

## SimAGENT Accessibility <br> 2

## Opportunity-Based Dynamic Accessibility Indicators in SimAGENT

Konstadinos G. Goulias, Chandra R. Bhat, Ram M. Pendyala, Yali Chen, Ting Lei, Srinath Ravulaparthy, Kathleen Deutsch, Pamela Dalal, and Seo Youn Yoon

Phase 2 Report Submitted to


## SOUTHERN CALIFORNIA ASSOCIATION Of GOVERNMENTS

[^0]January 31, 2013

## OPPORTUNITY-BASED DYNAMIC ACCESSIBILITY INDICATORS IN SIMAGENT

Table of Contents
PREFACE ..... 3

1. AUTOMOBILE ACCESSIBILITY ..... 4
1.2 DATA USED ..... 6
1.3 METHOD AND SAMPLE MAPS ..... 10
2. TRANSIT ACCESSIBILITY ..... 23
2.2 METHODOLOGY ..... 25
2.3 ACCESSIBILITY COMPUTATION AND EXAMPLES ..... 33
3 FUTURE WORK ..... 39
3. REFERENCES AND BIBLIOGRAPHY ..... 40

## Preface

In this report we present accessibility computation that preceded development of explanatory variables used in SimAGENT. Accessibility, defined as the ease (or difficulty) with which activity opportunities can be reached from a given location, can be measured using the cumulative amount of opportunities from an origin within a given amount of travel time. This report discusses the accessibility measures for automobile and a two mode walk-transit accessibility respectively. Both methods have in common the time of day variation of availability of opportunities and the changes of the level of service offered by the transportation system.

The work described in this report is heavily based on two Annual Transportation Research Board Meeting papers that are:

Chen, Y., S. Ravulaparthy, K. Deutsch, P. Dalal, S.Y. Yoon, T. Lei, K.G. Goulias, R.M. Pendyala, C.R. Bhat, and H-H. Hu (2011) Development of Opportunity-based Accessibility Indicators. Transportation Research Record: Journal of the Transportation Research Board, No. 2255, Transportation Research Board of the National Academies, Washington D.C., 2011, pp.58-68.

Lei T., K. G. Goulias, and Y. Chen (2011) Opportunity-Based Dynamic Transit Accessibility in Southern California: Measurement, Findings, and Comparison with Automobile Accessibility. Paper 12-3813 presented at the January $2012911^{\text {st }}$ Annual Meeting of the Transportation Research Board, Washington, D.C., January 22-26, 2012.

## 1. AUTOMOBILE ACCESSIBILITY

Accessibility indicators are needed for a variety of regional planning and modeling purposes, such as characterizing quality of life (Wachs and Kumagai, 1973), describing transportation quality of service (Handy, 1993), explaining travel behavior choices (Lee and Goulias, 1997, Yoon et al., 2009) and intra-household task allocation (Yoon et al., 2009), predicting short and long term decisions in multiple contexts (Abreu and Goulias, 2009), and measuring "jobs-housing" balance (Ong and Blumenberg, 1998, Badoe and Miller, 2000, Grengs, 2001, Blumenberg and Manville, 2004, Alam, 2009). Recent developments also show accessibility can be developed as an "output" of activity-based travel demand forecasting models to study policy scenarios (Dong et al., 2006, Shiftan, 2007). Accessibility indicators also serve several other purposes, as enumerated and discussed in detail by Geurs and van Wee (2004).

A general definition of accessibility is the ease (or difficulty) with which activity opportunities may be reached from a given location using one or more modes of transportation. Defined in this way, accessibility indicators (or measures) incorporate the performance of a transportation system and the spatial distribution of land-use activities within a given region. In essence, accessibility captures the extent of attractiveness of each potential destination and weights that attraction by the associated travel "cost" to reach the destination from a given location. The travel "cost" itself may be represented explicitly in the form of an impedance measure to reach the destination from the origin point (as is the case with gravity-based formulations of destination choice behavior) or implicitly in the form of a cumulative accounting of opportunities that are within a certain travel time from the origin point. This latter formulation is particularly attractive and intuitive, because it represents the "intervening opportunities" or amount of activity potential reachable within a given amount of travel time from an origin location. One can identify different travel time thresholds (e.g., 10 minutes, 20 minutes, and 50 minutes) and create geographic "buffers" within which activity opportunities that can be reached are counted. In this manner, the accessibility formulation is both a function of land use patterns and the performance of the transportation system, and provides a compact measure to examine the impact of land use policies in computer simulation scenarios or
in before-after infrastructure project studies. At the same time, the accessibility formulation can also be used to evaluate the extent of distributional justice, measure spatial (in-)equity in the provision of opportunities, and provide indicators of the overall cost of reaching work places, shopping centers, and social and recreational opportunities.

The techniques to construct accessibility indicators based on the "intervening opportunities" formulation have evolved from very simple calculations to more complex and detailed methods that use algorithms within a Geographic Information Systems (GIS) platform to extract and assemble data from multiple spatial databases at very fine levels of spatial resolution. Kwan (2000) and Lee and Goulias (2007) have pioneered the computation of such GIS-based accessibility indicators, and we extend their concepts to develop accessibility indicators for a very large metropolitan area (mega-region). Our ultimate objective is to describe the region by mapping opportunities to show availability of activity locations by the type of industry and time of day. This is also an attempt to develop methods that allow measurement and description at fine spatial resolution that eventually may lead to land parcel by parcel analysis. In this way land parcels can be classified by the type of accessibility they are provided with by the surrounding land use and transportation system. We also envision using these accessibility indicators as explanatory variables in long term choices (e.g., job location and car ownership) and short term choice (e.g., daily activity patterns) model systems.

The large metropolitan area of interest in this project is the Southern California Association of Governments (SCAG) region, which represents the largest Metropolitan Planning Organization in United States with approximately 19 million residents and 191 cities. However, the methods developed and illustrated here for the SCAG region uses data largely available throughout the United States from agencies that routinely provide information about the spatial distribution of employed persons by industry type and the transportation network that serves them. The unique aspect of our current research is that we combine these readily available "static" sources of data with secondary data on the temporal (within a day) availability of opportunities and the condition of the transportation network to develop dynamic accessibility indicators that vary by time of
day. In particular, the outcome of the research here is a set of time-sequenced maps of activity opportunity availability and a classification of the US Census blocks by their access to these opportunities. To achieve this, network and socioeconomic data at a fine level are prepared, and a methodology that integrates spatial/temporal factors reflecting the variation in available opportunities and travel time during the day is proposed. The next section describes major data sources used in the current research effort and includes data processing and preparation details. The following section discusses the methodology for the computation of accessibility indicators, and presents sample maps of accessibility.

### 1.2 DATA USED

The three primary data sources used to generate the accessibility indicators are: (1) geocoded block group and block data within the SCAG region; (2) SCAG roadway and transit network; and (3) employment data from the Census Transportation Planning Package (CTPP) and Dun \& Bradstreet (D\&B).

The block group and block shape files for the six counties in the SCAG region (the six counties are Los Angeles, Orange, San Bernardino, Imperial, Ventura, and Riverside) are available from the Census website (http://www2.census.gov/cgi-bin/shapefiles2009/statefiles?state=06). These county-specific shape files are combined to form the complete SCAG region GIS maps for both block groups and blocks. The SCAG region consists of 10,631 block groups and 203,191 blocks. The GIS maps and layers provide the basis to compute block group-specific and block-specific measures, such as area, population, and length of roadway segment by functional classification.

The roadway network with link speeds is a vital database when adding the temporal dimension to the accessibility indicators. The network, embedded in the SCAG four-step model, provides a geo-coded roadway database with roadway link speeds for the AM peak (6am-9am), PM peak (3pm-7pm), off-peak (9am-3pm), and night time (7pm-6am)
periods. However, this network does not cover a sufficient number of local roadways to capture the variation in blocks in terms of roadway infrastructure. In fact, a denser network with more streets is necessary to obtain good fidelity in the accessibility measures at the block level. To address this issue, the roadway network from the SCAG four-step model is enriched by combining it with the roadway network in TeleAtlas (Dynamap) 2000, which includes the entirety of local roadways. Once enriched, this roadway network GIS layer is overlaid on the block group and block shape files to obtain highway network attributes specific to each block group and block. These block groupspecific and block-specific network attributes are used later to obtain block-specific employment and its discussed in the next section. The roadway network is also used in the computation of the time-sensitive accessibility indicators, as discussed further under the "method" section.

Along with the roadway network, a comprehensive transit network in the region that includes all the transit stops, routes, and headways is also developed and discussed later in this report. Similar to the roadway network, the transit network is associated to the block group and block shape files, thus enabling computation of accessibility indicators specific to transit operations. The measure of activity opportunity, used in the accessibility indicators constructed in this study, is the number of employees "reachable" within a set of time thresholds of each block. The CTPP employment data is the primary dataset for obtaining information on the number of employees. Specifically, the CTPP data contains the number of employees within each block group, categorized in 15 industry types based on the North American Industry Classification System (NAICS). In addition, the $\mathrm{D} \& \mathrm{~B}$ data, containing more than 100 million business records, in a summary format is used as the supplementary information to verify the CTPP data. The inconsistency between the two datasets in the number of employees at the block group level lead to a data matching approach to reconcile the two sources of information as follows:

1. If Diff ${ }^{*}<=10$, use the number of employees from CTPP
2. If Diff $>10$, use the average of CTPP and $\mathrm{D} \& \mathrm{~B}$ data

* Diff $=($ Absolute number of employee difference between D\&B and CTPP)/( Area of block group in squared km )

The D\&B data are used to enhance the CTPP dataset in one other way. Specifically, the CTPP data combine the education and health industry types, and provides the total number of employees in both these industries. However, as discussed later, our accessibility indicators account for the fact that the number of employees at a location will vary by time of day, based on the work schedules of the employees. Since the work schedules for those in the education and health industries are likely to be quite different, this should lead to differential patterns of accessibility for education and work activity purposes at different times of the day (for example, one would anticipate that accessibility to health care would be better than accessibility to education during the early hours of the morning). So, we separate out the numbers of education and health employees according to the proportions for the two industries from the $\mathrm{D} \& \mathrm{~B}$ dataset. The final 15 industry types used in our accessibility computations 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) Education; k) Health; 1) Arts, entertainment, recreation, accommodation and food services; m) Other services (except public administration); o) Public administration; p) Armed forces.

The employment data available from the CTPP and D\&B data is at the block group level. However, our objective is to compute accessibility indicators at the finer block level too. This requires the use of a spatial disaggregation mechanism to obtain the employment within each block from the employment within each block group. To do so, we assume that the employment in a block is influenced by the area of the block, the population of the block, and the sum of the roadway segment lengths by functional classification (freeway, primary arterial, minor arterial, collector, and ramp) to capture the role of roadways in providing access to opportunities and their competing role with consuming land. These block-specific variables are computed by overlaying demographic GIS files
over the block shape files, and doing the same with the highway network files. To do this we develop a relationship between employment and these "independent" variables. We use the block-group spatial level for this purpose, and estimate a Poisson regression model for each industry type using the number of employees in the block group as the dependent variable and the variables mentioned above as the independent variables. In a preliminary analysis we used a variety of regression formulations to identify the most appropriate form and these included linear regression, Tobit (to account for the presence of zero employment block groups), Poisson, Negative Binomial (NegBin) and zero inflated versions of Poisson and NegBin. Poisson regression reproduced the observed variation in the number of employees in the most satisfactory manner because it was able to replicate areas with high number of employees. Once estimated, we transfer the blockgroup level regression to the block-level to complete the disaggregation of employment data down to the blocks. A sample estimated regression model for the public administration industry is shown in Table 1 . This model shows that all of the independent variables are very highly statistically significant in influencing the number of employees within the block group. Also notable is that some predictor variables (e.g., area, length of freeway and collector segments, and population) have different coefficient signs on the models for different industry types, indicating that these variables play different roles in determining the distribution of employment by industry type. In this example freeways and collectors are competing with land allocated for public administration and have negative signs.

Using these regression models (one for each industry type), the block group employment for each industry type is distributed into each block within a block group as shown below:
a. Calculate the estimated block employment ( $\hat{E}_{i}$ ) for block $i$ by applying the block characteristics and the estimated regression model
b. Calculate the percentage of employment ( $P_{i}$ ) for each block $i$ within each block group $j$.
c. $\quad P_{i}=\frac{\hat{E}_{i}}{\sum_{i \in B_{j}} \hat{E}_{i}}$, where $B_{j}$ is the set of all blocks within block group $j$.

Calculate the block employment ( $E_{i}$ ) by multiplying the percentage with the block group employment
$E_{i}=P_{i} \times($ employment in block group $j$ that block $i$ belongs to $)$

The same process is repeated for $\mathrm{j}=10,631$ block groups and 15 industry types.
Figure 1 illustrates the education employment disaggregation for block groups located in the Santa Monica area. The color intensity in the map represents the number of employees. A lighter shade indicates a lower number of employees within the block/block group, while a darker shade indicates a higher number of employees. The top part of the figure is drawn to scale, and shows the block group level layer on the left and the block level layer on the right. Note that the observed pattern of employment for the block group level and the estimated employment pattern at the block level are consistent with one another. The bottom part of the figure is not drawn to scale, but is drawn to focus in on one particular block group. The right hand side of this part of the figure shows how the block group employment has been disaggregated to different numbers of employment within blocks belonging to the same block group.

### 1.3 METHOD AND SAMPLE MAPS

Figure 2 illustrates the structure of accessibility indicators developed in this study at the block level. As shown in red, three sets of indicators are constructed -- number of employees by industry type and time of day, accessible roadway segment length by functional classification, and number of transit stops within a certain traveling time. The first two sets are based on the highway network, while the third is based on the transit network. For all of these indicators, one first needs to define the time thresholds for use in computing accessibility. In the current research, we choose three time bands - 10 minutes, 20 minutes, and 50 minutes. The selection of these time bands is based on the trip length distributions from the 2001 post-census SCAG region household travel survey.

TABLE 1 Poisson Regression Models for Public Administration (estimated at the block group level)

| Variable | Coefficient | Standard Error | t statistics | $[\|\mathrm{Zl}\|>\mathrm{z}]$ |
| :--- | ---: | ---: | ---: | ---: |
| Constant | 2.786 | 0.003 | 886.828 | 0.0000 |
| Area | 0.034 | 0.001 | 27.879 | 0.0000 |
| Population | 1.794 | 0.013 | 136.081 | 0.0000 |
| Total length of freeway sections | -0.228 | 0.006 | -40.098 | 0.0000 |
| Total length of primary arterials | 0.357 | 0.003 | 124.843 | 0.0000 |
| Total length of minor arterials | 0.203 | 0.004 | 56.592 | 0.0000 |
| Total length of collector roadways | -0.033 | 0.001 | -56.366 | 0.0000 |
| Total length of ramp sections | 1.724 | 0.007 | 238.618 | 0.0000 |

Log likelihood function $=-704050.2$ Info. Criterion: AIC $=132.45381$
Chi squared $\quad=100262.9 \quad$ Degrees of freedom= 7
Overdispersion tests: $\mathrm{g}=\mathrm{mu}(\mathrm{i}): 1.802 \quad$ Overdispersion tests: $\mathrm{g}=\mathrm{mu}(\mathrm{i})^{\wedge} 2: 1.055$
Marginal effects

| Variable | Coefficient | Standard Error | t statistics | $[\|\mathrm{Zl}\|>\mathrm{z}]$ |
| :--- | ---: | ---: | ---: | ---: |
| Constant | 71.559 | 1.764 | 40.558 | 0.0000 |
| Area | 0.884 | 0.064 | 13.924 | 0.0000 |
| Population | 46.079 | 1.317 | 34.998 | 0.0000 |
| Total length of freeway sections | -5.859 | 0.306 | -19.129 | 0.0000 |
| Total length of primary arterials | 9.177 | 0.278 | 33.054 | 0.0000 |
| Total length of minor arterials | 5.221 | 0.216 | 24.218 | 0.0000 |
| Total length of collector roadways | -0.856 | 0.036 | -23.709 | 0.0000 |
| Total length of ramp sections | 44.273 | 1.220 | 36.287 | 0.0000 |



FIGURE 1 Employment disaggregation at block level.


FIGURE 2 Establishment of accessibility indicators at block level.
According to this survey, 25 percent of trip lengths were less than or equal to 7 minutes, 50 percent of trip lengths were less than or equal to 25 minutes, and more than 75 percent of trip lengths were less than or equal to 50 minutes. So, we select the 10 -minute buffer to represent local accessibility, defined as the number of activity opportunities that can be
reached within 10 minutes. At the other extreme, we select a 50 -minute buffer to represent regional accessibility, defined as the number of activity opportunities that can be reached within 50 minutes. The 20-minute buffer is added for completeness and to provide indicators for activity opportunity between the local and regional scales. This threshold is also chosen because research elsewhere claims that a desired ideal commute time is somewhere between 15 and 19 minutes (Redmond and Mokhtarian, 2001).

In all the computations of the time buffers just discussed, the highway network time is used. However, the highway network time varies by time of day. This may result in different buffer areas for the same block at different times of the day, implying different numbers of activity opportunities for the block over the course of the 24 -hour period. To account for the travel time variance, travel times between blocks for different time periods in a day are needed. As mentioned earlier, the current SCAG four-step model provides travel speed and time for each roadway segment for four time periods, AM peak (6 AM to 9 AM), PM peak (3 PM to 7 PM), Midday off-peak hours ( 9 AM to 3 PM), and Nighttime off-peak hours (7 PM to 6 AM). This allows the calculation of shortest path travel time between blocks for each of these four different periods in a day. But, given the large number of blocks within the SCAG region, it is almost impossible to directly use either GIS tools or the built-in tools provided by existing GIS software to create the shortest paths between block centroids. An alternative approach is to identify the nearest network nodes for the block centroids, assuming that these nodes represent the block centroids. By applying the travel speed of roadway links, the travel time between these nodes (proxies now for block centroids) are computed using the shortest path tool in TransCAD ${ }^{\circledR}$. By doing so, the travel time matrices between blocks are created for the four time periods. The SCAG region consists of 203,191 blocks. Accordingly, each time period has a 203,191*203,191 shortest travel time matrix. Table 2 lists the block-toblock highway network travel time for a few randomly selected blocks. The rows represent origin blocks and the columns represent destination blocks. For example, the travel time from block 1 to block 10 is 22.6 minutes, while the travel time from block 10 to block 1 is 19.6 minutes. The 10,20 , and 50 -minute buffer areas for each block can be generated on the basis of these travel time matrices. The accessibility indicators can be
subsequently created by counting the related block characteristics within the buffer area, including the number of employees by industry type, amount of roadway length by functional classification, and the number of transit stops. For the roadway length by functional classification and transit stop indices, it is reasonable to assume that, once the buffer zone is defined, the roadway lengths and number of transit stops will not be a function of time of day. Thus, variations in these indicators by time of day are purely because of change in the buffer areas by time of day. However, the accessibility indicator based on the number of employees by industry type should vary by time of day, even for a pre-defined buffer zone, because of the work schedules of employees. That is, there will be times when employees will not be at work, and this should be considered when computing the number of "reachable" employees by industry type for use in constructing these accessibility indicators.

## TABLE 2 Sample Block Travel Time Matrix (Minutes)

| Origin | Destination |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| 1 | 0.0 | 1.3 | 3.7 | 10.9 | 13.0 | 20.1 | 19.8 | 19.8 | 22.4 | 22.6 | 19.6 | 21.1 |
| 2 | 1.3 | 0.0 | 2.4 | 9.6 | 11.6 | 21.4 | 21.1 | 21.1 | 23.7 | 23.9 | 20.9 | 22.4 |
| 3 | 3.7 | 2.4 | 0.0 | 7.3 | 9.3 | 23.8 | 23.5 | 23.5 | 26.1 | 26.3 | 23.2 | 24.8 |
| 4 | 10.9 | 9.6 | 7.3 | 0.0 | 2.0 | 31.0 | 30.7 | 30.8 | 33.4 | 33.5 | 30.5 | 32.0 |
| 5 | 13.0 | 11.6 | 9.3 | 2.0 | 0.0 | 33.0 | 32.7 | 32.8 | 35.4 | 35.5 | 32.5 | 34.0 |
| 6 | 19.1 | 20.4 | 22.7 | 30.0 | 32.0 | 0.0 | 8.7 | 8.8 | 11.4 | 11.5 | 8.5 | 10.0 |
| 7 | 22.4 | 23.7 | 26.1 | 33.3 | 35.4 | 3.3 | 0.0 | 3.1 | 2.6 | 2.8 | 11.7 | 4.3 |
| 8 | 19.6 | 20.9 | 23.3 | 30.5 | 32.6 | 0.5 | 9.3 | 0.0 | 11.9 | 12.1 | 9.0 | 10.6 |
| 9 | 19.8 | 21.1 | 23.4 | 30.7 | 32.7 | 0.7 | 0.5 | 0.4 | 0.0 | 0.2 | 9.1 | 1.7 |
| 10 | 19.6 | 20.9 | 23.3 | 30.5 | 32.5 | 0.5 | 0.3 | 0.3 | 2.9 | 0.0 | 8.9 | 1.5 |
| 11 | 19.8 | 21.1 | 23.5 | 30.8 | 32.8 | 0.8 | 0.4 | 0.5 | 3.1 | 3.3 | 0.0 | 1.7 |
| 12 | 21.0 | 22.3 | 24.7 | 32.0 | 34.0 | 2.0 | 1.7 | 1.6 | 4.4 | 4.6 | 10.4 | 0.0 |

To estimate the percent of reachable employees by industry, we use the post-census SCAG region household travel survey that recorded the daily activity schedules for individual workers during a 24 -hour period. In addition to daily activities, the survey also provides information associated with person, household, and activity locations. Specifically, for each respondent $q$ that works, we have the arrival time at work (say $t_{q a}$ ) and departure time from work (say $t_{q d}$ ). Also, define a dummy variable $\delta_{q g h}$ that takes a
value of one if individual $q$ works in industry type $g$ and county $h$, and zero otherwise. Now, consider a specific hour of the day $k$, and let $T_{s}$ be the start time of this hour $k$, and let $T_{e}$ be the end time of this hour $k$. Define another dummy variable $\alpha_{q k}$ that takes a value 1 if $t_{q s} \geq T_{s}$ and $t_{q e} \leq T_{e}$, and zero otherwise. Intuitively, $\alpha_{q k}$ equals one if the employee $q$ is at the work place at the hour $k$ and zero otherwise. From the travel survey, we also have a weight $W_{q}$ for person $q$, which expands the individual so that the expanded sample across all surveyed individuals is representative of the population. With these notational preliminaries, an estimate of the number of reachable employees in industry type $g$ at county $h$ at time $k\left(A_{g h k}\right)$ is as follows:

$$
A_{g h k}=\sum_{q} \delta_{q g h} \alpha_{q k} W_{q}
$$

For application purposes, it is convenient to translate the total number of reachable workers in industry $g$ at county $h$ at time $k$ into a percentage of reachable workers in industry $g$ and county $h$ :

$$
P_{g h k}=\frac{A_{q h k}}{\sum_{q} \delta_{q g h} W_{q}} .
$$

Table 3 shows an example of the reachable number of the retail trade workers in Los Angeles County by time of day. The above percentage can be computed for each time of day. However, the buffer zones which are a function of network times vary only by the four time periods available from the SCAG model. So, we also compute measures of the percentage of number of reachable employees for each of these four periods. Since there are substantial variations in the $P_{g h k}$ values within the four time periods (for example, this value varies between $17.65 \%$ for the $6-7$ am period to $42.14 \%$ for the $8-9$ am period within the AM peak period), we develop minimum and maximum percentages of reachable workers for each industry type $g$, county $h$, and time period $k$. For example, based on the percentages in the main part of Table 3, the bottom portion of the Table 3 provides the minimum and maximum percentages of reachable retail trade employees in LA County by each time period.

## TABLE 3 Worker Reachability for Retail Trade in Los Angeles County ( $g=$ =retail trade, $\boldsymbol{h}=\mathrm{Los}$ Angeles county)

| Time <br> Period | Time of Day <br> $(k)$ | Number of Reachable <br> Workers <br> $\left(A_{g h k}\right)$ | Percentage of Reachable <br> Workers |
| :---: | :---: | ---: | :---: |
| AM Peak | $6-7 \mathrm{am}$ | 50254.27 | $\left(P_{g h k}\right)$ |

## Minimum and Maximum Percentage of Workers from Retail Trade in LA County Time of Day <br> Minimum Percentage Maximum Percentage of of Reachable Workers Reachable Workers

AM peak (6:00 AM - 9:00 AM)
Midday (9:00 AM - 3:00 PM)
PM peak (3:00 PM - 7:00 PM)
Night time (7:00 PM - 6:00 AM)

| $17.65 \%$ | $42.14 \%$ |
| :---: | :--- |
| $46.79 \%$ | $52.83 \%$ |
| $17.30 \%$ | $43.66 \%$ |
| $3.34 \%$ | $13.30 \%$ |

The minimum and maximum percentages by industry type, county, and time period are applied to all blocks belonging to the county. Since the total employment within each block by industry type is available based on the discussion in the section entitled "Data
used", one can immediately compute the number of reachable employees by industry type, block, and time period. Finally, the accessibility measure based on the number of reachable employees at any time $k$ for any block is simply equal to the sum of reachable employees at that time $k$ across all blocks that are within the buffer area of the block at that time $k$. Considering the large number of blocks within the SCAG region, a C++ program is developed to complete the aggregation task. The next section presents sample maps of the accessibility indicator corresponding to the number of reachable employees.

## Retail Industry

Figure 3 presents the maximum number of reachable retail employees within 10 minutes during the four time periods in the Santa Monica area of Los Angeles County. The reader will note the expansion of the dark area as one moves from the AM peak to the Midday period, and the subsequent shrinkage in the dark area during the PM peak and night time periods. The variation in the percentage of the reachable employees as well as in travel time lead to the time-of-day changes in accessibility.

## Education and Health Industry

As mentioned earlier, the combined education and health employment in the CTPP data is separated into two groups with the help of the $\mathrm{D} \& \mathrm{~B}$ data. The maximum number of reachable education employees within 10 minutes during each of the four time periods in the Santa Monica area of Los Angeles County is presented in Figure 4. Figure 5 presents the corresponding map for the health industry. Both sets of graphs exhibit similar change trends as the retail industry, which again demonstrates that the accessibility indicators can capture activity opportunity changes during the day. The AM peak and Midday periods have the highest accessibility based on the number of reachable employees. As time progresses, the number of reachable employees decreases and reaches the lowest point during the night time. There are, however, also differences between Figures 4 and 5 . First, the accessibility map for the health industry is much darker than the accessibility map for the education industry for all time periods, indicating the higher number of reachable health industry employees relative to the education industry. Second, the fading of the dark shade as the day progresses is decidedly much lower for the health industry
than for the education industry. This is because a substantial fraction of health care workers are needed at their work place round the clock.


FIGURE 3 Maximum number of reachable retail employees for a 10-minute buffer by time of day in Santa Monica.


FIGURE 4 Maximum number of reachable education employees within 10 minute buffer by time of day in Santa Monica.


FIGURE 5 Maximum number of reachable health employees within 10 minute buffer by time of day in Santa Monica.

## Public Services

Figures 6a to 6d compare the maximum and minimum number of reachable public service employees for the entire SCAG region, using a regional level buffer of 10 minutes. In each figure, the map on the left represents the case of maximum number of reachable employees, while the map on the right represents the case of minimum number of reachable employees. The usual darkening of the shading from the AM peak to the mid-day period, and its subsequent fading, is discernible as one goes down the figure column-wise. In each row, and particularly for the case of the AM peak period and the

PM peak period, there is a clear lightening of the shading as one goes from the left to the right. This indicates that the maximum number of reachable public service employees for the blocks are significantly higher than the minimum number of reachable employees during the AM and PM peaks periods. Thus, by employing both maximum and minimum numbers of reachable employees, the accessibility indicators reflect the fluctuation within the AM and PM peak due to work schedules. Although the row-wise comparisons for the midday and nighttime periods shown in Figures 6 b and 6 d , respectively, are not as significant as for the AM and PM peak periods, there is still a detectable difference between the accessibility indicators based on the maximum and minimum reachable employees.


FIGURE 6a Comparison of maximum and minimum public service employees (AM peak).


FIGURE 6b Comparison of maximum and minimum public service employees (Midday).


FIGURE 6c Comparison of maximum and minimum public service employees (PM peak).


FIGURE 6d Comparison of maximum and minimum public service employees (Nighttime).

## 2. TRANSIT ACCESSIBILITY

Although transit travel is generally deemed as a potential means to solve some of the issues associated with the reliance on private automobiles, travel by transit has a number of limitations compared to travel by automobile. For example, travel by transit involves walking in the first and last legs of a trip, and potentially in the transfer between different routes if a direct route from the origin to the destination of the trip is not available. The walking time, although a healthy mode of transportation, can be intolerable if transit stations are far away either from the origin and/or to the destination. Therefore, the use of transit may be limited by the physical access to transit stations/stops. This first level of access to the transit system has been called "system accessibility" by Lei and Church (2010) to distinguish it from the notion of overall accessibility enabled by the public transportation system. Even when the potential user is close enough to the transit stops, travel time by transit is highly dependent on the routes and schedules of the regional transit system. Firstly, this is because there may be a significant amount of wait time at a transit stop if the arrival time of the traveler at the stop does not match the incoming time for the next transit vehicle. Secondly, the transfer times between different routes may be highly dependent on the start time and the scheduled times for both routes. Moreover, a decision that often has to be made in transit planning (for a single route) is to balance between providing good geographical coverage with a route that makes frequent stops and providing better level of service with an express route that makes fewer stops. The time lost in making stops can significantly increase travel time by transit. This second level of accessibility, which incorporates transit travel times is called "system facilitated accessibility" (Lei and Church, 2010), and it is more complicated to measure than the physical access to transit stations. The method here allows assessments about service gaps (Mamun and Lownes, 2011), optimal spacing of stops (Li and Bertini, 2009), and to compare accessibility between private cars and transit in urban areas (Benenson et al., 2010). The development presented here follows the footsteps of the methods presented by Polzin et al. (2002) and Bhat et al. (2006).

A key finding of our research with automobile accessibility in this region is the extreme difference of accessibility to different types of activity opportunities in space and time (e.g., retail accessibility is relatively high throughout a day and accessibility to other activities drops substantially during the evening times). Moreover, accessibility in the vicinity of major highways is consistently higher than at places served by lower level roadway facilities. Similar patterns can be seen here as illustrated later but with important transit specific spatio-temporal trends. The bi-modal, pedestrian and transit, network we built for the SCAG region consists of 1,748 routes and 89,980 stops. Figure 7 offers a glimpse at the density of transit routes and stops in the center of Los Angeles. This is also another new element in the transit accessibility we present here because it is a study of massive amounts of data that was not attempted before and represents a feasibility study for other applications.


FIGURE 7 Transit Routes and Stops in Central Los Angeles

The next section offers an overview of the method, describes the construction of the bimodal network and the application of the schedule-based shortest path algorithm. A following section also shows experimental results in which we show the transit accessibility for different sets of opportunities and compares the results with automobile accessibility, followed by a summary and next steps.

### 2.2 METHODOLOGY

At the heart of the computation of transit accessibility is a schedule-based shortest path algorithm which is a computationally efficient implementation based on early work in Church et al. (2005) and Lei and Church (2010). Similar path-finding algorithms have been developed by other researchers (O'Sullivan et al., 2000, Huang, 2007,Huang and Peng, 2008, ). O'Sullivan et al. (2000) described a shortest (time) path algorithm based on the Dijkstra algorithm, but details of the algorithm or data structure were not given. They applied the algorithm to a transit network of bus and rail and mapped transit travel times to a CBD (central business district) as a set of isochrones of travel times (i.e., contour lines representing locations that can be reached by the same travel time from an origin) in the GIS platform. In the path-calculation, they assumed that the waiting time at a transit stop between bus routes or between bus and rail is one-half of the headway time. Huang (2007) proposed a path-finding algorithm based on what is called the pattern-first-search method. The author proved the correctness of the algorithm. Then, Huang and Peng (2008) presented the transit network data model used by the algorithm. Lei and Church (2010) and Church et al. (2005) developed a schedule-based shortest path algorithm which extends the Dijkstra algorithm. The authors presented isochronic maps of transit travel times in Santa Barbara, California as well as a ratio map of travel times by public transit based on their algorithm and travel times by car based on a travel survey. In that paper an improved version of the modified Dijkstra's algorithm described in Church et al. (2005) was used and published in Lei and Church (2010). Here we improved that algorithm using an efficient implementation of the Dijkstra algorithm in the Boost C++ open source library as is required by the sheer scale of the network in the SCAG region.

One limitation of past research in transit accessibility is lack of consideration for opportunities available to travelers, even though accessibility is by definition the ease with which people can reach their destinations or activity sites (Dalvi, 1978). One way to model accessibility is to consider every origin and every destination and for each origin count the amount of opportunities that a traveler can reach in 10 or 20 minutes, or any other travel time to create a travel time buffer around an origin. The number of opportunities a trip maker can reach within each buffer can be the number of locations in a specific industry (e.g., the number of medical centers, schools, retail stores). Another option is to use the number of employees in each industry or each employment location of each industry. More complicated accessibility measures involve discounting opportunities using functions of distance from each origin so that the accessibility measure is an integral centered on the origin location. Examples range from the wellknown spatial interaction (gravity) model, to negative exponential discounts(Hansen, 1059), to axiomatic systems (Weibull, 1976) defining properties that accessibility measures should satisfy with respect to origin, attraction and distance. The latter class of methods considers the effect of distance decay or generalized cost (a weighted mix of travel time and travel cost) to represent the loss of desirability for locations that are far away or more expensive to reach (in terms of time, distance, and/or cost) from an origin. Yet, another set of metrics can be derived using random utility-based discrete choice models of destination-mode-activity choice (Dong et al., 2006). However, these indicators make behavioral assumptions reflected in a time-distance-cost decay function or a random utility function that sometimes are not testable and require local calibration. More recent work on metrics needed to assess the activity opportunities available to participants of activities during specific time windows in a day (Yoon and Goulias, 2010), which motivates us to measure transit accessibility in terms of the number of opportunities that can be reached within a set of travel time buffers that can be modified at will. So far, we have described the main components of measure transit accessibility. That is, for a realistic transit accessibility indicator we need to: 1) accurately measure travel times by transit and 2) take into account the spatial and temporal distribution of
opportunities as it evolves during a day. We have developed a software package to measure transit LOS accounting for both aspects and its workflow is depicted in Figure 8.

As depicted on the top of Figure 8, the first task to make the analysis work is to create a transit network. This is achieved by developing two utility programs that 1) create transit links from coordinates of transit stops and 2) collects schedule information, encodes them appropriately, and stores them as attributes of transit links. Given a specific time hh:mm in a day, the formula to encode a given time is as follows:

$$
\operatorname{chr}\left(h h-\operatorname{asc}\left('^{\prime}\right)\right) \& \operatorname{chr}\left(m m-\operatorname{asc}\left('^{\prime} 0^{\prime}\right)\right)
$$

Where $\operatorname{asc}(c)$ is the ASCII code of a character $c, \operatorname{chr}(n)$ is the ASCII character for a number $\boldsymbol{n}$. This coding scheme reduces the number of bytes needed to store a time from four to two and meanwhile retains some readability.


## FIGURE 8 An Overview Flowchart of Transit Accessibility Computation

The source data used in this study is the LACMTA Trip Master Database (for the fourth Quarter of 2008) provided by the Southern California Association of Governments staff.

As a side note, it is somewhat typical in practice for transit authorities to publish schedules only for a subset of points of any given route called its "timed points". They may or may not be actual stops. Therefore, the schedules for the rest of the stops in a route need to be inferred by the schedule-building program, e.g. based on their (linear referencing) distances to the immediate neighboring timed points. Non-stop points need to be removed.

The next step is to merge transit network with the regular road network. This is needed because the positions of transit stops from the transit database will not usually match the road network since they often come from different sources. In our case, the transit database comes from LACMTA data and the (regular) road network comes from Dynamap 2000 dataset, respectively. There are three types of spatial mismatch that need to be addressed in conflating the transit network/stops with the regular road network: 1) a transit stop may be too far from any road link, 2) a stop may be close enough to a road link but far from any road junction point, and 3) two consecutive transit stops in a route may be attached to the same junction point on the road network. This last case will create a zero length transit link effectively bypassing the encoded transit schedules. The problems are demonstrated in Figure 9. The dots represent road junctions, and the triangles represent transit stops.


FIGURE 9. Issues in matching transit stops with the regular network

To address the first issue, we modified the (regular) road network as follows. First, if a transit stop is 50 meters away from any road links, a special access link from the stop to the nearest location on the nearest road link is added, as is shown in Figure 9 (b). At the same time, a junction node is inserted at the intersection point of the access link and the road link. Secondly, if a stop is more than 50 meters away from any existing junction in the road network after the first step, then a new node is inserted in the closest location on the network (similar to the first case). The stop is then moved to the closest point. Altogether 6,370 such stops are identified and processed. To address the issue of zero length transit links, we have identified 499 such stops. We insert a junction node in the road network for each of these stops regardless of how close they are to junctions.

As is the case with many transportation analyses, the data collection and preparation procedures described so far are often time-consuming yet critical as they dictate the accuracy of the analysis and types of analysis that can be made. For the analysis of transit accessibility, the details captured in the above procedures are particularly important since walking is costly in terms of its share in the total transit travel time. Over-optimistic transit travel times will be generated if transit stops are attached to the nearest road junctions directly.

After creating the appropriately augmented road network, the next task is to build data structure for describing the connectivity (or topology) of the combined transit and road network. This is required for the shortest path algorithm to run on the bimodal network. While there are alternative ways to accomplish this, we chose to use the geometric network from ESRI ArcGIS as it can be used easily to combine line data with heterogeneous data structures.

The core algorithm for computing transit travel time is a schedule-based shortest path algorithm developed based on Church et al. (2005) and Lei and Church (2010). The algorithm is implemented using the open source C++ Boost Graph Library (BGL). The connectivity information is directly loaded from the geometric network into BGL's
internal data structure using APIs (Application Programming Interface) from each package respectively. The Dijkstra implementation in BGL is enhanced with capability to calculate time cost for traversing a given transit link. The calculation is based on the encoded departure and arrival time tables stored on the link and the current distance/time label in the label-setting Dijkstra algorithm.

The last step is to compute transit accessibility for each population center. As described earlier, we use a measure of accessibility based on counting the number of opportunities that can be reached within pre-specified time limits. A population center in this experiment represents a census block centroid in the SCAG region. Walking times from the origin and destination block centroid are calculated and added to the total travel time for each O-D pair. In the automobile version of this accessibility calculation we have 203,000 origins and destinations and travel times are computed using a combination of a simulation model and assumed travel speed for local roadways. For the transit exercise reported here we use the published schedules and assumptions about walking speed. For each expected departure or arrival time, travel times between all O-D pairs for the 203,191 block centroids are computed and stored in a distance (travel time) matrix file. A utility program is developed to compute the accessibility indicators based on the distance (travel time) matrices. The first and last legs of a trip are not counted in calculating automobile travel time as they are negligible compared to total travel time; in the transit case, they can be significant or even dominant in short trips. In this algorithm walking time is based on the assumption that the transit user will walk to the nearest node in the bi-modal (walk and transit) network from the centroid of his/her block following the straight line between the two points. The walking time is calculated as distance divided by a walking speed of 60 meters/minute. In addition, the distance is multiplied by a discount factor of 0.5 . Using the block centroid represents the worst case walking time for all points in a street block and locations by the sidewalks have zero walking time. The discounted distance from the centroid to the streets is an estimate of the average walking time. It should be noted, however, that this factor is modifiable when local walking data are available.

To illustrate the method consider Figure 9(b) as the example. Suppose a potential transit user starts his/her trip from a block centroid in the upper right corner of Figure 9(b). Then, this user will first walk to the intersection of $6^{\text {th }}$ and Lincoln street, which is a network node. From this point on, the revised Dijkstra algorithm takes over. It marks this node with a time cost equaling the initial walk time (to reach this node) and records the initial arrival time at the node. Then, similar to the regular Dijkstra's algorithm, the revised algorithm iteratively chooses the node with the smallest label of time cost and computes cost labels for its immediate neighboring network nodes. If the arc to a neighboring node is a regular road, then the cost of traversing the link is computed as link length divided by the walking speed. Otherwise, the link being traversed is a transit link. The revised algorithm computes the cost to traverse this link based on the array of departure times and arrival times that were stored in the attributes of the transit link when building the transit network. After computing labels for all the neighboring nodes, the incumbent smallest cost node is marked as permanent and excluded from further consideration. The revised Dijkstra algorithm stops when all network nodes are marked with their appropriate time costs. Then travel time is computed for the walk between the destination and its nearest network node in a similar manner to the computation of walking time on the origin side. The procedure of the modified Dijkstra algorithm is presented below:

1. Set the label for the source node to zero and the labels for all other nodes to infinity. Mark all nodes as unvisited.

2 . Set the source node as the current node.
3. For the current node, calculate a tentative label for each one of its neighboring nodes by adding the label of the current node and the cost to traverse the arc connecting the current node and the neighboring node. Update the label for the neighboring node if the tentative label for the neighbor is less than its current value.
3.1. If the link connecting the current node and a neighboring node is a regular road link, then the cost to traverse the link is the length of the link divided by the traveling/walking speed.
3.2. If the connection link is a transit link, then look up the array of departure times and find the earliest transit departure time after the passenger arrival time at the current node. The arrival time at the current node is just the sum of the passenger departure time for the entire trip plus its cost label.
4. When all the neighbors of the current node are updated, mark the current node as visited (and its distance is now permanent). Mark the unvisited node with the lowest tentative distances as the current node repeat Step 3 until the set of unvisited nodes is empty.

### 2.3 ACCESSIBILITY COMPUTATION AND EXAMPLES

The output of the shortest path computation is a matrix of travel times. Each row contains travel times from a given origin to all possible destinations. Next, a buffer for each origin is defined based on cutting off the travel times at a given time value and all the blocks within this buffer are identified. The attributes of these blocks (in this case, the number of persons working in each industry) are summed and considered to represent the amount of opportunities that can be reached within the pre-specified travel time value that defines the buffer. We use 15 industry types that are: 1) Agriculture, forestry, fishing and hunting and mining; 2) Construction; 3) Manufacturing; 4) Wholesale trade; 5) Retail trade; 6) Transportation and warehousing and utilities; 7) Information; 8) Finance, insurance, real estate and rental and leasing; 9) Professional, scientific, management, administrative, and waste management services; 10) Education; 11) Health; 12) Arts, entertainment, recreation, accommodation and food services; 13) Other services (except public administration); 14) Public administration; and 15) Armed forces. Not all employees in each industry are available at all times of a day and for this reason we develop time-of-day profiles of percent of employees available with a procedure that is based on survey data and used for highway accessibility described in this report. Below we provide a few examples of "transit accessibility".

Retail Accessibility

Figure 10 presents the maximum number of reachable retail employees within 10 minutes during the two time periods in the center of Los Angeles. We select the morning peak and evening (after pm peak hour) to show the difference by time of day and because they correspond to the periods in the travel time calculation of the highway travel network. As one moves from the AM peak to the evening period the number of reachable opportunities shrinks. The change in the percent of reachable retail employees as well as in travel time due to different transit schedules lead to these time-of-day changes in accessibility. Repeating the same calculations but using a 20 minute travel time buffer we obtain the maps of Figure 11. As one would expect the time of day pattern is similar to Figure 10 but with a clearly identified neighborhood of the widespread availability of retail stores.

## Education Accessibility

Similar computational steps for education accessibility are followed for Figures 12 and 13 that we arranged in a way that show the differences with automobile accessibility. For public transportation these maps exhibit similar time of day change trends as the retail industry. As expected we obtain a clearly different shape in activity opportunities between retail and education, which is the outcome of differences in spatial and temporal distribution of these two "industries." These are the differences we study in explaining activity location choice and mode.

In sharp contrast with transit accessibility indicators when we develop similar maps for automobile travel we obtain the maps of the second quadrant of Figures 12 and 13. High accessibility is obtained not only for the evening (when the highways are less congested) but also during the morning peak in spite of the lower speed. This is a fundamental disadvantage of public transportation and points to the possibility of restraining automobiles in the AM peak and thus making transit more competitive. In addition, when travelers need to participate in activities after the evening peak, transit is not a viable option in stark contrast to the private car and again points to another possible policy of providing public transportation after the evening peak to serve specific activities such as education (e.g., to adult education and retraining facilities).


FIGURE 10 Maximum number of reachable retail employees for a 10-minute buffer in Central Los Angeles


FIGURE 11 Maximum number of reachable retail employees for a 20-minute buffer by time of day Central Los Angeles.


FIGURE 12 Morning Peak maximum number of reachable education employees for a 20-minute buffer in Central Los Angeles.

FIGURE 13 Evening After PM peak maximum number of reachable employees for a 20-minute buffer in Central Los Angeles.

## 3 FUTURE WORK

The transit accessibility indicators developed here can be used in a variety of ways. They can be used to study the spatial distributions of opportunities and their relationship to the resident population. In addition, these indicators are very good explanatory variables of behavior and can be used in the same way as it was done with their automobile counterparts. Moreover, these indicators are the base information needed for equity analysis at fine spatial resolution and to perform gap analysis. Furthermore, this is the type of analysis needed to identify food deserts when additional data about the supply of stress with healthy foods is added (Walker et al. 2010). One can also use components of the method here for optimal service designs and assessments of service improvements when making small changes to schedule and stop locations. In phase 3 of this project we will compute automobile accessibility indicators and simplified transit accessibility indicators using longitudinal data of the SCAG region. In fact, we are experimenting with a database that was developed using the $\mathrm{D} \& \mathrm{~B}$ information at multiple years. However, year-to-year accessibility computation also requires year-to-year network changes that are not available as of the writing of this report. For the immediately next phase of SimAGENT we will match the vintage of the networks with the vintage of opportunity maps and study their differences using geospatial statistical methods.

## 3. REFERENCES AND BIBLIOGRAPHY

Abreu J. and K.G. Goulias. Structural Equations Model of Land Use Patterns, Location Choice, and Travel Behavior in Seattle and Comparison with Lisbon. Transportation Research Record, 2135, 2009, pp. 106-113.
Alam, B. M. Transit Accessibility to Jobs and Employment Prospects of Welfare
Recipients without Cars. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2110, 2009, pp. 78-86.
APTA. Transit Ridership Report (First Quarter). Washington, 2011.
Ashiru O., J.W. Polak, and R.B. Noland. Space-time user benefit and utility accessibility measures for individual activity schedules. Transportation Research Record, 1854, 2003, p.62-73.
Azar, K. T., J. Ferreira Jr and L. Wiggins. Using Gis Tools to Improve Transit Ridership on Routes Serving Large Employment Centers: The Boston South End Medical Area Case Study. Computers, environment and urban systems, Vol. 18, No. 3, 1994, pp. 205-231.
Badoe D. A. and E. J. Miller. Transportation-land-use interaction: empirical Findings in North America, and their implications for modeling. Transportation Research Part D 5, 2000, pp. 235-263.
Ben-Akiva, M., \& Bowman, J. Integration of an Activity-based Model System and a Residential Location Model. Urban Studies, 35(7), 1998, 1131-1153.
Benenson, I., K. Martens, Y. Rofé and A. Kwartler. Public Transport Versus Private Car: Gis-Based Estimation of Accessibility Applied to the Tel Aviv Metropolitan Area in Israel. Paper presented at the 2010 Annual Transportation Research Board Meeting, Washington D.C., 2010, pp.
Bhat, C. R., S. Bricka, J. LaMondia, A. Kapur, J. Y. Guo and S. Sen. Metropolitan Area Transit Accessibility Analysis Tool. 2006.
Blumenberg, E. and M. Manville. Beyond the Spatial Mismatch: Welfare Recipients and Transportation Policy. Journal of Planning Literature, Vol. 19, No. 2, 2004, pp. 182205.

Chen, Y., S. Ravulaparthy, K. Deutsch, P. Dalal, S. Y. Yoon, T. L. Lei, K. G. Goulias, R. M. Pendyala, C. R. Bhat and H. H. Hu. Development of Opportunity-Based Accessibility Indicators. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2255, 2011, pp. 58-68
Church, R. L., V. Noronha, T. Lei, W. Corrigan, S. Burbidge and J. Marston. Spatial and Temporal Utility Modeling to Increase Transit Ridership. 2005.
Dalvi, M. Q. Behavioural Modelling, Accessibility, Mobility and Need: Concepts and Measurement. In Behavioural Travel Modelling, Croom Helm, London, 1978.
Dong, X., Ben-Akiva, M., Bowman, J., \& Walker, J. Moving from Trip-Based to Activity-Based Measures of Accessibility. Transportation Research Part A: Policy and Practice, 40(2), 2006, 163-180.
Dong, X., M. E. Ben-Akiva, J. L. Bowman and J. L. Walker. Moving from Trip-Based to Activity-Based Measures of Accessibility. Transportation Research Part A: Policy and Practice, Vol. 40, No. 2, 2006, pp. 163-180.

Donnelly, R., G. D. Erhardt, R. Moeckel and W. A. Davidson. Advanced Practices in Travel Forecasting. National Cooperative Highway Research Program, Synthetsis 406. Washington.D.C., 2010.

Geurs K.T. and B. van Wee. Accessibility evaluation of land-use and transport strategies:review and research directions. Journal of Transport Geography 12, 2004, pp. 127-140.
Goulias, K. G., C. R. Bhat, R. M. Pendyala, Y. Chen, R. Paleti, K. C. Konduri, T. L. Lei, D. Tang, S. Yoon, G. Huang and H. Hu. Simulator of Activities, Greenhouse Emissions, Networks, and Travel (Simagent) in Southern California. Paper prepared for presentation at the 2012 Transportation Research Board Annual Meeting, 2011, pp.
Grengs, J. Does Public Transit Counteract the Segregation of Carless Households? Measuring Spatial Patterns of Accessibility. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1753, 2001, pp. 3-10.
Grengs, J. Job Accessibility and the Modal Mismatch in Detroit. Journal of Transport Geography, Vol. 18, No. 1, 2010, pp. 42-54.
Handy, S. and D. Niemeier. Measuring Accessibility: An Exploration of Issues and Alternatives. Environment and Planning A, Vol. 29, No. 7, 1997, pp. 1175-1194.
Handy, S. L. Regional Versus Local Accessibility: Variations in Suburban Form and the Effects on Non-Work Travel. Doctoral Dissertation, University of California, Berkeley,1993.
Hansen, W. G. How Accessibility Shapes Land Use. Journal of the American Institute of Planners, Vol. 25, No. 2, 1959, pp. 73-76.
Hillman, R. and G. Pool. Gis-Based Innovations for Modelling Public Transport Accessibility. Traffic engineering \& control, Vol. 38, No. 10, 1997, pp. 554-559.
Huang, R. A Schedule-Based Pathfinding Algorithm for Transit Networks Using Pattern First Search. Geoinformatica, Vol. 11, No. 2, 2007, pp. 269-285.
Huang, R. and Z. R. Peng. A Spatiotemporal Data Model for Dynamic Transit Networks. International Journal of Geographical Information Science, Vol. 22, No. 5, 2008, pp. 527-545.
Kwan, M. Interactive geovisualization of activity-travel patterns using threedimensional geographical information systems: a methodological exploration with a large data set. Transportation Research Part C 8, 2000, pp. 185-203.
Lee M. and K.G. Goulias. Accessibility Indicators for Transportation Planning Using GIS, 76th Annual Transportation Research Board Meeting, January 12-16, 1997, Washington D.C.
Lei, T. L. and Church, R. L. Mapping transit-based access: integrating GIS, routes and schedules, International Journal of Geographical Information Science, 24: 2, 2010, 283-304
Lei, T. L. and R. L. Church. Mapping Transit-Based Access: Integrating Gis, Routes and Schedules. International Journal of Geographical Information Science, Vol. 24, No. 2, 2010, pp. 283-304.
Li, H. and R. L. Bertini. Assessing a Model for Optimal Bus Stop Spacing with HighResolution Archived Stop-Level Data. Transportation Research Record: Journal of the Transportation Research Board, Vol. 2111, 2009, pp. 24-32.

Mamun, M. and N. Lownes. Measuring Service Gaps: Accessibility-Based Transit Need Index. Paper presented at the 90th Annual Transportation Research Board Meeting, Washington D.C., 2011, pp.
O'Sullivan, D., A. Morrison and J. Shearer. Using Desktop Gis for the Investigation of Accessibility by Public Transport: An Isochrone Approach. International Journal of Geographical Information Science, Vol. 14, No. 1, 2000, pp. 85-104.
Ong, P. and E. Blumenberg. Job Access, Commute and Travel Burden among Welfare Recipients. Urban Studies, Vol. 35, No. 1, 1998, pp. 77-93.
Polzin, S. E., R. M. Pendyala and S. Navari. Development of Time-of-Day-Based Transit Accessibility Analysis Tool. Transportation Research Record: Journal of the Transportation Research Board, Vol. 1799, 2002, pp. 35-41.
Redmond L. S. and P. L. Mokhtarian. The positive utility of the commute: modeling ideal commute time and relative desired commute amount. Transportation 28, 2001, pp. 179-205.
Shiftan, Y. (2007). The use of activity-based modeling to analyze the effect of land-use policies on travel behavior. The Annals of Regional Science, 42(1), 2007, 79-97.
TRB. Making Transit Work: Insight from Western Europe, Canada, and the United States. Washington, 2001.
Wachs M. and T. G. Kumagai. Physical Accessibility as a Social Indicator. Social economic planning science, 7, 1973, pp. 437-456
Walker, R. E., C. R. Keane and J. G. Burke. Disparities and Access to Healthy Food in the United States: A Review of Food Deserts Literature. Health \& place, Vol. 16, No. 5, 2010, pp. 876-884.
Weibull, J. An Axiomatic Approach to the Measurement of Accessibility. Regional Science and Urban Economics, Vol. 6, No. 4, 1976, pp. 357-379.
Yoon S. Y. And K.G. Goulias (2009) Impact of Individual Accessibility on Travel Behavior and its propagation Through Intra-household Interaction. Paper presented at the $12^{\text {th }}$ International Conference on Travel Behavior Research, December 13-18, Jaipur, India, and included in the CD ROM proceedings.
Yoon S.Y, T. Golob, and K. Goulias. California Statewide Exploratory Analysis Correlating Land Use Density, Infrastructure Supply and Travel Behavior. Paper 090130 in the CDROM proceedings and presented at the $88^{\text {th }}$ Annual Transportation Research Board Meeting, January 11-15, 2009, Washington D.C.
Yoon, S. Y. and K. G. Goulias. Impact of Time-Space Prism Accessibility on Time Use Behavior and Its Propagation through Intra-Household Interaction. Transportation Letters: The International Journal of Transportation Research, Vol. 2, No. 4, 2010, pp. 245-260.


[^0]:    Geotrans Laboratory, 1832 Ellison Hall, University of California Santa Barbara, Santa Barbara, 93106-4060

