Simplified model of local transit services

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This paper discusses the development of a simplified model to efficiently represent local public transportation services in a large-scale travel demand model. The California Statewide Travel Demand Model (CSTDM) is a comprehensive model system designed and developed for use in transportation policy analysis and travel demand forecasting, including representation of both long and short distance transportation covering the entire state of California. A novel hybrid system is used to represent the full range of rail and bus transit services that are available. Rail services – including all long-distance rail, commuter rail and light rail services – are represented in the standard manner, using explicit node and link networks; the relevant in-vehicle and out-of-vehicle service characteristics for journeys are determined as standard skims of these networks. On-street bus services are not represented using explicit networks; rather, the relevant in-vehicle and out-of-vehicle service characteristics are determined using functions of other transportation network variables, land use descriptors and relevant policy indicators. These functions are simplified econometric models estimated using observations of transit service obtained from Google Transit Data Feeds. The network and simplified components are integrated in order to allow transit paths with both rail and on-street bus components to be considered by the various travel choice models included in the modelling framework. This hybrid system provides a suitable representation of transit for an area of such size. This facilitates consideration of transit service policies, while obviating the need for extensive transit coding, a daunting task for a large area.

Keywords: *public transportation, travel time, travel demand modelling, urban density, Google transit data, statewide modelling.*

1. Introduction

Public transportation is an important component of the transportation system. It offers affordable scheduled services and a valid alternative to driving for all classes of users, including those that,

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for economic conditions or physical inabilities, do not have access to private vehicles. The development of efficient public transportation services is also an important tool to promote accessibility of regions and cities and to promote the economic development and easy access to workplaces and central business districts.

The realistic representation of public transportation services is an important task in transportation modelling, which is required for the correct estimation of travellers' choice behaviour and transportation demand. The definition of the best way to model public transportation services depends on the scale of the specific project and the objective of the modelling framework. The explicit representation of each public transportation line and stop is certainly required for small-scale projects and microsimulation studies at the neighbourhood or urban area level. However, this task represents a very demanding activity in areas of vast geographic extension or extreme network density. Detailed representation in these cases represents substantial modelling efforts and cost burdens that are not feasible for many public transportation authorities and planning agencies.

This paper discusses the development of a simplified representation of public transportation services that was introduced in the California Statewide Travel Demand Modelling (CSTDM) Framework. The proposed methodology allows an efficient representation of public transportation services in a large-scale travel demand model, while appropriately capturing the existing interactions between public transportation and the other components of the transportation system. The proposed approach is sensitive to changes in public transportation infrastructures and funding, and limits the coding burdens required to develop (and maintain) detailed networks for all public transit services offered in the area of study. It uses a hybrid approach to model the two main components of the public transportation system: railways and buses. In this approach, all rail-based services, including long-distance intercity railways, commuter railways, subways and light-rail systems, which have fixed guide-way and require major investments for any route modifications, are explicitly coded in the public transportation network. However, bus services, which account for the vast majority of local transit services, are more easily subject to service modifications, often share the routes with private vehicles and sometimes serve local streets that are not included in a statewide road network, are represented with a simplified methodology. This approach reduces the number of input variables used in the model, and the explicit coding required for the representation of bus services. The methodology is based on the estimation of simplified econometric models that express local public transportation attributes (in-vehicle and out-of-vehicle times) as functions of other transportation and land use variables.

The methodology is based on the theoretical assumption that local public transportation attributes are influenced by other observable characteristics of transportation and land use. Therefore, it is possible to establish appropriate functional forms that relate the characteristics of public transportation supply in a spatial extent to other land use and transportation explanatory variables. In this project, we explore this topic with the objective of expressing these public transportation attributes as functions of other transportation variables, as average speed and congested travel times on the car network, and of the land use characteristics of the neighbourhoods that are served by public transportation. We estimate multiple linear regression models for these local transit attributes using observed data for public transportation travel time collected from internet sources (*Transit Data Feeds* from the Google platform). Data on the land use and the transportation system are obtained from other available sources in order to create the required datasets for the model estimation. Different models are estimated for different time periods in order to account for the variability of public transportation service during the day.

This approach is novel, and its potential to inspire new applications to modelling studies is promising. Online data for public transportation services are still rarely used in research and modelling projects, even if the availability and quality of these data have considerably improved in recent years. The proposed simplified local transit model provides insights into the ways these

data can be used to explore the relations between public transportation supply and other characteristics of transportation and the built environment. It is also a suitable tool to model changes in local transit supply in policy evaluation and scenario testing. As such, it provides a practical modelling approach, which is expected to inspire additional research and modelling solutions that can more efficiently represent travel behaviour and improve travel demand forecasts.

The remainder of the paper is organized as follows. Section 2 presents the theoretical background of the research, and discusses the relationships among the development of public transportation systems and the urban form and other sociodemographic variables. Section 3 presents the California Statewide Travel Demand Modelling (CSTDM) Framework and the objectives that have supported the development of the simplified methodology for the representation of local public transportation. The simplified methodology for the representation of local public transportation services is the object of Section 4. Section 5 presents the estimation of the final models that describe local public transportation attributes as functions of other transportation and land use variables, and discusses some considerations on the use of the proposed approach in the CSTDM Framework. Finally, Section 6 presents the conclusions on the estimation of these models, and discusses the use of the proposed simplified approach in a statewide travel demand model and the advantages that derive from the adoption of this approach when modelling travellers' behaviour.

2. The characteristics of public transportation and the built environment

Several studies have investigated the relationships among the characteristics of public transportation, land use features and travel behaviour. In this brief literature review section, we first review previous experiences from the literature that focus on the relationships between public transportation demand and other characteristics of transportation and land use. Then, we discuss some studies that have analysed the links between public transportation supply and other features of the transportation system and of the built environment.

Significant experience is available in literature on the analysis of the relationships among the demand for public transportation and the characteristics of the land use and the built environment. Urban density, in particular, is an important determinant for public transportation use (Cervero and Kockelman, 1997; Badoe and Miller, 2000): neighbourhoods with higher density are usually associated with higher use of local transit services, although the increase in demand for public transportation is sometimes limited (Cervero, 1994).

From the comparison of public transportation demand at international level, several variables beside land use characteristics are found to affect ridership. Public transportation demand is particularly affected by the amount of services provided (public transportation supply), the area of coverage of public transportation services and the fare levels (Kain and Liu, 1999; Taylor et al., 2009; Litman, 2007). Many other characteristics of the transportation network and of the local geographic context are significant, such as auto ownership (Cervero, 2007; Paulley et al., 2006) and public transportation policies. Gas price has traditionally not been considered determinant in the definition of transportation (and, specifically, of transit) demand, which is usually considered inelastic (Wang and Skinner, 1984). Recent studies, however, have found an increasing role of gas price in affecting mode share and the demand for public transportation, in part as a response to the sharp increase in gas price in the years 2007-2008, which might have contributed to modifying travellers' behaviour towards the use of public transportation (Lane, 2009; Maley and Weinberger, 2009).

In the majority of most developed countries, public transportation has lost significant ridership during the last few decades: this phenomenon is the result of many contemporary changes in the society, in the priorities of policies in planning, as well as in consumers' habits and attitudes

(Dittmar et al., 2004; Crawford, 2000). In the US, public transportation has not received enough support through policies and adequate funding. In the same years, cities were quickly reshaped in dependence of an extensive use of cars and other private vehicles. However, public transportation still plays an important role in higher density and more historical cities (Dunphy and Fisher, 1996). Urban areas that significantly expanded in the last 40 years generally present lower density and more sparse urban form, with high separation of land uses, which do not incentivize the use of public transportation. From the comparison with other countries, differences in gas pricing, policies and funding for transportation, and urban density account for the large differences in public transportation patronage observed, for instance, between the US and Canada (Schimek, 1996) and the U.K. (Giuliano and Dargay, 2005).

The distance from public transportation stops (accessibility to transit services) is an important determinant of public transportation patronage (Cervero, 1994). This confirms the important role of urban density: usually, better transportation services are found in more compact urban areas. In particular, the number of public transportation users is affected by the number of employees and workplaces in the central business district (CBD), more than by residential density (Hendrickson, 1985). Following the study from Newman and Kenworthy (1989), many studies have focused on the relationships among land use variables and transportation demand. Kenworthy and Laube (1996) proved that the mode share for public transportation significantly increases with an increase in the urban density and with the population of the urban area. The results were confirmed both in the most advanced and in developing countries.

The experience in literature on the relationships between public transportation supply and land use and socio-demographic variables is more limited. Few studies have discussed the topic, and limited findings are available: for instance, in an international comparison of public transportation in 45 European cities, Albalate and Bel (2010) found that better public transportation services are usually associated with higher GDP. Moreover, public transportation supply is usually better in National Capitals. Additional regional patterns are observed, and better services are usually found in more historical regions with higher density.

As suggested by Badoe and Miller (2000), a "more direct relationship [...] almost certainly exists between employment density and transit service supply (i.e., such centres are readily identifiable foci for transit services)". The authors suggest that the urban form and neighbourhood design should be better investigated with regard to the provision of transit services and the analysis of accessibility to activities and connectivity as part of the travel demand forecasting process (Badoe and Miller, 2000). The role of subsidies and policies to support public transportation is also found to be important in shaping public transportation supply, although the efficiency of the subsidies highly depends on the size of the local public transportation network and on the way the subsidies are provided (Karlaftis and McCarthy, 1998). In addition, better public transportation supply is usually associated with a better integration of services with other transportation solutions, and with its coordination with pedestrian and bike networks (Buehler, 2009).

Despite the reported experiences, still additional investigation is needed in this field. Even if some studies have started to analyse the relationships existing between the characteristics of public transportation services and the urban form, this has not led yet to the development of quantitative analyses that relate public transportation characteristics to other land use and transportation variables. The topic is of particular interest for transportation modellers: the development of studies that relate public transportation supply characteristics to other more easily measurable (and readily available) characteristics of the land use and transportation systems could greatly simplify the applications to modelling studies in which a fine level of details is not required. Several groups of variables could be used as potential explanatory variables to represent public transportation attributes. These include aggregated variables, e.g. the level of funding for public transportation in a city or region, or measures of the public transportation network density, detailed land use and transportation variables, as employment and residential density, neighbourhood diversity and the characteristics of the street network,

and origin-destination based variables, as distances measured on the road network and travel times. Many of these variables are already measured in many large-scale modelling frameworks, as in the case of the CSTDM. The development and application of such an approach, in addition to the increased availability of large online repositories of transportation data, provide an important set of tools that could potentially benefit many modelling applications.

In most travel demand modelling specifications, public transportation networks are coded through the identification of each specific route served by public transportation services as a unique sequence of links in a network. This representation method is very labour intensive and is often more complex than coding the road network itself (Ortúzar and Willumsen, 2011). It requires the identification of the locations where stops are possible and those where interchange with other services is allowed. The explicit representation of public transportation networks is necessarily required in the development of detailed urban and regional models and microsimulation studies. However, their development poses serious challenges when applied to large scale interregional and statewide modelling projects. The efforts required for the development, and continuous update, of public transportation networks in the large-scale models is often not justified by the scale of these models and the finite resources available for their development. For these reasons, these models often completely ignore local public transportation services. These large-scale modelling studies can benefit from the availability of solutions that lead to a simplified representation of local transit.

3. Public transportation in the California statewide travel demand modelling framework

This research was developed as part of the creation of the California Statewide Travel Demand Modelling (CSTDM) Framework. The CSTDM Framework is a comprehensive modelling framework designed for forecasting travel demand in the State of California (37.7 million population in 2011 - as a comparison, only Russia, Germany, Turkey, France, U.K., Italy, Spain, Ukraine, and Poland of all European countries are larger - on a total area of 158,648 square miles, or 410,896 km² - only Russia, Turkey, Ukraine, France, Spain and Sweden of all European countries are larger). The program was launched in 2009 to support transportation planning and the evaluation of policy packages for transportation and was funded by the California Department of Transportation. The CSTDM Framework includes all major components of long and short distance travel demand. It adopts a tour-based microsimulation approach and is based on the analysis of 5191 Travel Analysis Zones (TAZ). The CSTDM includes five main models: the short distance personal travel model, the short distance commercial vehicle model, the long distance personal travel model, the long distance commercial vehicle model and the external trip model. All relevant means of transportation for both long distance and short distance trips throughout the State are included in the model: Single Occupancy Vehicle (SOV), High Occupancy Vehicle with 2 passengers (HOV2), High Occupancy Vehicle with 3 or more passengers (HOV3), Public Transportation (Bus and Rail), Airlines (for long distance trips), School Bus, Bike and Pedestrian. The model simulates travel demand for all trip purposes in the average weekday during the regular work and school season. Four times of the day are explicitly simulated in the model: AM Peak (from 6:00AM to 10:00AM), Midday (10:00AM to 3:00PM), PM Peak (from 3:00PM to 7:00PM) and Off-Peak (rest of the day). Additional details on the development of the CSTDM are provided by ULTRANS and HBA Specto (2011).

The road network in the CSTDM Framework is coded in the Citilabs CUBE software package. The road network was developed for the years 2000 (calibration scenario) and 2008 (validation scenario), and it includes all road links that are relevant for a statewide travel demand model. Additional information is included regarding the location of HOV lanes and dedicated ramps, bridges and tolls, and the access to all major transit and airport terminals.

Public transportation is represented by the local transit (rail and bus) services, the long-distance intercity railways and the air network. Different approaches are used for the representation of the public transportation networks, depending on the different needs and the level of relevance of public transportation services for either one or more of the five component models. The air network, which is used in the long distance personal travel model, is coded explicitly through the definition of the airports that provide intra-state commercial air services, and the characteristics of the services offered on each route (travel time, headways, average fares, and reliability). All railway services are also explicitly coded in the public transportation network. The rail network is used in both the short distance and the long distance personal travel models. It accounts for a limited number of intercity and commuter railways, light rail and subway systems, which provide scheduled passenger services on fixed routes throughout the state.

A simplified methodology was developed for the representation of the bus public transportation services. Bus services, which include hundreds of lines operated and managed by several different public transportation agencies and operators, are represented in CSTDM through an innovative numeric approach, which allows a robust representation of the local transit services, without extensive coding requirements.

3.1 The rail network

Limited railway services are currently offered in California. In 2008, only three intercity railways were operated in the state. Besides, the rail network also includes four commuter railways and some light rail and subway systems. In 2009, there were 39 lines of rail transit in California, with average weekday ridership of approximately 1.12 million passengers.

The rail network is a relatively high cost, long-term capital system. Only limited modifications are introduced in railway operations over the years: this is due to the large investments required by rail projects, the fixed routes (railway tracks) and high sunk costs associated with this means of transportation. In consideration of the characteristics described above, and the importance that the rail network has in providing a reliable alternative for both long distance and short distance trips in a statewide model, the explicit coding of all railway lines is adopted in the development of the CSTDM public transportation network.

3.2 Local bus services

Many bus lines are operated in California, with level of service that varies from the frequent mass services in densely populated urban areas to sparse, low frequency service among more remote locations in rural counties. In 2008, bus services were provided through more than 50 local transit operators in California, with over 1500 local bus routes. These services are an important component of the transportation system, and many times are the only alternative available to reach a destination for many users that do not have access to a private vehicle.

Bus services, on average, provide a limited contribution to the total public transportation ridership if compared to the large amount of service provided (number of bus operated lines): according to ridership data from 2009, 191 bus routes were in service in the Los Angeles Metro bus system, with a total daily ridership of 1.18 million. Similarly, the three major transit agencies in the San Francisco Bay Area combine for daily bus ridership of 0.84 million across 262 bus routes.

The right part of Figure 1 provides an example of the extensive bus network that is operated in downtown Sacramento, the State Capital: several different lines provide public transportation services on a rather dense network, each one counting dozens of bus stops in which users may access/egress the service. The bus routes shown in the example are only a very limited subset of the whole bus network system operated in California (left part of Figure 1).

The explicit coding of all bus lines and transit stops represents a time-intensive task that would require the allocation of a considerable amount of resources, and which is not justified by the

normal purposes of a statewide travel demand model. Furthermore, the characteristics of local bus services change frequently to adapt to modifications in travel demand, changes in the land use and the urban form of cities, funding and subsidies for public transportation. In addition to the high initial development costs, the explicit coding of all public transportation services in the area of study would also imply increased on-going modelling efforts required for any update and maintenance of such a detailed network. For all the reasons above, the definition of a valid alternative to the explicit coding of the bus network is a valuable solution to adopt in such a large-scale modelling framework.
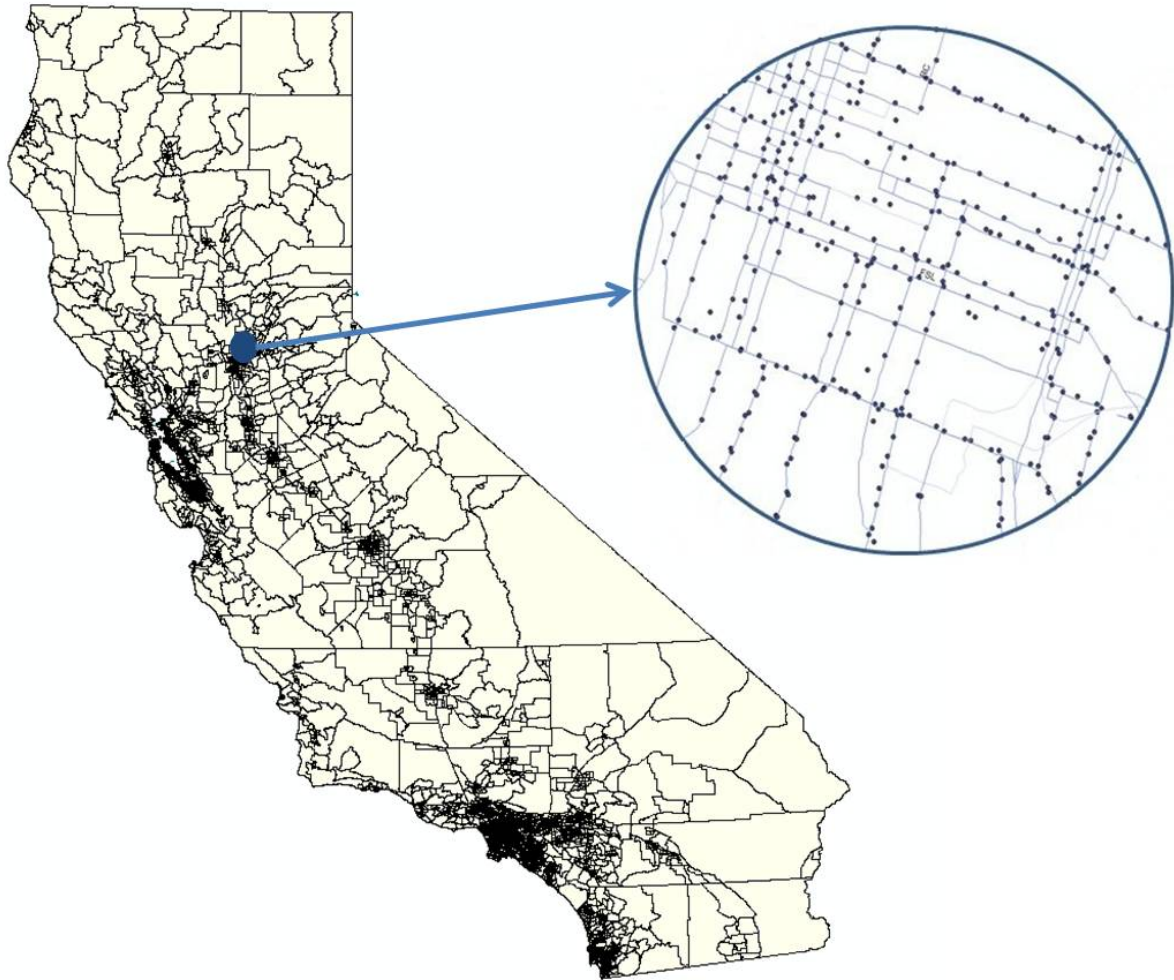

Figure 1. Distribution of local public transportation services in California. The right part of the figure shows an enlarged map of the local bus lines and stops in downtown Sacramento

4. The simplified model for local transit

The simplified methodology for the representation of local public transportation was developed with the aim of providing a robust representation of local bus services without the explicit coding of all local bus routes. In the simplified methodology, the characteristics of local public transportation services are estimated using a limited number of key input variables. Apart from reducing the initial coding burden, the methodology is designed to reduce the efforts required for updating the information and scenarios for testing future policies for the development of public transportation.

The simplified methodology is applied for the representation of local bus services in the short distance personal travel model. This model component simulates all passenger travel for work, school and other purposes made on distances shorter than 100 miles. This cut-off distance was determined as a good threshold separating regular short distance trips from low-frequency longer distance trips through the analysis of travel patterns from travel survey data in California.

4.1 Assumptions

The proposed numeric methodology for the representation of local public transportation travel attributes is based on the identification of the catchment areas for local public transportation services and on the estimation of simplified econometric models that express the local public transportation attributes (in-vehicle and out-of-vehicle times) as functions of other more easily measurable transportation and land use variables. The catchment areas represent the groups of geographically adjacent zones in the modelling framework that are served by public transportation services of any local operator (therefore, they identify the areas where trips by public transportation are possible). The methodology builds on the assumption that public transportation characteristics, in each catchment area, are strongly correlated with relevant features of the road network (e.g. distances and average speed) and land use variables, and can be represented through the estimation of simplified econometric models. The potential explanatory variables that were explored for the estimation of these models include general variables, e.g. information on the level of funding for public transportation in each catchment area and the level of service provided by each operator, detailed land use data, e.g. employment and population densities, and origin-destination based variables, such as congested travel times and distances on the car network. The public transportation travel time attributes, obtained with the estimated simplified econometric models, together with the public transportation fares, which are included as input data for each catchment area, are used in the CSTDM travel demand model to represent the local transit choice options available (in the areas served by bus services) for short distance trips (under 100 miles). Specific coefficients are used in the model for weighting these components of travel time separately, and to account for the value of time.

4.2 Catchment areas

At the base of the development of the model is the definition of the catchment areas for public transportation. The catchment area is a measure of the geographical accessibility to local public transportation services. Each of the 5191 TAZs in the modelling framework is eventually assigned to a catchment area depending on the distance from the available public transportation lines in the area. TAZs that do not have access in a reasonable range to any local transit services are not included in any catchment area.

The local public transportation functions use four key inputs:

1. *Transfer areas* (broader catchment area): the areas within which a person can travel (they include the possibilities of transfers among different operators in a region);

2. *Service areas*: the areas within which public transportation is generally provided by a single operator (they are subdivisions of the larger transfer areas with multiple public transportation operators);

3. *Level of Service*: a single number representing the quantity of local bus service provided by the operator; and

4. *Fare*: a composite value, expressed in US dollars, indicating the typical fare paid by a customer for a one-way trip by public transportation in each service area.

The development of the model is based on the adoption of specific assumptions on the relationships among public transportation travel times and other relevant transportation and land use variables, which are described in the following paragraphs.

Transfer and *service areas* concur to the definition of the catchment areas for public transportation. The transfer areas measure the accessibility to public transportation in the various regions. It is a measure of the portion of a region in which public transportation trips are possible, using any of the operators that offer local bus services. A service area is a smaller region that is usually served by only one operator. This is a representation of the local area in which travellers can use local bus services usually without having the need to transfer to other modes and/or operators. 32 transfer areas are defined in California. Multiple service areas are sometimes found in the largest transfer areas, as a result of the presence of multiple operators in a geographically large area, which allows for longer trips using multiple public transportation operators. Service areas are indicated through the addition of a digit to the number of the transfer areas (from 1 to 32) they belong to (for example, service areas 7.0, 7.1, 7.2 and 7.3 form the transfer area no. 7 in the "Sacramento region" in the CSTDM framework).
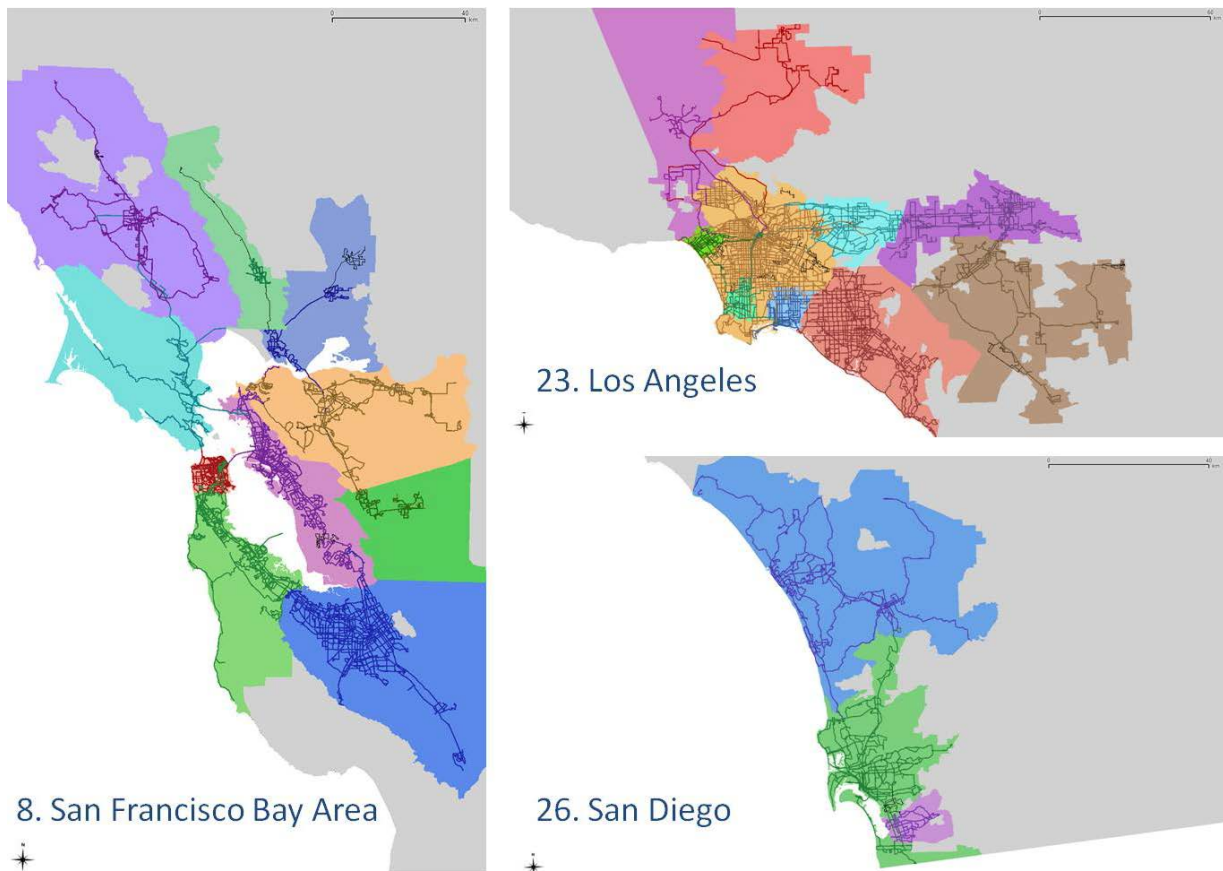

Figure 2. Local Transit Catchment Areas (Transfer and Service Areas) in the CSTDM system for three of the four major metropolitan areas of California: 8. "San Francisco Bay Area"; 23. "Los Angeles"; and 26. "San Diego"

The catchment areas (transfer and service areas) are defined through the analysis of GIS-based data for public transportation services in California. A GIS shapefile of public transportation lines provided by the California Department of Transportation was used in the CSTDM framework: each of the 5191 TAZs in the CSTDM framework is eventually assigned to a catchment area, depending on the proximity from the TAZ centroid to the closest bus line(s). The TAZ is assigned to the corresponding service and transfer area of the operator that runs the transit lines if such distance does not exceed 3 miles. If this test fails (some TAZ centroids are often located far from any bus line), but at least one bus line crosses the TAZ, then the TAZ is also included in the corresponding catchment area. Otherwise, the TAZ is not included in any catchment area (no public transportation services).

The simplified local transit model also allows a realistic representation of multimodal trips that require the use of rail and bus through the simulation of the access/egress trips to/from a railway station using the local bus system. In the CSTDM framework, a local bus option to travel to/from a railway station is offered every time a rail station is located in a zone included in a local bus service area. The travel attributes for this multimodal trip are computed based on the travel times (and costs) associated with the selected trip on the railway network and on the estimation of the travel times (and costs) required to reach the railway station by bus using the simplified local transit model (and/or vice versa, in the case of the egress leg from a railway station). The total travel times and costs for the multimodal trip will be given by the combination of the two sets of attributes (plus a transfer penalty fee associated with the time needed to wait for the additional transfer and to physically access/egress the station).

Eventually, in more isolated urban areas and rural counties, transfer and service areas are identical. In these cases, public transportation trips are possible only among the TAZs of the same service area, and there are no possibilities for connecting trips that extend into other contiguous service areas. In the CSTDM framework, the four major urban areas in California (Los Angeles, San Francisco Bay Area, Sacramento and San Diego) are the only areas in which a single transfer area contains multiple service areas. In these regions, multiple operators can be used for creating longer trips that originate in one service area and are directed to a destination in a different service area. This two-level approach handles the major urban areas served by many operators (for instance, permitting local bus service from San Mateo, located in the southern part of the San Francisco Bay Area, into downtown San Francisco). However, it prevents a traveller taking a local bus between e.g. Sacramento and San Francisco (located in rather contiguous catchment areas, but in reality not properly connected by connecting local bus services). More realistically, the overall transit skim process used in the modelling framework does permit this public transportation trip by taking the AMTRAK Capitol Corridor intercity train in addition to the local bus services in the two urban areas.

Fares for local bus services were computed as the average single trip fare for each operator in a service area. When travel happens between two service areas that are included in the same transfer area, it requires the payment of the fare for both areas.

4.3 Level of service

The Level of Service (LOS) is a single number that represents the quantity of public transportation services provided by the local operator(s) in each service area. The LOS variable used in this numeric approach is defined as the ratio of the *population served by a public transportation operator* (in its service area) divided by the *Annual Revenue Service Miles Provided* (in thousands). This variable is an overall measure of the quantity and density of the service provided related to the population served by public transportation in each service area. As such, it is a useful general variable that identifies average differences, in the quality and quantity of the public transportation services, across various transfer and service areas, as an effect of different levels of funding for public transportation, frequency levels, and average accessibility to public transportation services. For the way it is defined, the numeric value of the LOS decreases with an increase in the quantity of service provided by a public transportation operator. The LOS variable is computed using data from the National Transit Database of the Federal Transit Administration (FTA). In this measure, the amount of service is limited to that provided by bus and trolleybus, and does not include rail, which is modelled explicitly in the CSTDM, nor *demand responsive transit* (which is not covered by the CSTDM).

Travel within a service area is determined by the level of service of the operator in that service area. This measure for LOS has a number of beneficial properties:

- the value is a single number, which is easy to establish and interpret;
- it relates to the actual public transportation provided, and is a policy input;

- by being based on population, a future "status quo" scenario with the same per capita service is an easy default option (by maintaining the LOS index constant); and

- the value, which is lower for *better* transit service, can easily be used directly in model estimation, and offers multiple possibilities for policy evaluation. For example, a doubling of service frequency or a doubling of service coverage would be numerically represented by a halving of the LOS value.

In each service area, the local characteristics of the road network (travel times and distances) and of land use (population and employment densities) are used to determine travel times (both in-vehicle and out-of-vehicle times) for local public transportation between two TAZs in that service area using the same functional forms, estimated parameters and value of the level of service index. All else equal, service areas with lower LOS scores are associated with shorter public transportation (in-vehicle and out-of-vehicle) travel times.

Observed values for LOS range from 39.3 for San Francisco MUNI, to 484 in Thousand Oaks (a rather high-income community and master-planned city located in Ventura County, in the proximity of the greater Los Angeles metropolitan area). In model operation, the value of LOS is capped at 200 (which affects three catchment areas, respectively Thousand Oaks and Gold Coast Transit in the Ventura County, and Santa Clarita, in the Los Angeles County, all predominantly suburban communities), as an upper numeric bound for the LOS associated with lower quality bus services. This capping prevents unreasonable travel times being created in these areas, and reflects transit service that provides a modest level of service along the transit corridors most likely to be used and next to no service in other areas, rather than the very weak service in the entire area that would be represented by the larger number. Several minor rural transit operators with rather sparse service and without data available were also assigned 200. Average LOS were computed for those service areas that are served by more than one operator. The weighted average LOS is 111, which is similar to the level provided by the Orange County Transportation Authority (OCTA), or the Santa Clara Valley Transportation Authority (VTA)[1].

When travel happens between two service areas that are included in the same transfer area, a 5 minute penalty is incurred for transfer between services, and a weighted average of the Level of Service is used with 2/3 of the weight on the poorer quality service to account for the increased difficulties for transfers among lines operated by operators that provide lower quality services.

4.4 In vehicle time

The model specification for the local public transportation functions is based on the assumption that local public transportation attributes are correlated with other transportation and land use variables used in the CSTDM framework. In particular, the In-Vehicle Time (IVT) is correlated with the travel time of the private vehicles that share the road, as an effect of the distance to the destination and of the traffic congestion on the network. Since HOV lanes and ramps (where available) can be used by buses in California, it is reasonable to expect that IVT is correlated with the congested travel time measured in the CSTDM for car users in high occupancy vehicles (HOV3 travel time). Different model specifications were tested in the development of the methodology, exploring the possible relationships between the characteristics of transportation supply and other features of land use and transportation. We tested the possibility of a quadratic relation between IVT for local public transportation and the congested HOV3 travel time, as a way to allow non-linear relations between HOV3 auto travel time and in-vehicle transit time. The quadratic function acts as a reduction factor in the functional form, allowing higher travel times for buses than for cars especially for shorter trips due to the frequent bus stops. This effect is reduced for longer distances: the slope of the IVT curve depending on HOV3 time is expected to

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[1] These communities are served by denser local transportation networks than the suburban communities cited above but are still far from the levels of service provided by operators in denser areas, as the cities of San Francisco or Sacramento.

diminish for longer trips (diminishing marginal effects of auto travel time on IVT), and as an effect of the eventual availability of express bus services and bus routing on faster roads without many stops. IVT is also expected to depend on the LOS index, which measures the quantity and density of service provided (and it is affected by the investments in the public transportation system and other local conditions). As the LOS index increases, and less services per capita are provided, travel times are expected to increase as a result of longer detours and indirect routes needed to reach the desired destination.

4.5 Out of vehicle time

Similar assumptions to those introduced for the IVT functions were used in the estimation of the Out-of-Vehicle Time (OVT) functions. This measure of time represents the sum of all components of out of vehicle time that are associated with a public transportation trip:

1. the *time to access* the bus stop from the origin of the trip (generally by *walk*);

2. the *waiting time* at the first stop;

3. (eventual) *transfer time(s)* in any intermediate stop(s); and

4. the *egression time* from the last bus stop to reach the final destination.

Different model specifications were tested. We expect OVT to depend on the distance on the road network between the origin and the destination of the trip: longer trips usually require higher OVT, because of the lower availability of direct services to a specific destination, and the higher waiting and transfer times required. We tested both model specifications that used road distances or car travel times as explanatory variables. The final version of the model uses the road distances measured on the HOV3 congested network. Such distances may differ from the single occupancy vehicle (SOV) road distances depending on how common HOV lanes and ramps are in the specific area of service. Moreover, we tested the relationship of OVT as a function of the residential and employment densities of the TAZs of origin and destination. This is in line with the results from the literature, which report better public transportation coverage in higher density areas. Similarly to the IVT function, OVT is expected to depend on the LOS: lower waiting and transfer times are required in those areas that have better level of service. This is the result of more frequent public transportation services available in these areas, and a denser network, which increases the probability of easier transfers between lines, and higher availability of direct lines to the destination (which all concur to a lower OVT). The proposed numeric methodology does not explicitly account for the number of transfers required by a trip with local buses. However, the time required for additional wait and transfer times is accounted for in the estimation of the OVT functions. In particular, one effect is captured by the relationship with road distances (the longer the trip, the less probable the availability of a direct bus for the entire trip). In addition, population and employment densities (and the combination of the two) are a proxy for measuring the different availability of bus services in various types of neighbourhoods and for various types of trips, as respectively from downtown to a suburban area, or cross-town tangential trips. We will further discuss this topic in the following section of the paper.

5. Estimation of the models

In order to investigate the relationships between the characteristics of public transportation supply and other land use and transportation variables, and inform the modelling application, we estimated two sets of models for the local public transportation functions: one represents In-Vehicle Time (IVT), and the other represents the Out-of-Vehicle Time (OVT). The estimation of these two models was carried out with observed data for travel times collected through the Google Transit Data Feed (database with public transportation service data optimized to provide travel information through the online Google platform), merged with additional information on

the transportation system, land use patterns and sociodemographics available from other sources.

5.1 Public transportation data
The simplified econometric models for In-Vehicle Time (IVT) and Out-of-Vehicle Time (OVT) were estimated using observed data collected from internet sources. A large sample of public transportation travel time records was obtained through the databases stored by public transportation agencies on the Google platform and that generate the information for travel solutions by public transportation available on http://maps.google.com/.

Public transportation data available from the internet are still not often used in transportation research. However, the quality of the information of these sources has considerably increased in recent years: as public transportation agencies put considerable efforts in promoting their services through online platforms, the availability of reliable information from these sources has sharply increased. Besides, the standardization required by the adoption of the common platform and interface, defined by the provider of the internet services, allows easy collection of information for multiple operators in geographically separated areas through the same procedure, and with similar margins of error.

Public transportation data obtained from internet sources can provide useful information on available public transportation services, which in theory could also directly inform travel demand modelling applications on the level of service and travel times on specific routes. However, such an approach would limit the information available for the modelling applications. First, online transportation data might not be available for all service areas and operators in the region that is studied. In addition, the direct use of these data would provide a static set of travel time values, which depends on the specific conditions (and times) in which the data were collected, and are not sensitive to traffic conditions (which might alter travel times for buses that share the road with private vehicles) and to possible modifications in the transportation network or policy framework. An alternative approach, and the approach that is used in this study, is to use these data as the base for the creation of a comprehensive dataset that links the travel times collected from the internet sources to additional information on the specifics of the road networks and the land use of the zones where the transportation services are provided. This approach allows the estimation of models that relate public transportation travel times to other variables in the modelling system. It can then be applied for the prediction of travel times in several areas in the region of study and used as a policy instrument to test the eventual impact of policies on public transportation and therefore on passenger ridership. Moreover, the use of the congested travel times as explanatory variables in the estimation of the local public transportation models makes the model sensitive to the local traffic conditions, and an integral part of the modelling framework. Therefore, the travel times required to travel by bus are updated in the system at each modelling iteration in the CSTDM framework, thus updating the characteristics of the local transportation as part of the model solution (towards the convergence of the entire model).

The total dataset that was used for this study includes 91,074 records extracted from the internet data, which include complete public transportation travel times for interzonal trips having origins and destinations in the centroids of the TAZs within the CSTDM region. Each record contains information on:

- the time of the day of the travel record;

- the exact time of departure from the origin of the trip;

- the exact time of arrival at the final destination;

- the walking time from the origin to the first bus stop;

- the time spent on board of the first bus;

- the time for the first transfer (if any);

- the time spent on board of the second bus (if more than one bus is required);

- any additional transfer times and in-vehicle times for additional parts of the trip;

- the walking time from the last bus stop to the final destination.

These data refer to the shortest times available for each selected trip, as returned by the Google public transportation database (excluding trips with more than two transfers on public transportation, considered as unrealistic for most travellers). Data are collected at specific departure times during the day, thus simulating the availability of those trips for specific trips in the different time periods used in the modelling framework.

In order to generate the dataset for the model estimation, additional information was collected through the integration of the data with the CSTDM TAZ system, based on:

- the transfer and service area of the selected itinerary;

- the TAZ of origin;

- the TAZ of destination.

The data were collected from 29 different service zones and referred to the four periods of time of the day. The data were merged with information available from other sources (e.g. Caltrans, US DOT, other components of the CSTDM framework) to create the required datasets for the estimation of the IVT and OVT functions. The additional information that was merged in the dataset included HOV3 auto travel times and distances for each itinerary (estimated on the CSTDM road network), the LOS in each service area, and the residential and employment densities for each TAZ.

5.2 In vehicle time
The dataset available for the estimation of the IVT model included 91,074 observations. Several alternative model specifications were tested, and a number of parameters tried as inputs. The final solution that was selected is a linear regression model that provides the best goodness of fit and that predicts IVT with several explanatory variables. Four different functions were estimated for the four times of the day (AM Peak, Midday, PM Peak and Off-Peak). Due to their similar trends and goodness of fit, in order to increase parsimony in the final solution these four functions were combined in only two final models, respectively estimated for the Peak (6:00AM to 10:00AM and 3:00PM to 7:00PM) and the Off-Peak time (rest of the day). The sample sizes for the estimation of the final models were respectively 50,727 (Peak) and 40,347 (Off-Peak). Both models have quite good goodness of fit, with r-square respectively of 0.916 for the Peak model, and of 0.909 for the Off-Peak model. The estimated coefficients for the two models are reported in Table 1.

The estimated models describe IVT as a function of the HOV3 auto travel time with both variables measured in minutes. The model suggests interesting findings on the relationship between local bus travel time and the travel time required by shared private vehicles to complete a similar trip between the same origin and destination. Bus travel time is positively correlated with car travel time. The observed relationship represents the effect of network speed, connectivity and road geometry, as well as the effects of traffic congestion captured through the use of the congested HOV3 travel time on the road network, on bus travel times. The squared term (with a statistically significant negative coefficient) provides attenuation for longer trips, which is likely due to the presence of limited service or express long haul service on longer routes. The final term in the IVT models provides a policy sensitivity tool: as additional public transportation coverage is provided, the in-vehicle time is reduced. This is due to both the provision of more direct lines (operators providing a poor level of service typically provide very circuitous routes to ensure a minimum access to all residents), and also the increased likelihood

of there being a route serving the specific OD pairs, rather than travelling to/from a transfer point.

Table 1: In Vehicle Time (IVT) Functions for (a) Peak and (b) Off-Peak Time

a) Peak Period Model (N=50,727)

Parameter	Estimated coefficient	Std. Error	t-statistic	p-value
HOV3 Time	2.8921040	0.01478	195.69460	<0.001
(HOV3 Time)^2	-0.0174477	0.00040	-43.99996	<0.001
LOS*(HOV3 Time)	0.0057270	0.00011	52.59453	<0.001
R-Square	0.915505			
Std. Error of the Estimate	14.44533			

b) Off-Peak Period Model (N=40,347)

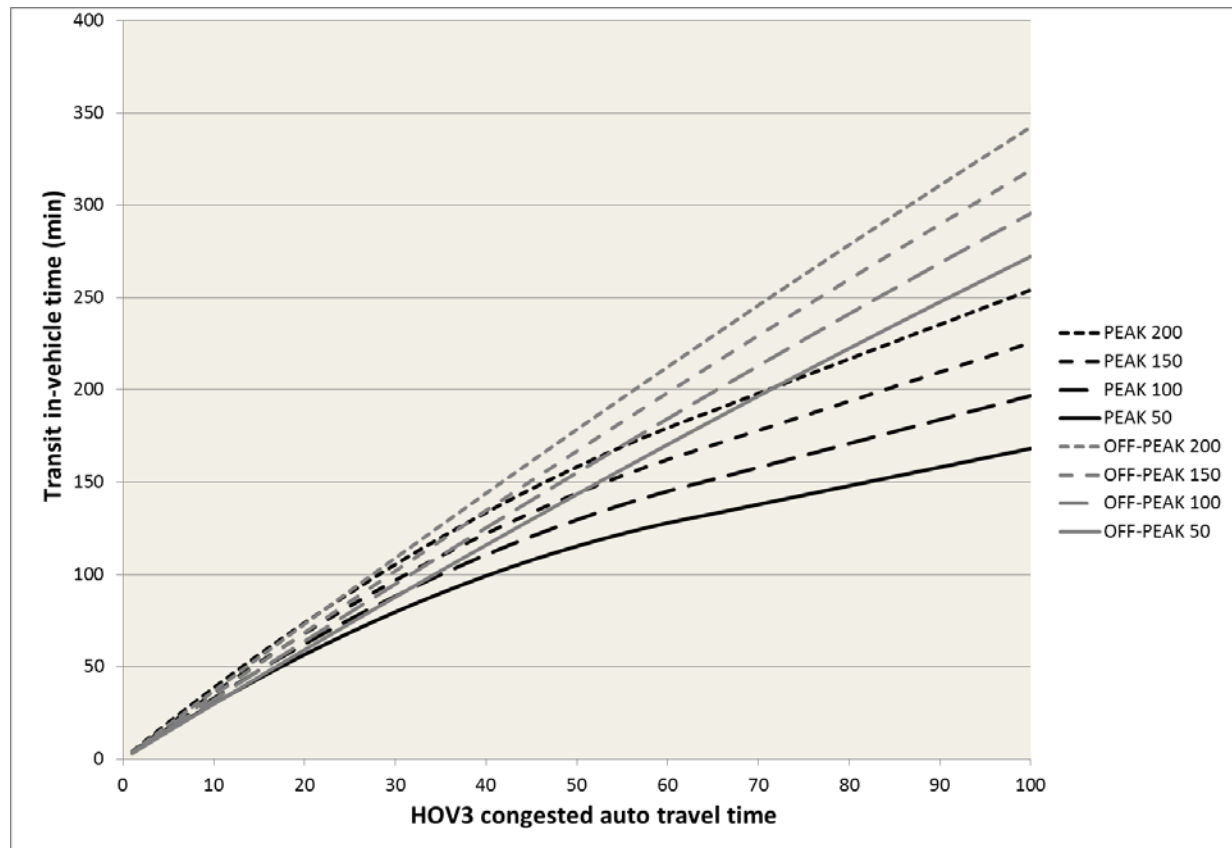| Parameter	Estimated coefficient	Std. Error	t-statistic	p-value
HOV3 Time	2.7813943	0.01734	160.42225	<0.001
(HOV3 Time)^2	-0.0029318	0.00055	-5.29485	<0.001
LOS*(HOV3 Time)	0.0046781	0.00013	35.90664	<0.001
R-Square	0.909412			
Std. Error of the Estimate	13.63288			

Figure 3. Transit In-Vehicle Time as a function of HOV3 congested auto travel time for Peak (in black) and Off-Peak (in gray) time, with different LOS Curves

5.3 Out of vehicle time

We also estimated the Out of Vehicle Time (OVT) functions using a linear regression model specification. The available observations for the estimation of this function were 88,730 observations, after excluding 2344 records with missing values for at least one of the variables used in the model. Similarly to the in-vehicle time model, several different model specifications and explanatory variables were tested in order to investigate the relationships linking out of vehicles time for trips by local bus to other transportation and land use variables. As for the IVT model estimation, four different models were initially estimated for the four times of the day. The final solution is based on two models estimated respectively for the Peak and for the Off-Peak time. Table 2 reports the estimated coefficients for the OVT equations.

Table 2: Out Vehicle Time (OVT) Functions for (a) Peak and (b) Off Peak Time

a) Peak Period Model (N=49,263)

Parameter	Estimated coefficient	Std. Error	t-statistic	p-value
Square Root LOS	3.219780	0.018315	175.79624	<0.001
LOS*(HOV3 Distance)	0.006140	9.9E-05	62.042392	<0.001
Square Root P2E Density*	-0.016737	0.000669	-25.02035	<0.001
R-Square	0.839672			
Std. Error of the Estimate	16.24132			

b) Off-Peak Period Model (N=39,467)

Parameter	Estimated coefficient	Std. Error	t-statistic	p-value
Square Root LOS	3.087907	0.021532	143.4103	<0.001
LOS*(HOV3 Distance)	0.007235	0.000124	58.35179	<0.001
Square Root P2E Density*	-0.007630	0.000745	-10.2447	<0.001
R-Square	0.829657			
Std. Error of the Estimate	16.78981			

Note: *this variable includes the sum of the square roots of population and employment (with double weight) densities, measured at the origin and at the destination of the trip.

Sample sizes for the estimation of these models are respectively 49,263 for the Peak model and 39,467 for Off-Peak. Both models have quite good measures of goodness of fit, with r-square respectively of 0.840 for the Peak model and of 0.830 for the Off-Peak model. R-square values are lower than in the IVT models, probably because out-of-vehicle time has many more possible causes, including a sparse network leading to long walks, infrequent headways and variable transfer times, which cannot be entirely captured under the current modelling assumptions and specifications.

The OVT model is highly dependent on the level of service provided. Several possible transformations of the variables were tested in order to improve the goodness of fit and at the same time reduce the total number of variables included in the model to increase parsimony and the simplicity of the application of this approach to travel demand modelling projects. In the final solution, OVT depends on the squared root of the LOS: a better level of service results from more closely spaced routes (and better coverage), lower headways and more efficient transfers (or direct service without a transfer). The square root transformation of the LOS variable provides an attenuation factor for the relationship between out of vehicle time and level of service and better matches the trend observed in the data between LOS and out of vehicle travel time. We want to stress that the OVT includes all components of out of vehicle time for a bus trip (including access and egress times, initial wait and transfer times). The dependence of OVT on the HOV3 distance

is presumably the result of the effects of the availability of fewer direct lines for longer trips, which therefore determines larger waiting and transfer times.
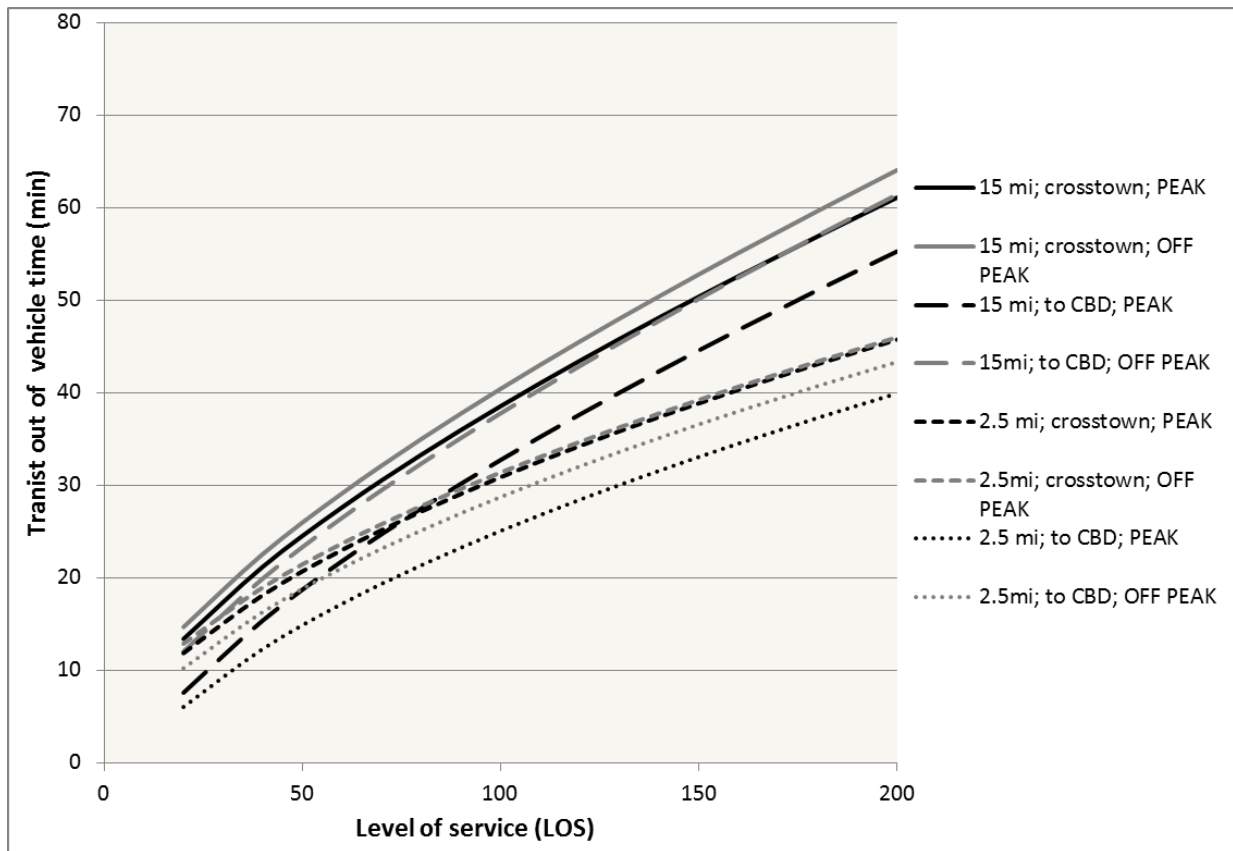

Figure 4. Transit Out-of-vehicle Time Curves for four examples of trip types, by LOS (horizontal axis), for Peak (in black) and Off-Peak (in gray) Time

The third term uses the sum of the square roots of the P2E (sum of population and two times employment) densities respectively for the TAZs of origin and of destination. Also for this variable, several different variable transformations were tested during the model estimation. In the final solution, the employment component is doubled to provide higher weight to the employment density, which is considered an important determinant for the location of better and denser public transportation services and identifies the areas where the use of public transportation is more common. This measure implies that denser areas will have lower out-of-vehicle times, which is due to operators typically focusing service on core activity nodes, as well as to the reduced walking distances likely found in denser areas, which determine shorter access and egress times. The origin and destination are considered separately, to account for the different conditions existing, for instance, between trips connecting more balanced OD pair (cross-town) and trips on radial routes from very sparse suburbs to a dense downtown.

Figure 4 provides some examples of how the OVT curves vary depending on the LOS index, for peak and off-peak time, and for various combinations of trip types diversified by the OD distance and the values of neighbourhood densities at the trip origin and destination. The specific patterns with which OVT varies in different context will depend on the specific combination of the levels assumed by the explanatory variables. For instance, an area with higher urban density will be associated with a reduction in the forecasted OVT for the use of local transit, which will be larger in magnitude for an increase in employment density rather than in residential density (all else equal). Improved level of service will contribute to reduce the OVT, and trips connecting two areas with similar density will usually have higher out of vehicle times than trips connecting areas in which a high density is concentrated at one end of the trip, as it is the case of trips to

CBD. The likelihood of this trend confirms experimental observations in the area of study, while the specific patterns for OVT will depend on the combination of the explanatory variable levels in each context.

5.4 Application in the CSTDM framework

The estimated local transit functions were integrated in the CSTDM framework in order to provide information on the attributes of local transit for travel demand modelling purposes. We used four Citilabs CUBE scripts, one for each time of the day, to fully integrate the local transit functions in the CSTDM modelling framework. This solution provides a realistic representation of multimodal public transportation trips through an efficient modelling solution that reduces coding efforts and fully integrates the estimation of local transit attributes in the iterative modelling process through the use of the simplified functions and the update of road and transit network skims at each iteration of the model. The proposed modelling approach includes the possibility to use local bus to and/or from a rail station, or to use the local bus for the entire duration of a trip. It is sensitive to land use patterns and congestion, and to policy decisions that alter the level of local transit service provided. Moreover, the model sensitivity to population and employment density can be used as policy variables in future scenarios.

A separate input file is generated for each scenario to provide the required information on catchment areas, LOS and fare levels under the policy assumptions that are tested. Policy testing can be carried out varying the input information on the catchment areas, LOS and fares for each service area, as well as population and employment densities according to the transportation and land use scenarios that are tested.

The proposed synthetic methodology was developed and applied for the representation of local public transportation networks in 2000 (calibration year) and 2008 (validation year) in the CSTDM modelling framework. As such, it proved to be a very practical and robust approach to deal with the inclusion of local public transportation in a large-scale statewide travel demand model (that does not require the "urban street" level of details). One of the consequences of the use of this modelling approach was the loss of some of the detailed information associated with public transportation trips. For instance, using the numeric approach, it is not possible to assign trips to specific local bus routes (and compute the corresponding ridership). However, this represents an acceptable trade-off in the development of the model, considering the statewide scale of the CSTDM modelling framework: more detailed urban models are available to perform this task. On the other hand, the simplified local transit model allows including information on local transit options also for many areas in which local bus services are provided on local neighbourhood roads that are not explicitly coded in a statewide model.

Additional scenarios were later created to model future development of the transportation system in 2020, 2035 and 2050, and they were used for the analysis of future travel demand in California. The update of the network consisted of the definition of the updated catchment areas and the conditions of LOS in these future scenarios, according to plans and forecasts for future development of local public transportation provided by the local metropolitan planning organizations. The creation of the future scenarios proved to be a manageable task even for such a large area of study. It confirmed the flexibility of the proposed approach for the definition of future local public transportation, and it also reduced the influence of coding errors in the development of the public transportation network (which would be eventually difficult to identify and correct in a very vast network and in a context of constrained available resources). Additional scenarios to test policies for public transportation can be developed as modifications of these baseline future scenarios. This allows testing the results of the implementation of several policies in future years.

6. Conclusions

This paper discusses the development of a simplified methodology for the representation of the local public transportation in a statewide travel demand model. The proposed approach provides an efficient solution for the representation of bus services based on a numeric methodology that describes the characteristics of public transportation supply as functions of other transportation and land use variables. The proposed approach was developed and integrated into the Short Distance Personal Travel Model (SDPTM) of the California Statewide Travel Demand Modelling (CSTDM) Framework.

The proposed approach provides useful insights into the analysis of the relationships between local public transportation supply and the characteristics of the built environment and provides a method for integrating a surrogate for local transit supply into travel demand models. As part of this project, we estimated multiple linear regression models that express local public transportation attributes (in vehicle and out of vehicle times) as functions of other transportation and land use variables. Two separate functions are estimated for the In-Vehicle Time (IVT) and the Out-of-Vehicle Time (OVT). Different models are estimated for Peak and Off-Peak time to account for variability in services during the day. The models are sensitive to different levels of service and local conditions through the definition of catchment areas for local public transportation operators and the use of a Level of Service (LOS) index. The model is estimated using observed data collected from the internet platform Google, with a total sample of more than 90,000 records. All models have very high goodness of fit, with measures of R-square that respectively exceed 0.9 for the In-Vehicle Time functions, and 0.8 for the Out-of-Vehicle Time.

The results of the model estimation provide useful insights into the relationships between the variability of local bus travel times and other transportation and land use variables. As expected, local bus in-vehicle times are found to be correlated with congested travel times of private vehicles: the longer the trip, the longer the time needed by either car or local bus. The use of congested travel times by private vehicles accounts for the effects of traffic congestion on travel times by local buses. The presence of a quadratic term in the in-vehicle time function accounts for the non-linearity of the relationship: travel times for bus trips are usually much higher than for car trips in this area of study. However, this effect is reduced for longer distances, where the impact of frequent stops is reduced and the availability of express services is more common. Similarly, the out of vehicle time (sum of the access and egress times, waiting and transfer times) is highly affected by the level of service provided by the local operator. For instance, the sparser is the network, the longer the wait for the availability of fewer direct services or for an increased number of transfers would be. The estimated models also highlight an important relationship with urban density, confirming the better availability of higher quality services in more densely inhabited areas. All else equal, employment density is associated with a higher impact on the supply of good quality public transportation services than residential density.

The application of this methodology to the representation of local public transportation in a statewide travel demand model has several advantages. It eliminates the need for explicit coding of all bus links and connections in the state, which would not be justified by the scale of such models, and is also appropriate in consideration of the limited mode share for bus services in California. Thus, it optimizes the use of resources, providing a robust model for local public transportation with efforts that are consistent with the output benefit in a large-scale statewide travel demand model.

The simplified methodology permits easier data input, and it allows several possibilities for policy testing in both land use and bus transit supply. Finally, the proposed approach allows easier maintenance of the public transportation network, which reduces the efforts required for the definition of future scenarios in the modelling framework. It also reduces the influence of coding errors in the development of the public transportation network, which would be

eventually difficult to identify and correct in a very vast network and in a context of constrained available resources.

The methodology is easily transferrable to other geographical contexts, in the United States as well as in other countries. The application to specific contexts may require re-estimating the models with local data, in particular in the presence of different structures of the urban form and characteristics of the transportation system. Alternative model specifications might be also tested for specific needs, or to improve the ability of the model to capture specific relationships. For instance, in the development of future research, the authors plan to test a two-level simplified methodology, in which different functions are estimated for the representation of the availability of respectively local buses vs. express services in specific areas. This represents an important field for further research, in order to evaluate the way to further increase the capacity of this approach to represent public transportation services and support modelling applications in various geographical contexts efficiently. Overall, the proposed approach represents a possible innovative solution for the advancement of other statewide and interregional models that nowadays usually do not include local public transportation. It can then significantly improve the representation of travellers' behaviour and increase the accuracy of travel demand forecasts from these models.

Acknowledgements

References

Albalate, D. and G. Bel (2010). What Shapes Local Public Transportation in Europe? Economics, Mobility, Institutions, and Geography. *Transportation Research Part E*, 46(5), 775-790.

Badoe, D. A. and E. J. Miller (2000). Transportation-Land-Use Interaction: Empirical Finding in North America, and Their Implications for Modeling. *Transportation Research Part D*, 5, 235-263.

Buehler, R. (2009). Promoting Public Transportation: Comparison of Passengers and Policies in Germany and the United States. *Transportation Research Records*, 2110, 60-68.

Cervero, R. (1994). Transit-Based Housing in California: evidence on ridership impacts. *Transport Policy*, 1(3), 174-183.

Cervero, R. (2007). Transit-Oriented Development's Ridership Bonus: a Product of Self-Selection and Public Policies. *Environment and Planning A*, 39, 2068-2085.

Cervero, R. and K. Kockelman (1997). Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D*, 2(3), 199-219.

Crawford J. H. (2000). *Carfree Cities*. International Books, Utrecht.

Dittmar, H. and G. Ohland (2004). *The New Transit Town. Best Practices in Transit-Oriented Development*. Island Press, Washington (DC).

Dunphy, R. T. and K. Fisher (1996). Transportation, Congestion and Density: New Insights. *Transportation Research Records*, 1552, 89-96.

Giuliano, G. and J. Dargay (2005). Car Ownership, Travel and Land Use: A Comparison of the US and Great Britain. *Transportation Research Part A*, 40(2), 106-124.

Hendrickson, C. (1985). A Note on Trends in Transit Commuting in the United States Relating to Employment in the Central Business District. *Transportation Research Part A*, 20(1), 33-37.

Kain, J. F. and Z. Liu (1999). Secret of Success: Assessing the Large Increase in Transit Ridership Achieved by Houston and San Diego Transit Providers. *Transportation Research Part A*, 33(7/8), 601-624.

Karlaftis, M. G. and P. McCarthy (1998). Operating Subsidies and Performance in Public Transit: An Empirical Study. *Transportation Research Part A*, 32(5), 359-375.

Kenworthy, J. R. and F. B. Laube (1996). Automobile Dependence in Cities: An International Comparison of Urban Transport and Land Use Patterns with Implications for Sustainability. *Environmental Impact Assessment Review*, 16(4/6), 279-308.

Lane, B. (2009). The Relationship between Recent Gasoline Price Fluctuations and Transit Ridership in Major US Cities. *Journal of Transport Geography*, 18(2), 214-225.

Litman, T. (2007). Transit Price Elasticities and Cross-elasticities. *Journal of Public Transportation*, 7(2), 37-58.

Maley, D. W. and R. Weinberger (2009). Rising Gas Price and Transit Ridership: Case Study of Philadelphia, Pennsylvania. *Transportation Research Records*, 2139, 183-188.

Newman, P. and J. R. Kenworthy (1989). Gasoline Consumption and Cities: A Comparison of U.S. Cities with a Global Survey. *Journal of the American Planning Association*, 55, 24-37.

Ortúzar, J. d. D. and L. G. Willumsen (2011). *Modelling Transport*, Fourth Edition. Wiley, New York.

Paulley, N., R. Balcombe, R. Mackett, H. Titheridge, J. Preston, M. Wardman, J. Shires and P. White (2006). The Demand for Public Transport: The Effects of Fares, Quality of Service, Income and Car Ownership. *Transport Policy*, 13, 295-306.

Schimek, P. (1996). Automobile and Public Transit Use in the United States and Canada: Comparison of Postwar Trends. *Transportation Research Records*, 1521, 3-11.

Taylor, B. D., D. Miller, H. Iseki and C. Fink (2009). Nature and/or Nurture? Analyzing the Determinants of Transit Ridership across US Urbanized Areas. *Transportation Research Part A*, 43(1), 60-77.

Wang, G. H. K. and D. Skinner (1984). The Impact of Fare and Gasoline Price Changes on Monthly Transit Ridership: Empirical Evidence from Seven U.S. Transit Authorities. *Transportation Research Part B*, 18(1), 29-41.