	523.1	636.7	198.1	149.2	1507.1	527	633.7	198.3	149.4	1508.4
Heavy Duty Vehicle	Average Speed (mph)	37.7	37	44.7	50.9	43.4	38.3	39	45.8	51.9	44.6	38.2	39	45.8	51.9	44.6
	VMT ('000)	3848.1	6290.5	10346.3	9121.4	29606.2	3847.2	6294.5	10350.9	9120.8	29613.4	3848.5	6292.2	10350.9	9120.8	29612.4
	VHT ('000)	102.2	170.1	231.2	179.3	682.9	100.5	161.6	226	175.8	663.9	100.7	161.3	226	175.8	663.8
	VHD ('000)	28.1	49.5	35.4	16.9	129.9	26.6	41.8	30.6	13.8	112.7	26.7	41.6	30.6	13.8	112.7
All Vehicle	Average Speed (mph)	32	31.5	37.8	40.5	35.2	32.5	33.1	38.7	40.9	36	32.5	33.1	38.7	40.9	36
	VMT ('000)	72676.9	102414.8	86426.1	104875.8	366393.5	70038.9	92500.4	75011.8	89784.3	327335.3	70139.8	92529.6	75054.5	89828	327551.9
	VHT ('000)	2269.8	3251.1	2287.9	2590.3	10399.1	2151.9	2798.4	1938.7	2193.5	9082.6	2158.9	2795.2	1939.9	2194.6	9088.5
	VHD ('000)	601.1	887	307.9	237.8	2033.8	549.7	678.5	228.7	163	1619.9	553.7	675.3	228.9	163.1	1621.1

Note: VMT – Vehicle Miles Traveled
VHT – Vehicle Hours Traveled
VHD – Vehicle Hours Delay

Table 11 Emissions in GC Based Scenarios (Tons/Day)

	ROG	CO	NOx	CO2	PM_EX	TIR_W	BRK_W	PM_TOT	SOx	Fl_Gas	Fl_Dsl
Baseline											
L+MDV	294.4	3062.9	312.4	167530.4	5.4	0.8	2.1	8.3	1.8	17579.5	109.5
HDT	59.1	471.1	432.4	40099.0	14.7	0.2	0.3	15.1	2.9	828.1	2942.2
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	357.4	3607.6	773.3	211320.4	20.5	1.0	2.4	23.9	4.8	18541.1	3277.4
DA cost increase 100%											
L+MDV	289.0	3007.0	307.0	164225.8	5.3	0.8	2.0	8.1	1.7	17233.0	107.7
HDT	59.0	470.4	432.6	40068.2	14.6	0.2	0.3	15.1	2.9	826.4	2941.1
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	351.9	3551.0	768.1	207985.0	20.4	0.9	2.3	23.7	4.8	18192.6	3274.4
Auto cost increase 100%											
L+MDV	291.5	3033.5	309.6	165751.8	5.4	0.8	2.1	8.2	1.7	17393.0	108.7
HDT	59.0	470.6	432.4	40077.5	14.6	0.2	0.3	15.1	2.9	826.9	2941.4
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	354.5	3577.7	770.5	209520.3	20.5	0.9	2.3	23.8	4.8	18353.2	3275.7
DA IVTT increase 25%											
L+MDV	260.3	2713.3	277.6	147591.0	4.8	0.9	2.1	7.7	1.5	15487.8	98.0
HDT	58.7	469.2	435.3	40016.4	15.0	0.3	0.3	15.7	2.9	825.2	2937.3
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	322.9	3256.1	741.3	191298.3	20.3	1.2	2.4	23.9	4.6	16446.4	3260.8
Auto IVTT increase 25%											
L+MDV	260.5	2715.4	277.8	147717.3	4.8	0.7	1.8	7.3	1.5	15501.1	98.0
HDT	58.7	469.3	435.2	40017.4	14.7	0.2	0.3	15.1	2.9	825.4	2937.2
Other	3.9	73.6	28.5	3690.9	0.5	0.0	0.0	0.5	0.2	133.3	225.7
TOTAL	323.1	3258.3	741.5	191425.7	19.9	0.9	2.1	22.9	4.6	16459.8	3260.9

Table 12 Emission Comparison between GC based baseline and Four Policy Scenarios

	ROG	CO	NOx	CO2	PM_EX	TIR_W	BRK_W	PM_TOT	SOx	Fl_Gas	Fl_Dsl
Difference between GC Baseline and DA Cost Increase 100%											
L+MDV	-1.85%	-1.83%	-1.74%	-1.97%	-2.21%	-1.81%	-1.73%	-2.04%	-2.00%	-1.97%	-1.64%
HDT	-0.19%	-0.15%	0.06%	-0.08%	-0.10%	0.00%	0.00%	-0.09%	-0.04%	-0.21%	-0.04%
Other	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
TOTAL	-1.55%	-1.57%	-0.67%	-1.58%	-0.65%	-1.36%	-1.57%	-0.77%	-0.75%	-1.88%	-0.09%
Difference between GC Baseline and Auto Cost Increase 100%											
L+MDV	-0.98%	-0.96%	-0.90%	-1.06%	-1.22%	-0.91%	-0.92%	-1.10%	-1.03%	-1.06%	-0.73%
HDT	-0.12%	-0.09%	0.01%	-0.05%	-0.07%	0.00%	-0.38%	-0.07%	0.00%	-0.14%	-0.03%
Other	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
TOTAL	-0.83%	-0.83%	-0.36%	-0.85%	-0.37%	-0.63%	-0.76%	-0.43%	-0.39%	-1.01%	-0.05%
Difference between GC Baseline and DA IVTT increase 25%											
L+MDV	-11.60%	-11.41%	-11.16%	-11.90%	-11.73%	11.25%	-1.25%	-6.94%	-11.82%	-11.90%	-10.50%
HDT	-0.67%	-0.39%	0.67%	-0.21%	2.64%	69.14%	28.20%	3.86%	-0.18%	-0.35%	-0.17%
Other	0.00%	0.00%	0.00%	0.00%	0.83%	25.00%	13.33%	1.60%	0.00%	0.00%	0.00%
TOTAL	-9.67%	-9.74%	-4.13%	-9.47%	-1.20%	22.30%	2.08%	0.07%	-4.39%	-11.30%	-0.51%
Difference between GC Baseline and Auto IVTT Increase 25%											
L+MDV	-11.53%	-11.35%	-11.09%	-11.83%	-12.55%	-11.25%	-11.22%	-12.12%	-11.76%	-11.82%	-10.50%
HDT	-0.66%	-0.38%	0.66%	-0.20%	0.00%	0.00%	0.00%	0.00%	-0.18%	-0.33%	-0.17%
Other	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
TOTAL	-9.61%	-9.68%	-4.11%	-9.41%	-3.32%	-9.11%	-10.01%	-4.21%	-4.37%	-11.23%	-0.50%

3. Future Research and Analysis

Although the SimAGENT version described here appears to work well for the policy analysis purpose that was designed, it is currently being tested and strategically modified using external data for verification and validation. In doing this we identified a variety of methodologically thorny issues about verification and validation that would be appropriate for microsimulated environments and the daily life of their residents that do not have a readily available solution or benchmark data. We have completed an extensive accessibility computation exercise using a combined network of walking and transit for comparison with highway-base accessibility indicators (Lei, 2011). This new set of indicators can be used for mode/destination type of models. However, this requires extensive testing of the algorithms used and re-estimation of the different behavioral facets in the current version of SimAGENT. We also planned for the development of a next version of model system that may be used in the next cycle of regional model development in SCAG that includes a much richer and larger zonal system of approximately 12,000 zones and finer network for all travel components. This new system follows on the heels of the most recently completed 2008 four step model.

From a behavioral viewpoint, we also performed sensitivity to a variety of explanatory variables used in the regression models that show high sensitivity to land use (e.g., density, mixed land use, and distance to major centers), high sensitivity to travel times, and low sensitivity to costs. This is particularly important when interfacing and integrating SimAGENT with other simulation software and we include in the next development phase a task to study the relationships depicted at different scales between travel costs and the spatial distribution of activities. In the past two months we also developed a MATSIM (Gao et al., 2010, Bekhor et al., 2011) application that has important similarities and differences with TRANSIMS to explore additional next steps. In parallel, an application using DynusT started and is expected to show initial results by June 2012. In the emissions estimation we also move along the development lines of second by second emissions estimation using the CMEM software developed at UC Riverside.

Moreover, we are developing the component labeled “household evolution” in Figure 1 that provides the demographic microsimulation needed to evolve the synthetic population in multiple years. Development is advancing rapidly and we are in the process of acquiring data and techniques that will strengthen this component further. Most of the work on this activity is in another project that will produce its own separate report.

In 2010 California started the design and implementation of the California Household Travel Survey, which is currently taking place (started in February 2012) and expected to be completed by early 2013. This survey will provide many of the data required for SimAGENT. One final comment is about computational speed and efficiency. In the experiments we performed with this model system, computational time was reduced dramatically employing multiple core computers (the cluster system at UT Austin) reducing computational time substantially as one would expect. However, the most time consuming task is the exchange of data among different modules with many of them requiring data manipulation by researchers. This calls for the design of interfaces among modules that are coded in different languages and platforms, an issue that we left for the future but intend to start tackling between March 2012 and December 2012.

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