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Methods for Improving Consistency between Statewide and Regional Planning Models

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16. Abstract Given the difference in scope of statewide and MPO models, inconsistencies between the two levels of modelling are inevitable. There are, however, methods to reduce these inconsistencies. This research provides insight into the current practices of statewide modelling across the USA and presents methods to not only to quantify the inconsistencies, but also to reduce them.		
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List of Acronyms and Abbreviations

CAMPO	Capital Area Metro Planning Organization
DOT	Department of Transportation
FHWA	Federal Highway Administration
HBW	home-based work
MPO	metropolitan planning organization
NHB	non-home-based
NHBW	home-based non-work
NHTS	National Household Travel Survey
OD	origin-destination
SAM	statewide analysis model
TAZ	traffic analysis zone
TxDOT	Texas Department of Transportation

Executive Summary

Transportation models are some of the most powerful tools commonly used by planning agencies in the United States. These agencies carry out their transportation planning efforts on numerous different scales and will regularly use their models to aid decision-making processes associated with various projects, such as new policies as well as the construction of new roadways.

For example, agencies like the Federal Highway Administration (FHWA) are likely to use large (yet simplified) models of the whole country that also contain its interface with other border countries, such as Mexico and Canada. Analogously, a small city will likely focus its modeling efforts on capturing what happens inside the city and its interface with neighboring cities and/or the rest of the state it belongs to. While the latter case is narrower in scope, it is likely to contain greater detail when representing individual roads.

In an ideal scenario, one might imagine all of these agencies planning their modeling efforts in a strategic fashion, with all other agencies simultaneously aware of what changes were being made so that all models used nationally would be simultaneously updated. This, however, is far from the actual practice, and is likely unachievable given differences in agency priority, model needs, and forecasting and model updating timelines. Most commonly, agencies in overlapping geographic areas collaborate during their model development, but given the difference in modeling scope, inconsistencies between the several organizations' models are inevitable.

This report focuses specifically on consistency-related issues between state departments of transportation (DOTs) and metropolitan planning organizations (MPOs). More specifically, it deals with the Texas Department of Transportation (TxDOT) and how to quantify and reduce inconsistencies between the statewide analysis model (SAM) and all the models used by the various MPOs located in Texas.

Initially, literature was reviewed in order to establish the state of the art as well as best practices and how other states deal with this issue. The main lessons learned were that the current practices of statewide and MPO model integration commonly lack integration, and frequently-used approaches include aggregation; stitching; excluding intra-urban trips from statewide models; and using common sub-modules. Most importantly, though, the clearest recommendation across all of the literature was that agencies should focus on developing MPO and statewide models in a coordinated fashion.

The main analyses carried out in this project focus on the Austin area and how both SAM and the Capital Area Metropolitan Planning Organization's (CAMPO) model are inconsistent with each other.

Three classes of inconsistency measures are established as the main tools to quantify the inconsistencies between the two models:

- **Network consistency**, measuring the difference between networks' topologies, such as their average node in- and out-degree as well as lane miles per zone;
- **Input consistency**, measuring differences between both models' demands between origin-destination (OD) pairs; and
- **Output consistency**, measuring the difference between the models' travel times between OD pairs.

After defining the three types of consistency measures, the results showed evidence of significant discrepancies between SAM and the CAMPO model.

Seven methods to reduce possible inconsistencies were then proposed. These seven methods are divided into three groups:

- Methods that don't involve inputting information back into SAM or the MPO model:
  - Simple override
  - Correction factors
  - Correction regressions
- Methods that involve inputting information back into SAM or the MPO model:
  - Inputting the MPO model's demand into SAM
  - Changing input parameters
- Methods that involve substantial remodeling of SAM:
  - Efficient aggregation
  - Decentralized implementation

The first and simplest set of methods to implement involved making minor adjustments in the models' outputs. While reducing inconsistency between SAM and the MPO model, they caused substantial inconsistencies within the SAM model. This result arose because these methods do not feed the new information generated back into SAM for a new run of the model.

The second group of methods involved re-running the models. While keeping the network consistency constant, these methods reduced the input inconsistencies to a minimum and significantly reduced the output inconsistencies.

The methods in the last group involved substantial resources to implement; given the scale of the models analyzed (SAM and the CAMPO model), these methods were tested in even smaller scales. Due to the difference in scope of the tests performed, the consistency benefits associated with these methods are not directly comparable to the other five methods. However, they still showcase these methods' potential to improve consistency.

Chapter 1. Introduction

1.1 Overview

Transportation networks are large-scale systems with complex interactions between supply (network) and demand (travelers). Studying these interactions is important in determining the success of investments made in the transportation systems. Travel demand models have been the best planning tools available in recent decades to assist planners and investors in determining the long-term benefits of transportation projects. Initially, metropolitan planning organizations (MPOs) started using these models for long-term planning within different cities and urban areas. However, these models are now being used at much larger scales in order to predict the current and future growth of traffic at the statewide or national levels (Horowitz 2005).

Statewide travel demand models usually include the areas covered by several MPO models within the state and involve some kind of interaction with these MPO models. These interactions can be the statewide model providing the internal-external or external-external traffic volumes to the MPO models as well as the statewide models using the aggregation of the networks in MPO models to construct the statewide network. In the United States, 77% of MPOs with populations greater than one million develop models of their own, with states only providing technical assistance in building the model (NRC 2007).

Hence, the statewide model and the MPO model can predict different outcomes for analysis of the impact of the same project or can lead to conflicting recommendations, depending on which one is used for decision-making. Identifying these inconsistencies and developing methods to evaluate and remove them are the primary focus of this research.

The focus of this research is the Texas statewide analysis model (SAM), which is regularly used by TxDOT for planning purposes, mainly with the aim of investigating future scenarios in which roadways are added or altered, or where changes are predicted in certain demographic trends.

1.2 Report organization

The work in this project consists of four main sections: Chapter 2 contains a literature review that was undertaken in order to understand how other state departments of transportation (DOTs) deal with the interactions between statewide and regional models and potential compatibility issues. In Chapter 3 we create ways to measure inconsistencies that might arise between statewide and regional models. Chapter 4 contains methods developed to minimize these inconsistencies. In Chapter 5 we implement the methods developed in Chapter 4 using SAM and the Capital Area Metropolitan Planning Organization's (CAMPO) model as a testbed. Furthermore, the measurement tools developed in Chapter 3 were used to assess the improvement in overall consistency between the two models; Chapter 5 contains a summary of the findings of the research conducted and general recommendations. Final conclusions are stated in Chapter 6.

Chapter 2. Literature Review

This section summarizes our review of the foremost literature regarding statewide and regional modeling and how state DOTs and MPOs deal with potential inconsistencies.

2.1 Background

2.1.1 Approaches for modeling travel demand

A travel demand model provides a platform to estimate the future demand by including different elements of a transportation network, such as roadways, transit routes, population, demographic, and employment data. These estimates are then used by planners to make informed decisions and develop efficient plans. The equations used within the models represent the behavior of individuals and can be used to study why people travel, where and when they start and end their trips, how they complete these trips, and what routes they take.

To develop a concrete planning model, researchers have employed various methods to understand travelers' behaviors. The earlier modeling approaches for travel demand included sketch planning models, which were meant to provide rough order-of-magnitude estimates of travel demand. These models relied on less data, and used simpler software tools. Strategic planning models were also an early demand modeling approach. These models, however, were very narrow in scope, and dealt with analyzing many scenarios quickly for a specific area of analysis.

Earlier intercity passenger models also used direct-demand modeling technique in both disaggregate or aggregate manners. The trend later shifted to having sequential models, which can better capture the sequential behavior of choices that travelers make (Horowitz et al. 1999). One of the most popular sequential approaches to modeling travel demand is the four-step modeling process (also referred as a trip-based model). Following are the four steps of trip-based models:

- *Trip generation:* In this first step, information from land use and employment are used to estimate the trip attraction and production rates. The trip rates are usually separated by trip purpose and are generated in household and zonal levels (a zone is a geographic area with homogeneous travel behavior).
- *Trip distribution:* The second step connects the production and attraction points by determining the origin and destination of each trip. Trips originating from each zone are distributed to different zones by evaluating different aspects such as attraction rates and travel times. The output of this step is a demand matrix with entries defining the number of trips between each pair of zones.
- *Mode choice:* The trips distributed in the second step are assigned to different transportation modes (car, transit, carpool, bicycle, walking) between their origin and destination zones. The mode split is performed by considering different aspects of travel such as cost, travel time, capacity, schedules, waiting and walking times, etc.
- *Trip assignment:* The last step of a four-step process determines the routes taken by travelers between their origin-destination (OD) zones based on the selected mode. The trip assignment is done based on the Wardropian principle, which assumes that users have perfect knowledge about the network condition and will follow the shortest route.

This assumption results in a set of routes where all used routes for each OD pair have equal and minimum travel times. Furthermore, unused routes cannot be quicker than the used ones.

More advanced travel demand modeling techniques include tour-based or activity-based models. These models offer the advantage of explicit representation of realistic constraints of time and space, and incorporate the linkages among activities and travel for an individual person as well as across multiple persons in a household (Castiglione et al. 2014). However, the present state of the practice in travel demand modeling utilizes four-step models, which was the focus in this project.

2.1.2 MPO models: uses and limitations

The planning process is an extensive endeavor and requires close collaboration between officials and citizens to ensure that the process and objective match the community's needs and the planning agency's constraints. Travel demand modeling and planning was developed almost 50 years ago and dealt mostly with travel demand and traffic congestion in small scales such as urban areas (Oppenheim, 1995).

Each state's governor creates MPOs for urban areas or groups of adjacent areas. These MPOs are then responsible for planning the associated urban area(s).

The urban models developed by the MPOs usually include short distance trips and neglect the long-distance trips, freight demand, and intercity travelers. The 2001–2002 National Household Travel Survey (NHTS) shows that less than one-third of all trips are long-distance (defined as distance more than 50 miles). Additionally, as verified by the 2002 Commodity Flow Survey, the vast majority of freight trips are long-distance trips. The study by Dargay and Clark (2010) showed that these long-distance and freight trips contribute to almost 31% of total vehicle-miles traveled. This indicates that long-distance trips play a major role in traffic congestion and emission issues, which are not addressed well in MPO models alone.

Some of the other shortcomings of current MPO models as highlighted in TRB Special Report 288 (TRB 2007) include:

- Missing dynamic aspect from majority of these models;
- The inability of four-step modeling to capture some of factors affecting travel behavior such as value of time, and value of reliability;
- Missing non-motorized modes and trips made by them; and
- A lack of robust and validated models to rigorously forecast freight movements.

Modeling the entire state, or statewide modeling, seems to be a viable option to overcome the shortcoming of modeling long-distance trips. Statewide models have received more attention recently and many states' DOTs have undertaken efforts towards implementing statewide models. The statewide forecasting model goes beyond the urban areas and predicts demand for travel by people and goods by all modes in the entire state. The next section provides a more detailed discussion on statewide modeling.

2.2 Statewide analysis model: best practices

2.2.1 General modeling practices across United States

As shown in Figure 1, more than 40 US states have a statewide model in one form or the other. Since 1968, when the first statewide model was established, the practices for developing the statewide models have become widespread. Some models have seen challenges and thus are being revised or considered dormant. The NCHRP Synthesis 358 report (Horowitz, 2005) highlights that in the last two decades statewide models have shown dramatic improvements in the socioeconomic and network databases, tools for accessing these databases, and the available computational power.

The statewide models can be classified into five general categories: (1) OD table estimation and assignment, (2) freight only, (3) passenger only, (4) combined passenger and freight, and (5) integrated passenger/freight/economic activity. Some states that do not have a statewide model continue to work with the historical trends for the prediction of traffic and rely on regression-based models for planning purposes. These include the states of West Virginia, Nevada, and Wisconsin.

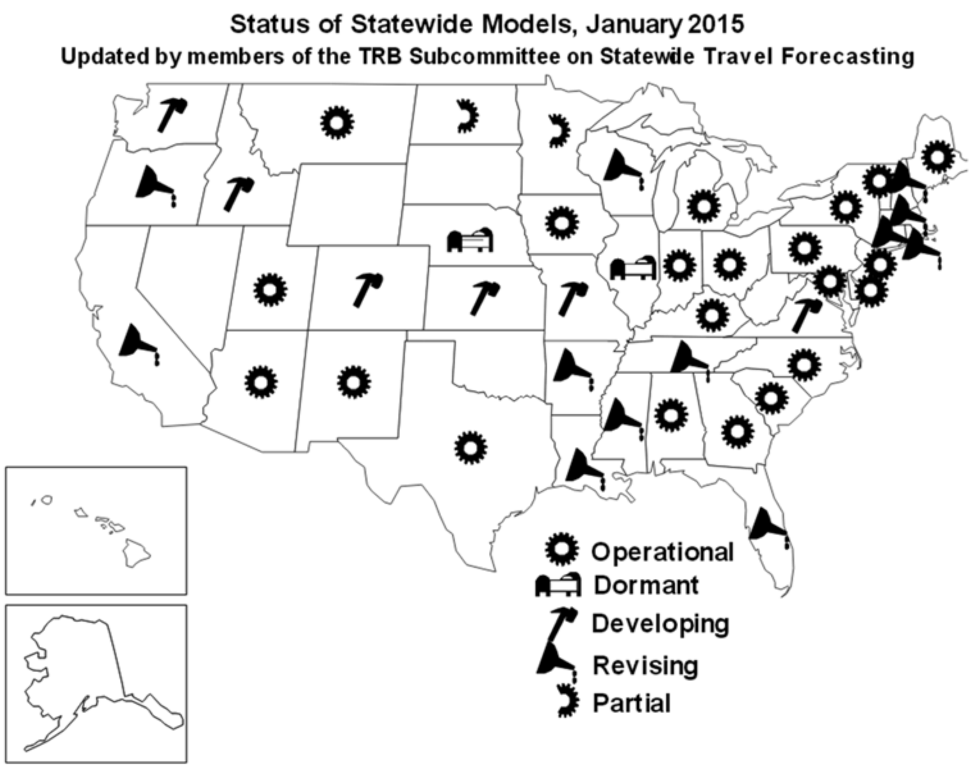

Figure 1 Status of the statewide models across the United States (TRB 2015)

The purposes for which statewide models have been built vary from state to state. The primary usages of these models are intercity corridor planning, statewide system planning, and bypass studies (Horowitz, 2005). The states also use their model results for providing input to MPO models, replacing MPO models, or serving as the main forecasting means for rural projects. These purposes also determine the way MPO models are integrated within the statewide models.

The majority of statewide models focus on passenger and freight components separately, developing separate models for the first three steps of the four-step model, and performing a combined assignment for the last step. These include the statewide models in Florida, Texas, Michigan, and Indiana. Most of the smaller states tend to perform peak period traffic assignment, while otherwise the assignment step is run for a full 24-hour day.

2.2.2 Key trends in passenger model components of statewide models

Statewide models have been found to closely follow the MPO models in structure within their passenger travel components. This includes having a predefined sequential four-step modeling of the trips. The trips are categorized based on the purpose (home-based work, home-based/other, long distance, etc.), time of day (morning peak, evening peak, etc.), and the choice of mode. Passenger components in most of statewide models consider multiple modes, always including the automobile mode. Other commonly found modes are intercity railroad (as in Texas); intercity bus (Wisconsin, Ohio); local buses (Arizona); and commuter railroad (Ohio) (TRB 2007).

Some states have improved their modeling procedures to include advanced modeling techniques. Oregon and Ohio are one such example where they use combined transportation-land use model for the planning purposes. The primary objectives served by these integrated models are to provide better estimates of how transportation investments affect economic development; consistent forecast of land use across the state; and land use sustainability. The states of California, Florida, Indiana, and Texas have also considered integrated models for specific planning applications (Cambridge Systematics, Inc. 2010).

For data input to the passenger models, most states have avoided data collection, relying instead on secondary data sources such as the Census Transportation Planning Package, NHTS, and MPO databases. Other common data sources providing input for passenger models are the American Travel Survey, in-house traffic counts, and the NHTS add-on purchased externally.

There has been a trend of shifting towards dynamic traffic assignment (DTA) models for the assignment step; however, the scale of implementation and the advanced data collection required for scenario analysis and calibration are the largest challenges this approach faces. A recent panel discussion report conducted under the Travel Model Improvement Program by the FHWA indicated that Virginia, Arizona, and California were interested in having DTA-based models (Lemp 2015; FHWA 2014). The Arizona DOT has considered a multi-resolution approach to incorporate the details of MPO models.

2.2.3 Key trends in freight components of statewide models

Freight transportation plays a key role in the development of statewide models. The two types of freight modeling in statewide models can be either commodity based or direct vehicle based. The latest statewide models have moved away from truck-based freight modeling mostly because the commodity-based freight models make better use of the available freight databases (Horowitz, 2005).

Most of the current freight models tend to avoid using mathematical expressions for determining mode choice within freight. Only three states had reported using mode split expressions for determining freight split, while the others continue to rely on historical data to determine the fixed percentage splits (Horowitz, 2005).

Common data sources used in freight models include the Vehicle Inventory and Use Survey, freight data vendors, the Commodity Flow Survey, and the Rail Carload Waybill Sample. Some states have relied on external cordon forecasts to develop their OD matrices.

Following are a few examples of freight modeling characteristics from three statewide models:

- **Florida** utilizes a separate freight model to predict trip tables for heavy trucks, medium trucks, and light trucks after categorizing them into freight and non-freight trip purposes. The assignment module is combined with the passenger cars

- **Virginia** uses a separate freight model as well; truck OD tables are derived from Reebie's TRANSEARCH database, and from systematic adjustments based on truck counts. It also implements two different forecasting models referred to as the micro and macro model. The macro model provides information on trips passing through Virginia having one end in Virginia, whereas the micro level operates within Virginia at the level of census tracts. For its four-step modeling, the Virginia statewide model uses Fratar factoring to get the trip table from the database, and uses a fixed share mode split between different types of trucks. A multiclass assignment is used to combine passenger cars and trucks.

- **Wisconsin** uses a four-step freight model with commodity flow data for 25 commodities. It considers all freight modes, including truck traffic, rail traffic, air freight, and water freight. Tons-to-trucks payload factors, determined from Wisconsin's Vehicle Inventory and Use Survey data, were used to convert commodity flows to truck movements. The model is validated using the Transearch county-to-county flow data.

2.2.4 Current practices of model integration across US

Several reports have highlighted the need for proper integration between the statewide and the MPO models. Proussaloglou (2004) states that the performance of MPO models can be enhanced by using the external forecasts from the statewide models. The NCHRP 338 Synthesis report (Horowitz, 2005) mentions the lack of integration between MPO and statewide models in the US, which still needs to be addressed. This integration has to be maintained two ways: the states helping the MPOs develop a uniform model consistent with the statewide objectives, and the MPOs providing consistent feedback to the states for accurate modeling.

The current practices across US can be categorized into two ways: integrating statewide model integration into MPO models and integrating MPO models into statewide models.

TRB Special Report No. 288 mentions the ways 30 states have played roles in developing or assisting in development of the MPO models. Figure 2 illustrates this interaction for three different groups of MPOs based on population size. The role played by the states in the MPO models falls in four categories:

- The state develops models and makes forecasts for the MPO;
- The state develops models, but the MPO makes forecasts;
- The MPO develops models, and the state provides technical assistance; or
- The MPO develops models and makes forecasts without state technical assistance.

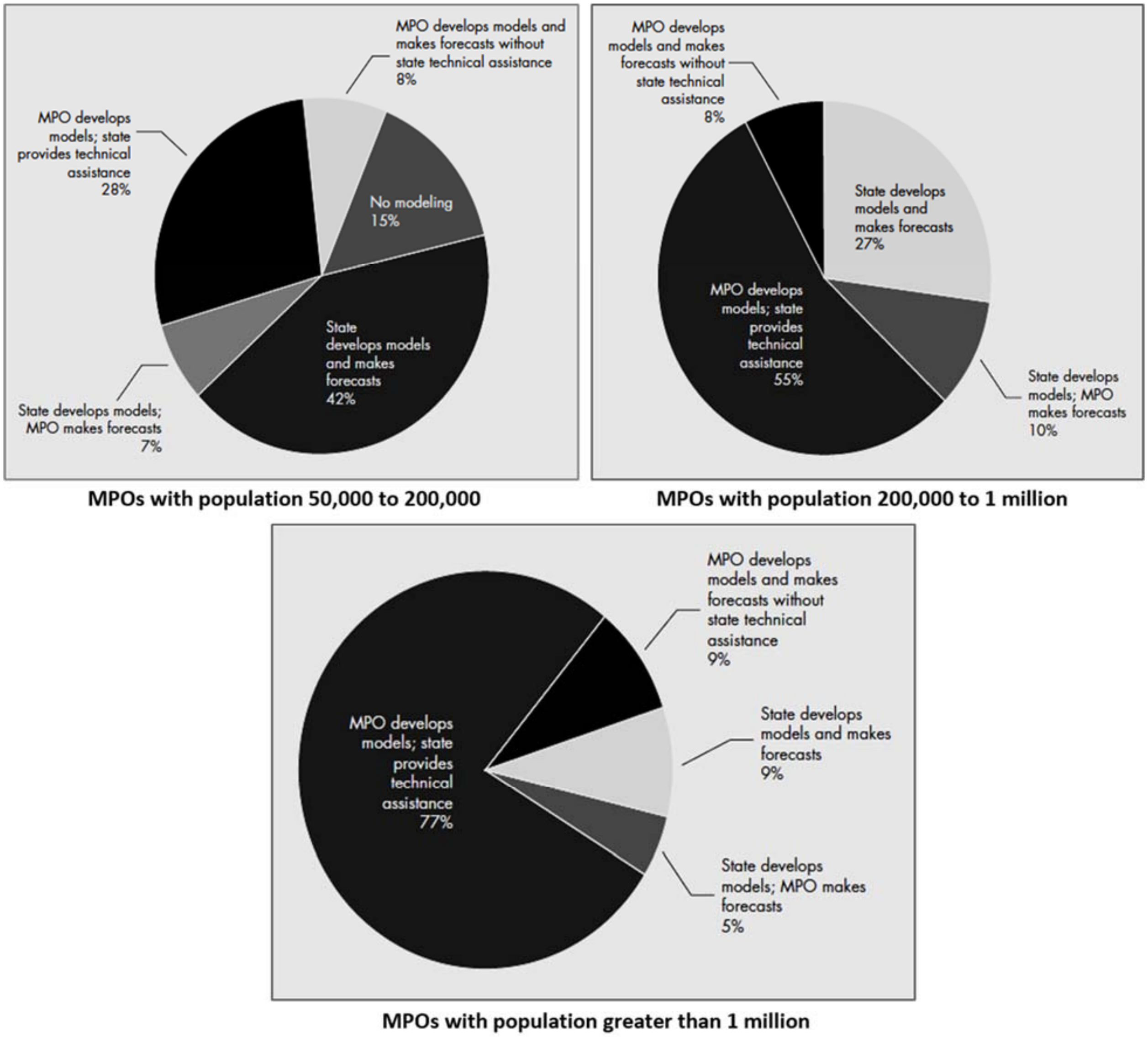

Figure 2 Involvement of states in making the MPO models (TRB SR288)

Smaller MPOs get more support from the states in developing their models. For larger MPOs, most states only provide technical assistance. The types of technical assistance provided by the statewide model range from providing the data-sources needed as inputs to developing the model, to providing the external-to-external trip forecasts for the MPO to capture external trips through their region. Also, the sensitivity analysis performed for the statewide model results are useful in improving the reliability of the MPO model forecasts (Cambridge Systematics 2010).

The key recommendation made by the TRB special report (TRB 2007) is that MPO models should be developed in coordination with the statewide models. The report also highlights that state DOTs should help MPOs in evaluating their socio-economic forecasts, which is also important in performing sensitivity analysis, but lacking in most current MPO models.

Currently, statewide models integrate MPO models in two general ways:

- *Stitching MPO models*: States like South Carolina, New Jersey, and New Hampshire use the MPO models spread across the states, and combine their models to perform statewide planning or investment analysis
- *Aggregating MPO models*: Some models base their zone systems and network on MPO models, although in a simplified manner. This involves aggregation of the zones in MPO models to be used in the statewide model. Giaimo and Schiffer (2005) highlight that the majority of the participating states in their study used aggregation of urban zones to develop zones in statewide models

Some states have considered these unique ways of using MPO models in the statewide model:

- *Excluding intra-urban trips:* Some statewide models have benefited from not including intra-urban trips in their model, and have focused only on regional and rural trips to avoid the potential duplication of efforts with respect to MPO models. These include the statewide models in Louisiana and Mississippi (Cambridge Systematics 2010). The MPO models provide internal-external trips for the statewide models, and the statewide models provide MPO models with external-internal trips. This approach, however, is not effective when the mode of travel traverses all across the urban area. For example, the California high speed rail model had to include intra-urban trips to predict the accurate estimates of travel demand. Another important issue with this approach is that the accuracy of the estimates is lost in the “hard-boundary” approximations made to represent the urban traffic in the statewide model. Boyles (2012) explains the need to have soft boundaries to capture the accuracy. However, this integration provides a better estimate than having no interaction at all.
- *Borrowing smaller models:* In order to develop statewide model components, some states borrow parts of the modeling procedure from the MPOs and use them in their statewide models. The Massachusetts DOT, for example, has borrowed the mode choice model component from the Boston MPO area. Such integration techniques ensure that the modeling procedure is consistent across MPO and states; however, without the consistency of inputs and the parameters, this integration is still incomplete.

There is often an overlap with the estimates made by both MPO and statewide models for the common regions. Statewide models provide independent estimate of traffic within urban areas, but the results from MPO models are given a preference in case of disagreement (Giaimo and Schiffer, 2005). The Cambridge Systematics report (2010) highlights three recommendations on possible comparative assessments to improve the statewide model predictions, and one of them includes comparing the link flows between statewide and MPO models at the study area boundaries and along the isolated network links, such as bridges or mountain passes.

2.3 Summary

Statewide models have undergone heavy development in the last decade. They are being developed and used in 40 states and serve multiple purposes, such as intercity corridor planning, statewide system planning, and bypass studies. The four-step planning model is one of the most widely used travel demand models. Although more advanced models are available, such as the activity-based models that take into account certain household and individual restraints and trip-chaining patterns, they are not common in the statewide planning level.

Generally, statewide models and MPO models are complementary: while the MPO models usually account for shorter distance trips, statewide models can be used to model longer distance trips as well as freight movement. Statewide models account for planning at the larger scale, and tend to incorporate MPO models in either of two ways: a) the stitch approach, where the MPO models are "stitched" together to form the statewide model; and (b) the aggregation approach in which the network and demand of the MPO model is aggregately represented in the statewide model.

The passenger travel components of statewide models usually follow the MPO models in structure, relying heavily on the traditional four-step model with segregated trip purposes. Some states, like Oregon and Ohio, have shifted to using integrated land use and economic activity model along with the four-step model. These shifts are governed by the purposes for which the statewide models are used. The freight component of statewide models is usually performed in one of two ways: commodity based or direct vehicle based. More than three-fourths of the states with statewide models incorporate freight modeling using the commodity-based approach as it makes accurate use of the available databases.

The methodology of integrating statewide and the MPO models has been another focus of this report. Given the difficulties of integrating the two planning levels, efforts have been put into the development of multi-resolution modeling. This consists of a unifying framework under which different parts of a system are described at different levels of details. This approach is a trade-off between the model accuracy and complexity. In it, urban areas are represented in a simple and easy-to-set-up fashion. Currently, a majority of US states rely on aggregation-based approaches to incorporate MPO models within the statewide model.

It is widely recommended that statewide and MPO models be developed in a coordinated fashion, under the cooperation of both state and MPO agencies. This coordination usually goes beyond using common data sources, as described in the remainder of this report.

Chapter 3. Quantifying Inconsistencies between the Models

This project defined three different categories of consistency measures: consistency in network, consistency in inputs, and consistency in outputs. The consistency measures were chosen based on their practicality, quantitative relevance, unambiguous definition, objectivity, and continuity (as opposed to binary with a yes/no answer).

- **Network consistency**: Depending on the planning purpose and the resolution of the model, travel forecasting models may use different networks representing the same area. The network structure is mainly defined in terms of the number of traffic analysis zones (TAZs), TAZ size, number of links, and number of nodes. To measure consistency in networks, visual inspection of the networks and an analysis of the networks' topologies were proposed (average node in- and out-degree and lane miles per zone). Due to implementation difficulties with visual inspection, network topology analysis was selected as the preferred measure of consistency for the networks.
- **Input consistency**: The main inputs to a travel planning model are the data used for trip generation and calibration parameters, such as population, household size, income, employment, auto ownership, and parameters of the gravity or logit models. To measure consistency in inputs, both models' demands were compared, and the differences between them quantified.
- **Output consistency**: The outputs of a travel forecasting model include the flow assigned to different links, and subsequently, the travel time along different links, corridors, and zone-to-zone travel times. To measure consistency in output, analyses of link flow consistency, travel time consistency, and model prediction consistency were proposed. The comparison of demand and the travel time were selected as the preferred measures of consistency.

The next sections illustrate the results of the analysis of the consistency measures that was performed on a testbed comprising of the Austin metropolitan area. It compared both SAM and the regional CAMPO models.

3.1 Network consistency

To test whether the network of the statewide model is consistent with the MPO model, the following methods were used: visual inspection of the network and network topology measures.

3.1.1 Visual inspection of the network

This measure analyzes the network of the statewide model in the geographical area where the MPO model is located. The measure looks at the boundary of the TAZs and locations of nodes, links, and centroids in both the models.

The performance of the four-step transportation planning process depends heavily on how the boundary of a TAZ is defined. The four-step process, in its simpler form as used within the statewide and the MPO planning models, assumes that the demand from (or to) a particular zone originates (or terminates) at the centroid of the TAZ. Baass (1980) highlights several criteria to be kept in mind while determining the boundaries of the TAZs, among which the primary one “achieves a maximum of homogeneity inside the newly created zones.” The boundaries of TAZs determine how the demand is aggregated and thus play a crucial role in how the model results are used in planning and prioritizing different transportation projects.

The statewide model TAZs are larger in size than the MPO model TAZs because of the aggregation made to simplify the model. A consistent system of models is, therefore, one where the boundaries of the TAZs in the statewide and the MPO model match with each other. This match ensures that both models have used similar criteria for aggregating the demand and ensuring homogeneity within different zones.

Visual inspection of the overlap of the TAZs in both the models can be performed using any GIS-based software. Figure 3 shows the similar analysis done for the SAM model where the TAZ boundary in the CAMPO area is compared with that of the SAM model. The inspection shows that since the boundaries more or less match, the network criteria for the consistency is satisfied. Similar analysis can be performed by comparing the geographical location of the links used in both the models.

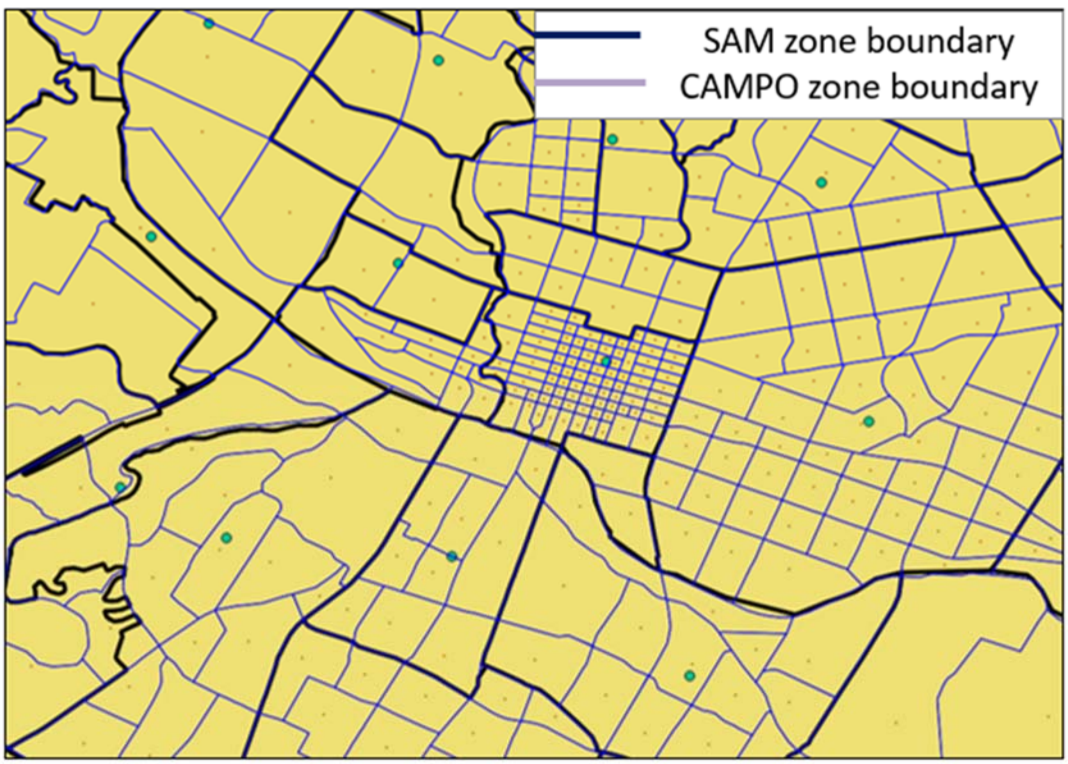

Figure 3 Visual inspection of TAZ boundaries for the SAM and the CAMPO model

However, the visual inspection technique suffers from the primary disadvantage that it is hard to quantify the level of mismatch between the boundaries. Hence, this consistency measure isn’t a practical approach for large-scale networks where the mismatch may extend to a larger scale and in different geographical locations where the visual inspection is hard to perform.

The direct comparison of both networks also proved to be extremely difficult, mostly because of the difference in complexity of the two networks. Figure 4 displays the area close to the intersection of Loop 1 with Lake Austin Boulevard, West 5th Street, and West Cesar Chavez Street. The difference in detail is quite evident: while the CAMPO model contains all the different possible turns and is, in general, much more complex and detailed, SAM's network is drastically simplified and only uses about ten links to represent the same connections.

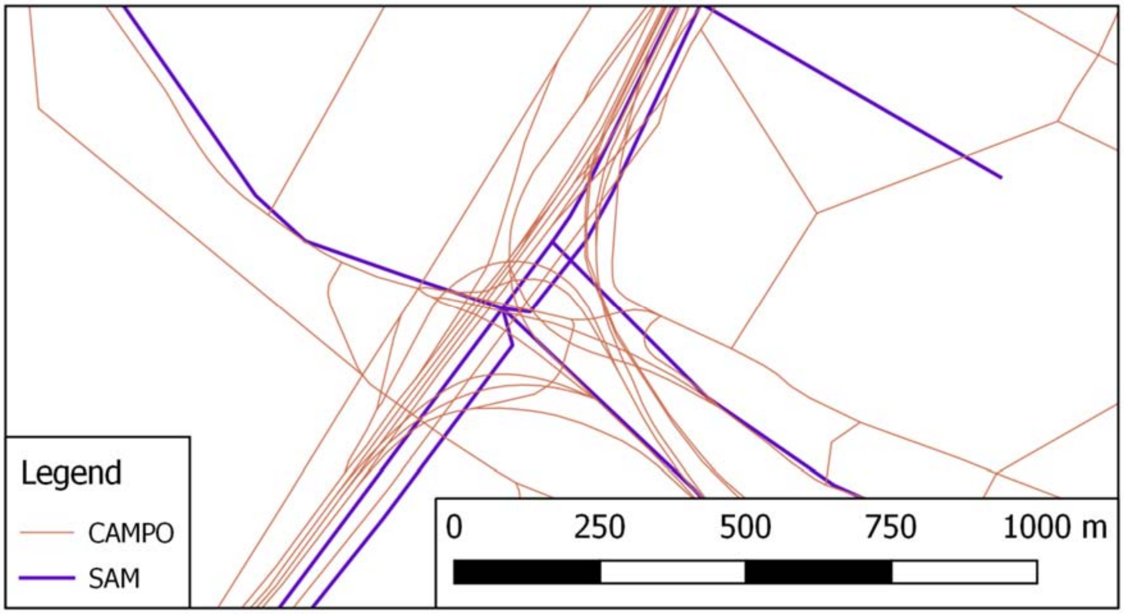

Figure 4 Complexity difference between SAM and CAMPO

The difference in detail also makes it impossible to identify pairings of the links between the networks. In other words, it is not possible to automatically point out which links from CAMPO's model are represented by each link in SAM. This may, in some instances, be done manually, but extending this operation to the whole network (or even to just the test bed) would be impractical.

3.1.2 Network topology measures

Topology of a network defines how the connection between different elements of a network is established. The elements of a transportation network include nodes, links, TAZs, centroid, centroid connectors, etc. Different topology measures can be established and compared across both the statewide and the MPO models to test the consistency of the network. The following measures are defined for purposes of this study:

- *Average node in- and out-degree*: The in-degree of a node in a network is defined as the number of incoming links for a node. The out-degree is analogous, but considers outgoing links for a node. This measure compares the average in- and out-degrees of the nodes in the statewide and the MPO model.
- *Total lane miles in a zone:* This measure sums the lane miles for all the links contained within a zone in a model, and compares it across the statewide and the MPO model for same geographical location of the zone.
- *Total capacity of the links in a zone:* This measure computes the total cumulative capacity of all the links contained within a zone in a model, and compares it across the statewide and the MPO model for same geographical location of the zone

3.1.2.1 In- and out-degree of nodes

For this part, we extracted the topology of SAM and CAMPO networks, and used it to evaluate the network consistency by measuring the out-degree (number of links originating from a node) and in-degree (number of links ending at a node) of nodes. Figure 5 shows the histogram of out-degrees. The horizontal axis indicates the out-degree value and the vertical axis is the percentage of nodes with each out-degree number for both the CAMPO and SAM networks. Figure 6 plots the same statistics as plotted in Figure 5, but for in-degree. Even though the out-degree values are similar, the in-degree values show a more significant difference. From Figure 6, one can see that in-degree 1 is dominant in the SAM network, while in CAMPO the highest percentage belongs to in-degree 2. This was expected: the SAM network is an aggregated version of CAMPO network in which the minor roads are removed and just the major roadways are modeled. This will decrease the degree of nodes.

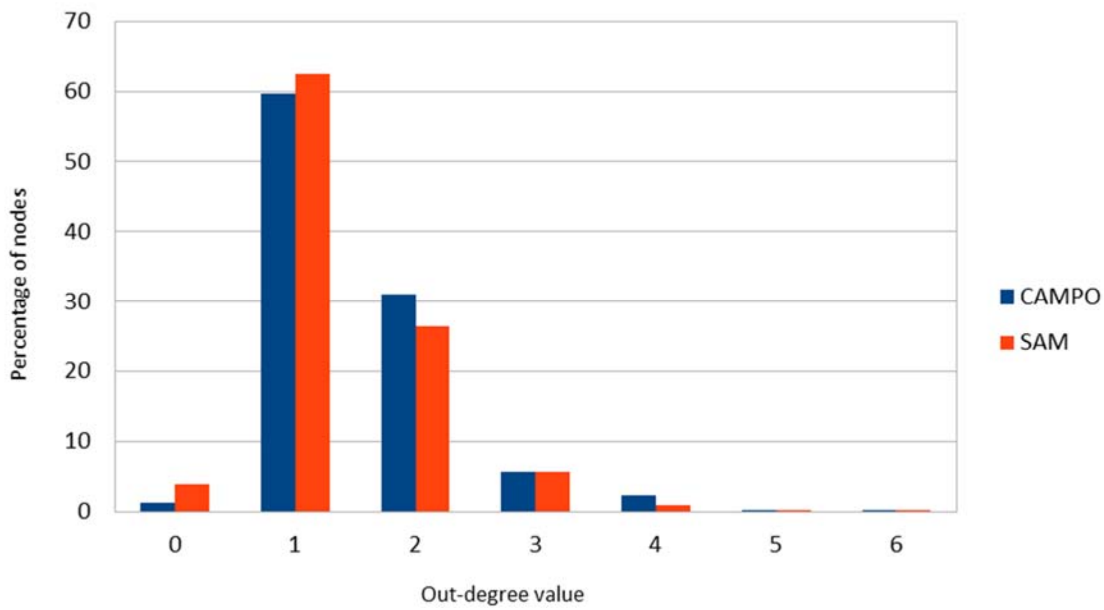

Figure 5 Histogram of node out-degree values

The average degree across the network, computed by summing up all node degrees and dividing it by the number of nodes, for SAM and CAMPO networks are 1.484 and 1.378, respectively. This number shows that, on average, the networks have some consistency in node degrees. This is consistent with the results described in Figure 5 and Figure 6.

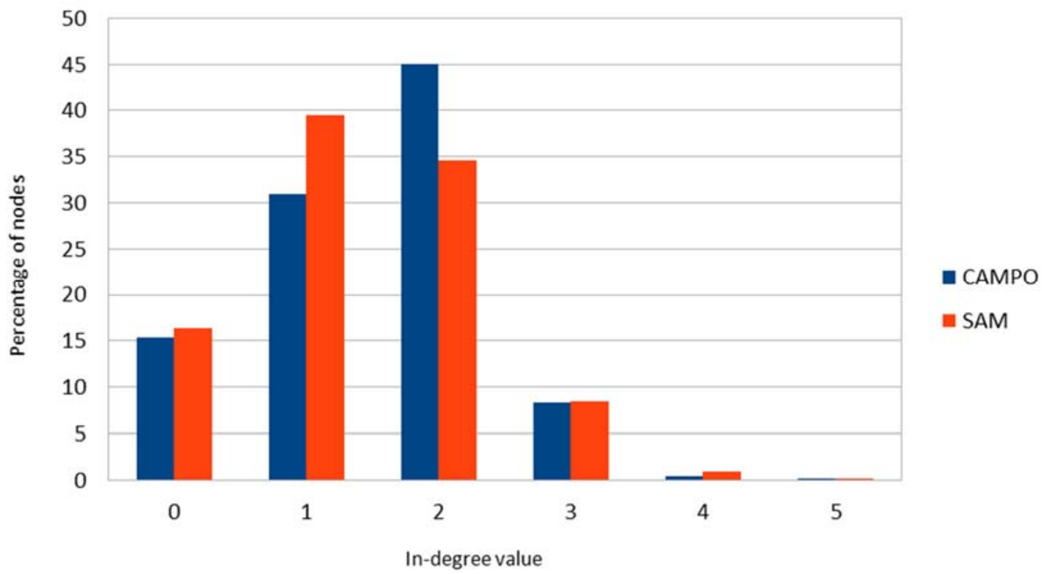

Figure 6 Histogram of node out-degree values

3.1.2.2 Lane-miles and road capacity by zone

The advantage of these measures is that they are easy to quantify and can be easily extracted from the network data available with the models. One way to measure network consistency is by comparing link lengths within each zone. The concept is that since both models represent the same real-world transportation network, they might have similar link lengths within the same areas, especially if the less-detailed network was designed by aggregating links from the more detailed network.

Figure 7 and Table 1 provide an example of how the calculations were performed.

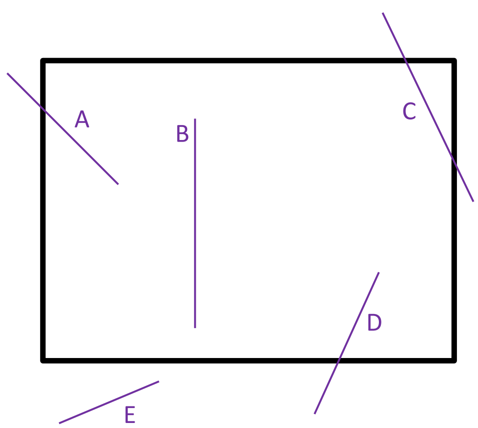

Figure 7 Example – links and TAZ

Table 1 Example – link characteristics

Link	Length	Length within TAZ	Lanes	Capacity
A	5	3	2	6000
B	10	10	2	8000
C	10	5	2	10000
D	5	3	3	6000
E	4	0	3	9000

For each zone, we calculated the total link lengths in three different ways:

- Simple link length within each zone, not accounting for number of lanes or capacity;
- Link length within each zone considering the number of lanes; and

- Link length within each zone considering number of lanes and weighted by capacity.

The equations for the three methods used are:

$$SLL = \sum LLW_i \qquad LLL = \sum LLW_i \cdot NL_i \qquad LLC = \frac{\sum LLW_i \cdot NL_i \cdot C_i}{\sum C_i}$$

These equations use the following notation:

SLL : Simple link length
LLW_i : Length of link i within the analyzed zone
LLL : Link length with lanes
NL_i : Number of lanes for link i
LLC : Link length with lanes and capacity
C_i : Capacity of link i

For links with unknown capacity, the default value considered was 3000 vehicles per hour per lane. Furthermore, for links with an unknown number of lanes, the default value considered was 1.

Therefore, in this example, we would have:

$$SLL = 3 + 10 + 5 + 3 = 21$$
$$LLL = 3 \cdot 2 + 10 \cdot 2 + 5 \cdot 2 + 3 \cdot 3 = 6 + 20 + 10 + 9 = 45$$
$$LLC = \frac{6 \cdot 6000 + 20 \cdot 8000 + 10 \cdot 8000 + 9 \cdot 6000}{6000 + 8000 + 8000 + 6000} = 11.67$$

These values were calculated for the CAMPO TAZs and then aggregated into the larger SAM TAZs. The values for SAM were also calculated and then compared to CAMPO's aggregated results. Figure 8, Figure 9, and Figure 10 illustrate the dispersions of the errors for each of these three measures. The errors were calculated with respect to the values in SAM.

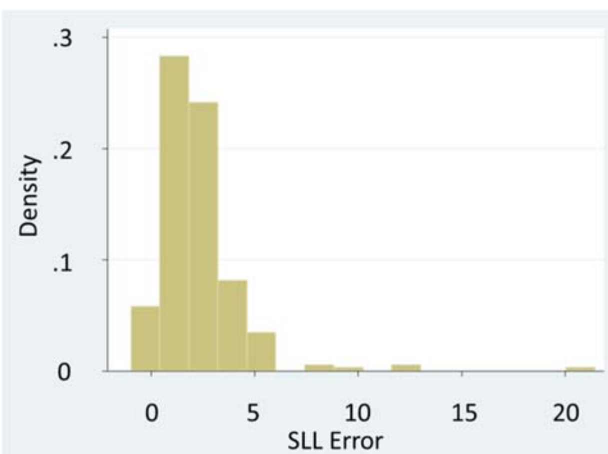

Figure 8 Errors in SLL

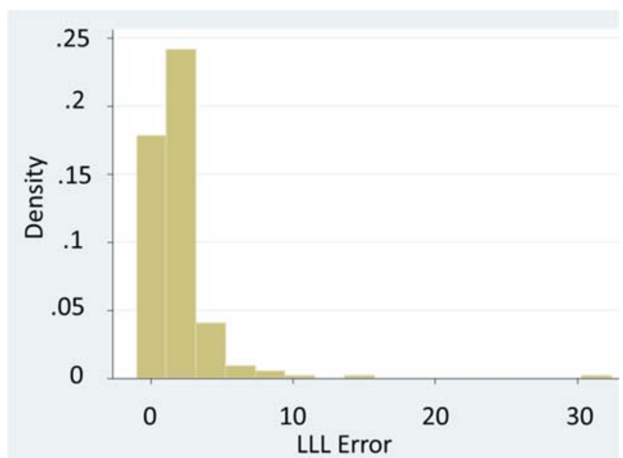

Figure 9 Errors in LLL

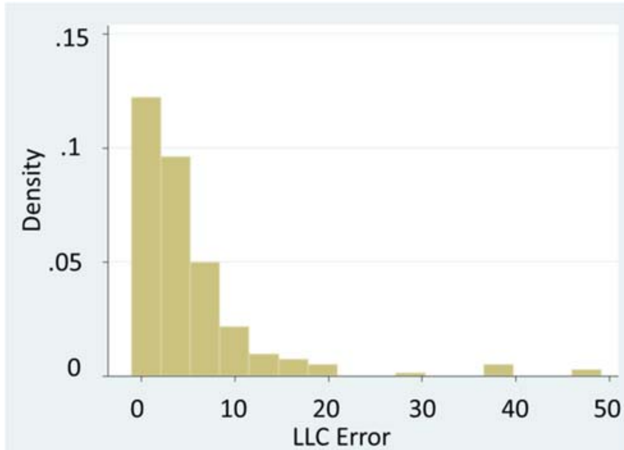

Figure 10 Errors in LLC

The three figures show us that errors larger than 100% are extremely common. The average errors for SLL, LLL, and LLC are 226%, 189%, and 662%, respectively. This is a strong indication that there is very little consistency between both networks being analyzed with respect to the link lengths.

3.2 Input consistency

Demand tables were used to evaluate the consistency in inputs between the SAM and the CAMPO model. To this end, the demand in CAMPO was aggregated to match the TAZ level used in SAM. Assume that TAZ r in SAM represents two TAZs A and B in the CAMPO model, and that TAZs C and D in CAMPO belong to the aggregated TAZ s in SAM. These associations in the actual networks can be obtained using any GIS software. Figure 11 shows this configuration.

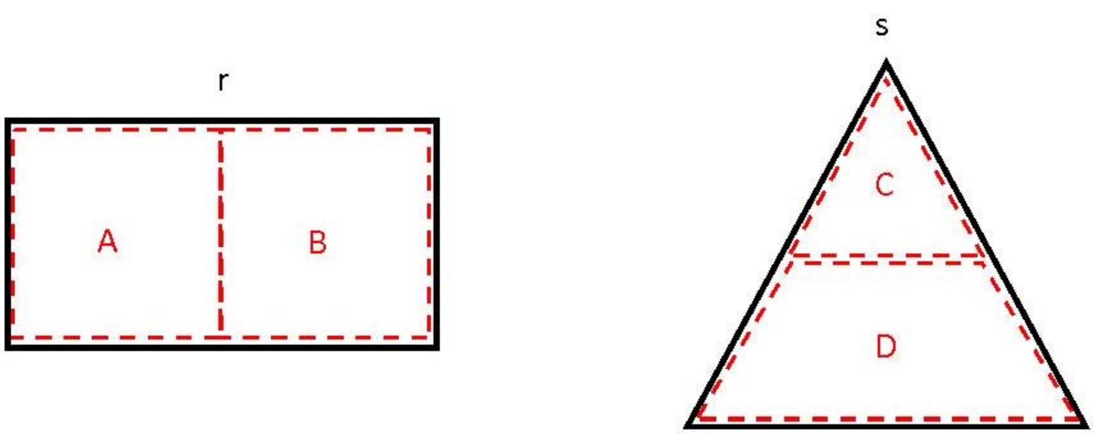

Figure 11 Aggregated SAM TAZs r and s (solid black) and their associated TAZs in CAMPO (dashed red)

Let D_{rs}^{S} denote the total trips between zones r and s in SAM. Furthermore, let D_{rs}^{C} denote the demand between the same two zones r and s computed by aggregating the CAMPO demand. The value of D_{rs}^{C} is given by:

$$D_{rs}^C = d_{AC} + d_{AD} + d_{BC} + d_{BD}$$

where d_{xy} refers to demand between zones x and y in CMAPO model. This process is repeated for all SAM TAZs. The percentage error in demand for each TAZ $r - s$ in SAM, with respect to CAMPO demand, is given by:

$$e_{rs} = \frac{|D_{rs}^C - D_{rs}^S|}{D_{rs}^C}$$

where $|.|$ is the absolute value operator. Note that if $D_{rs}^C = 0$, then an error of 100 is assumed, i.e., $e_{rs} = 1$.

Figure 12 shows the histogram of the errors, where the horizontal axis indicates the error and the vertical axis is the percentage of OD pairs falling into each category.

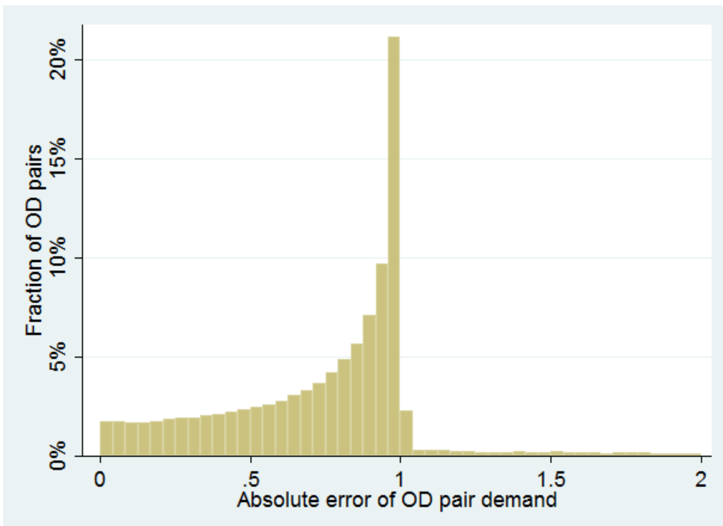

Figure 12 Distribution of absolute errors of OD pair demand[1]

The errors were scattered, with 4.1% of OD pairs presenting absolute errors between 100% and 200%, and 11.5% of them being 200% or larger. The absolute percentage error was on average 9,020% and had a median of 87.81%. The total difference was 871,700 minutes. This is substantial evidence of significant input inconsistency between both models with respect to the total demand in the Austin area.

3.3 Output consistency

As observed from the network-level consistency results, identifying common links between the SAM and the CAMPO network was challenging, and thus comparison of link flows wasn't used to determine the output consistency.

Zone-to-zone travel time was used as a measure for output consistency. Similar to what was performed for OD pair demands, the travel times between zones in SAM were compared with the aggregated travel times between the zones in the CAMPO model contained within the SAM zones.

For each SAM zone S, let Z_{CAMPO}^S be the set of all CAMPO zones contained within this S. The aggregated CAMPO travel time between two zones r and s is the average of travel time

[1] This figure does not contain errors larger than 200% for better visualization.

between each pair of CAMPO zones contained within Z^{r}_{CAMPO} and Z^{s}_{CAMPO}. For example, for the zones shown in Figure 11, the aggregated CAMPO travel time (τ^{C}_{rs}) between two zones r and s, is given by:

$$\tau^{C}_{rs} = median(\tau^{AC}_{CAMPO}, \tau^{AD}_{CAMPO}, \tau^{BC}_{CAMPO}, \tau^{BD}_{CAMPO})$$

where τ^{AC}_{CAMPO} is the travel time between CAMPO origin zone A to CAMPO destination zone C. The SAM travel time between two zones r and s is given by τ^{S}_{rs}. The absolute error between the travel times and the percent error were then defined as below, where the percent error is evaluated keeping CAMPO model travel time as the base.

$$Absolute\ error = |\tau^{S}_{rs} - \tau^{C}_{rs}|$$

$$Percent\ error = \frac{|\tau^{S}_{rs} - \tau^{C}_{rs}|}{\tau^{C}_{rs}} * 100$$

This process provided us with the travel time between each pair of SAM zone and corresponding aggregated travel time from CAMPO network. The absolute and the percent difference between the travel times (using CAMPO travel time as the base) were then calculated for each OD pair. Figure 13, Figure 14, and Figure 15 respectively show the distribution of the error, the average absolute error, and the average percent error further aggregated with respect to the free-flow travel time between SAM zones. The free-flow travel time gives an approximate idea of the distance between two zones.

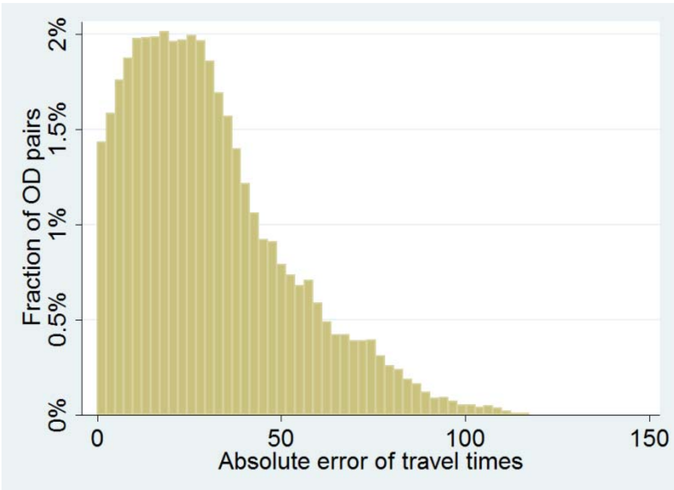

Figure 13 Distribution of absolute errors of OD pair travel times

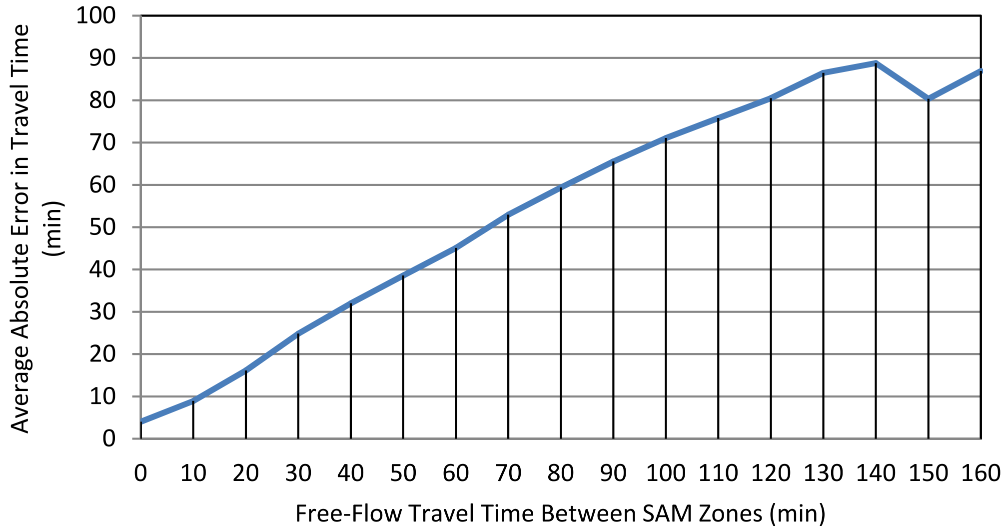

Figure 14 Average absolute error in travel time in minutes between the SAM and the CAMPO model with increasing free-flow travel time between SAM zones

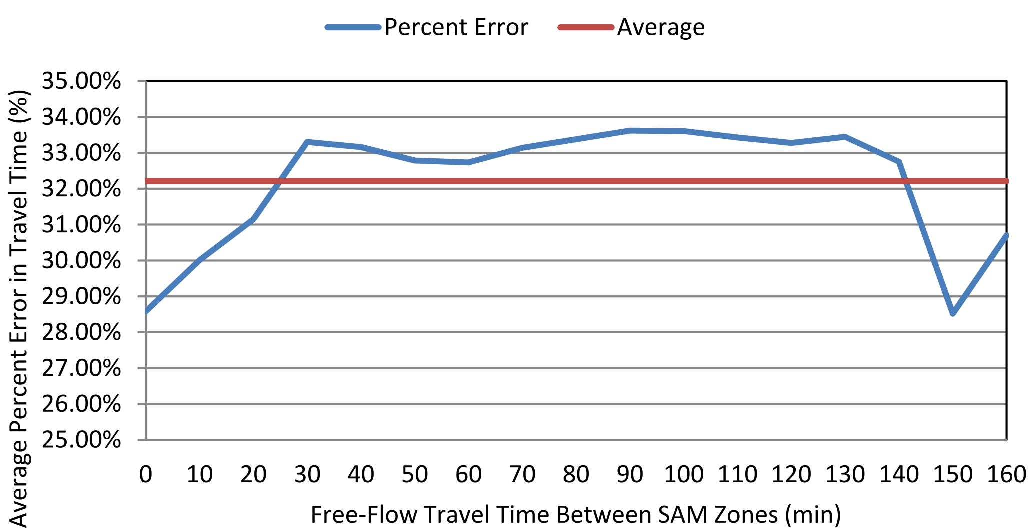

Figure 15 Average percent error in travel time between the SAM and the CAMPO model with increasing free-flow travel time between SAM zones

The analysis indicates that the total difference in travel times is 2,239,211.92 minutes and there is an average absolute percentage error of 32.93% in travel time over all OD pairs.

The absolute error between travel time predictions increases as the distance between SAM zones increases. For example, for two SAM zones separated by 160 minutes at free-flow, the average absolute error between SAM and the CAMPO model is 90 minutes, while for two SAM zones separated by 20 minutes at free-flow, the average absolute error is 10 minutes. When the error is presented as a percentage of the CAMPO model travel time, it is observed to be more or less constant. The primary summary statistic is thus the average percent error between the travel time predicted by SAM and CAMPO models and is found to be 32.21% for the selected testbed.

Figure 16 shows the plot of the percent error in travel time for a particular origin zone (20685), located in the center of the CAMPO area, to all destination zones. The plot indicates that some geographical locations in the SAM model have higher percentage error in travel time as compared to the CAMPO model. Such plots can provide visual information about the areas where the models are more inconsistent than the other locations.

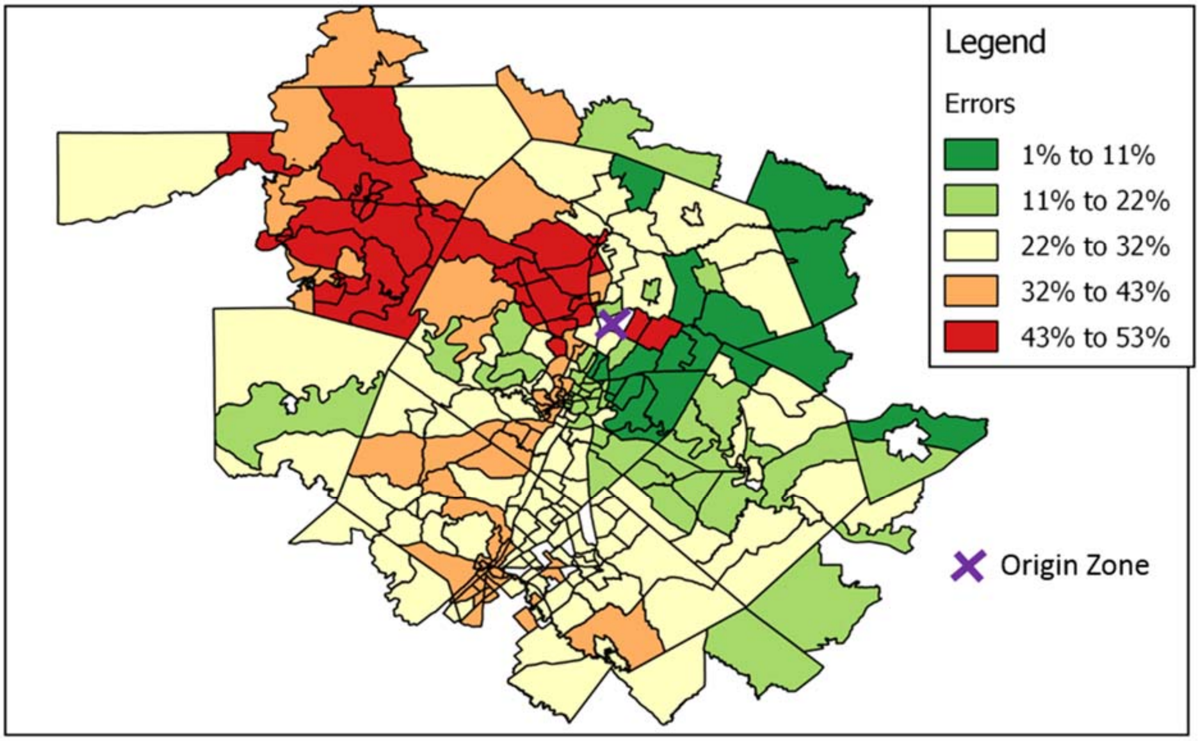

Figure 16 Percentage error in travel times predicted by SAM relative to the CAMPO model for the origin zone located in center of the region to each of the destination zone

The total system travel time predicted by both the models was also calculated. The total vehicle-hours traveled were 680,000 minutes for the CAMPO model, and 370,000 minutes for the same region within SAM, and thus SAM underestimated the travel times in the Austin area by approximately 45.66%. These results indicate that SAM and the CAMPO model are slightly inconsistent with respect to the output travel time measure.

3.4 Inconsistencies within SAM

Overcoming the inconsistency between SAM and the MPO models requires making changes to the demand and travel time values in SAM. However, changing these values can create inconsistencies within SAM itself. These inconsistencies arise when either the adjusted demand or the adjusted travel time between an OD pair does not match the demand and travel time originally obtained by SAM using its internal trip distribution and trip assignment steps.

Some of the proposed methods in the next section do not require running SAM again after adjusting the demand and travel time values. The consistency measures proposed in this section quantify the mismatch between the demand and/or travel time obtained by SAM and those obtained using the corrections provided by the MPO model's results.

Let d_{rs} and tt_{rs} be the demand and travel time, respectively, between OD pair (r, s) obtained through SAM's standard four-step procedure. Let $d_{rs}^{(adjusted)}$ and $tt_{rs}^{(adjusted)}$ be the adjusted demand and adjusted travel time (respectively) between OD pair (r, s) calculated using one of the first three methods proposed in Chapter 4. Finally, let $tt_{rs}^{(rerun)}$ be the travel time between OD pair (r, s) obtained by feeding an updated demand matrix containing $d_{rs}^{(adjusted)}$ for all OD pairs (r, s) within the MPO region.

The demand inconsistency within SAM can be measured by determining the difference between d_{rs} and $d_{rs}^{(adjusted)}$ and calculating the mean absolute percent error and the total absolute error over all OD pairs.

When only the demand is updated, the inconsistency within SAM regarding travel times can be measured through the difference between $tt_{rs}^{(adjusted)}$ and tt_{rs}. When dealing with methods that update both demand and travel times, the travel time inconsistency within SAM can be measured through the difference between $tt_{rs}^{(adjusted)}$ and $tt_{rs}^{(rerun)}$. In both of these cases, we calculate the mean absolute percent error and the total absolute error over all OD pairs.

Even though the first three methods proposed do reduce inconsistencies between SAM and the MPO models (as is shown below), these methods for adjusting demand and travel times will, in turn, generate inconsistencies within SAM.

Chapter 4. Methods for Improving Consistency

In this chapter, we propose seven approaches that could potentially improve consistency between multiresolution network models. These approaches can be used by TxDOT to improve consistency between SAM and regional MPO models. The approaches are ordered in increasing level of effort required by TxDOT and are split into three groups. The first three methods (Sections 4.1 – 4.3) provide simple guidelines for improved analysis and do not require feeding any information back into SAM or the MPO models. The second group (Section 4.4 & 4.5) involves some interaction with either SAM and/or the MPO models. The methods in the third and last group (Section 4.6 & 4.7) are expected to provide greater benefit in terms of consistency between models because they involve a substantial remodeling of SAM.

An underlying principle in the analysis is that where models overlap, the higher-resolution model is more likely to give the better prediction. For instance, the CAMPO model is assumed to give a better reflection of Austin-area transportation than the same portion of SAM.

4.1 Simple override

The simplest method for addressing inconsistencies is to choose results from the higher-resolution model, wherever there is geographic overlap. In practice, this entails using results from the MPO model in its area of coverage, and results from SAM elsewhere in the state.

Since the MPO model will usually have smaller TAZs, an association table is required to determine the MPO TAZs contained in each of the larger SAM TAZs. Figure 17 and Table 2 illustrate this association using CAMPO as an example. In Figure 17, we can see that the CAMPO TAZs 685, 686, 688, 689, 699, and 848 belong to SAM TAZ 20576.

Given these different zone sizes, a method to aggregate the MPO model's results is required in order to compare them with the results obtained from SAM. For travel times, the aggregation used was the median, since it represents the center of the distribution and is also robust to outlying observations. For the demand, the aggregation method used was the sum.

Table 2 Association between MPO and SAM TAZs

CAMPO TAZ	SAM TAZ
1	20708
2	20709
3	20708
4	20701
5	20702
6	20698
…	…

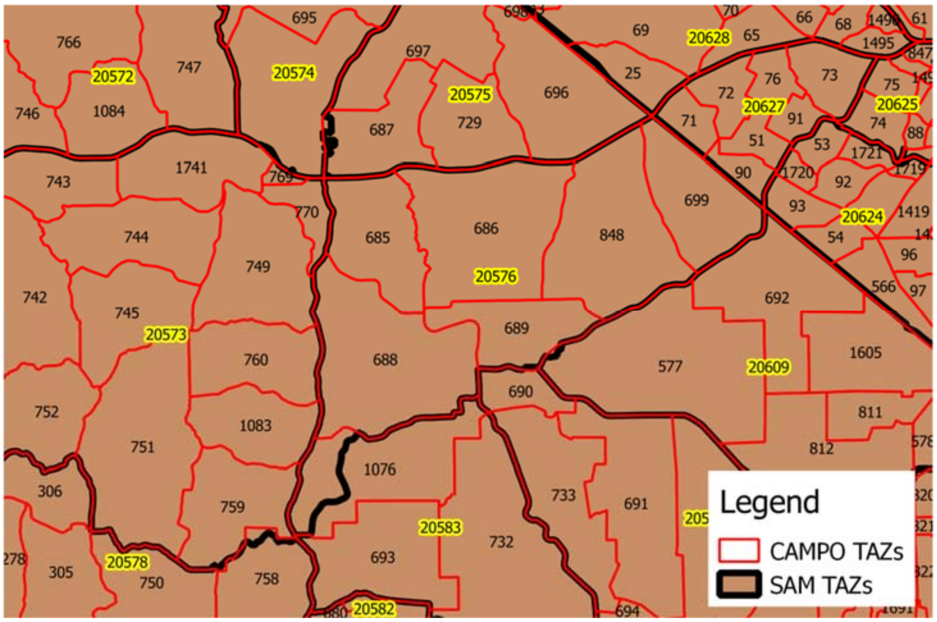

Figure 17 Association between MPO and SAM TAZs

In order to illustrate the override procedure, consider the case of OD pair demand in SAM and an MPO model. Since both models will likely have different types of demand, a conservative approach is to force consistency between the OD pair totals, but retain the distribution for each type of demand (e.g., home-based work [HBW], home-based non-work [HBNW], non-home-based [NHB]). Tables 3 and 4 illustrate this concept with an example.

Table 3 Example of OD pair demand before override procedure

Origin	Destination	SAM HBW	SAM HBNW	SAM NHB	SAM Total	MPO Total
1	2	55 (55%)	40 (40%)	5 (5%)	100	200
1	3	35 (70%)	10 (20%)	5 (10%)	50	120
2	1	5 (8%)	60 (92%)	0 (0%)	65	20
2	3	60 (60%)	10 (10%)	30 (30%)	100	500
3	1	0 (0%)	0 (0%)	0 (0%)	0	60
3	2	10 (29%)	15 (43%)	10 (29%)	35	15

Table 4 Example of OD pair demand after override procedure

Origin	Destination	SAM HBW	SAM HBNW	SAM NHB	SAM Total	MPO Total
1	2	110 (55%)	80 (40%)	10 (5%)	200	200
1	3	84 (70%)	24 (20%)	12 (10%)	120	120
2	1	2 (8%)	18 (92%)	0 (0%)	20	20
2	3	300 (60%)	50 (10%)	150 (30%)	500	500
3	1	0 (0%)	0 (0%)	0 (0%)	0	60
3	2	4 (29%)	6 (43%)	4 (29%)	15	15

Note that the distribution between the types of demand remains the same while respecting the new totals. However, this does not guarantee full consistency due to the occurrence of zeroes in SAM. This problem does not arise when dealing with OD pair travel times since the travel time will never be zero, regardless of the OD pair or the model at hand.

Of the observations, 1.7% presented errors in the demand after the simple override procedure due to the occurrence of zeroes. Aside from these cases, all other OD pairs have matching demands. Furthermore, all OD pairs presented matching travel times after the procedure.

Although the simple override method almost eliminates the input and output inconsistencies between SAM and the CAMPO model, it creates inconsistencies between SAM's demand and its own travel times. The simple override method runs both models and "picks" the results from the more disaggregate model in geographically overlapping areas and does not take into consideration the different procedures each model uses. In other words, the travel time associated with the demand in these overlapping areas are not travel times produced by SAM, rather they are simply travel times created by the CAMPO model.

In order to measure inconsistencies within SAM for this procedure, we use the method proposed in Section 3.4. For the travel times, the absolute mean percentage error is 39.65% per OD pair and the total absolute error is 31,000 hours. For the demand, the absolute mean percentage error is 399.45%[2] per OD pair and the total absolute error is 871,700 trips.

4.2 Correction factors

The objective of this method is to correct the predicted travel time from the traffic assignment step or the predicted OD demand from the trip distribution step by using a single numeric factor that updates the travel time and demand in SAM to that of the MPO model.

To correct a variable produced in SAM, we plot the variation of variables in the MPO model that are analogous to the variable of interest from SAM and fit a regression line with no intercept, which minimizes the least squared error of the prediction.

A fundamental difference between the simple override method and the correction factor method is that the former method requires running both SAM and the MPO model for all years, while the latter method only requires a single run of the MPO model where the correction factors are calculated. From this point onwards, the values from SAM can be adjusted using the same correction factors initially calculated.

4.2.1 Input correction factors

The input correction factor updates the demand between origin and destination in SAM. This factor is useful when looking at the changes in the demand matrix and is an important component of the project evaluation process. For example, consider the construction of a new link. If the agency has an estimate of the new demand between two zones (created using surveys before construction) and wants to compare it to the base demand, this factor can be applied to the base demand to report correct changes in the demand before and after the facility construction. Applying the correction factors will result in corrected demands. The travel times associated with these new demands, however, will not be readily available—running SAM with the updated demand might be required, which may or may not be desirable according to the agency's needs.

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[2] The top and bottom 20% were removed when calculating the absolute mean percentage error for the demand inconsistency within SAM.

Figure 18 plots demand data of the CAMPO model with respect to SAM. The demand data is spread widely, and it is difficult to predict CAMPO demand using SAM demand by using a single correction factor.

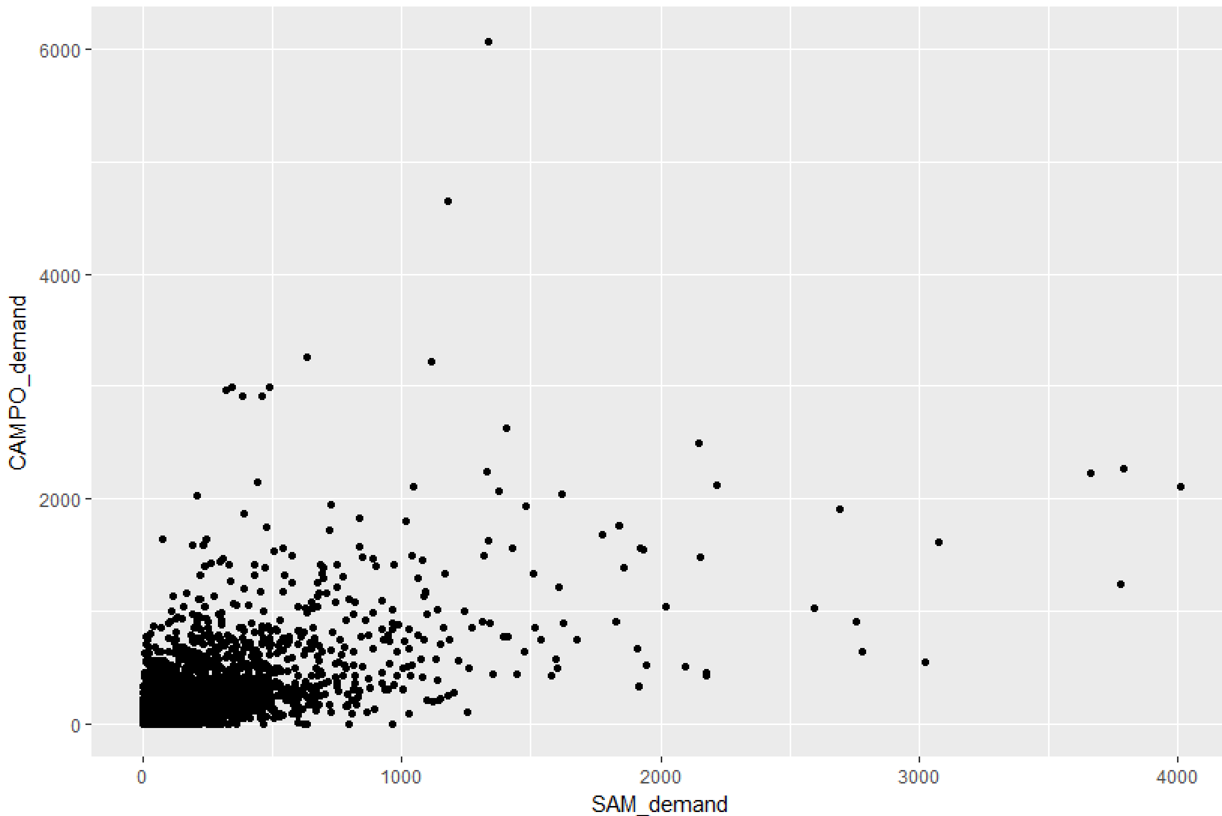


Figure 18 Variation of demand in CAMPO model with respect to SAM

Nevertheless, to quantify the approximate behavior, a line with zero-intercept is fit through the data points. The slope determined from the regression analysis is 0.7824, i.e., on average a CAMPO demand is 78.24% of the SAM demand between the same two zones. Hence, this factor can be multiplied by the SAM demand to correct it towards CAMPO model demand.

The adjusted R-squared value for the predicted correction factor is 0.4913, which does not indicate a good fit. This is because of the spread of the data. The percentage improvement in the total absolute error in demand was found to be 4.69%.

4.2.2 Output correction factors

The output correction factor updates the travel time output between an origin and a destination in SAM. This factor is useful in updating the output of planning models and in evaluating projects based on the corrected measures.

Figure 19 shows the distribution of CAMPO travel time to that of SAM travel time. Compared to the demand data distribution, the travel time data has a much lower spread and follows a uniform trend.

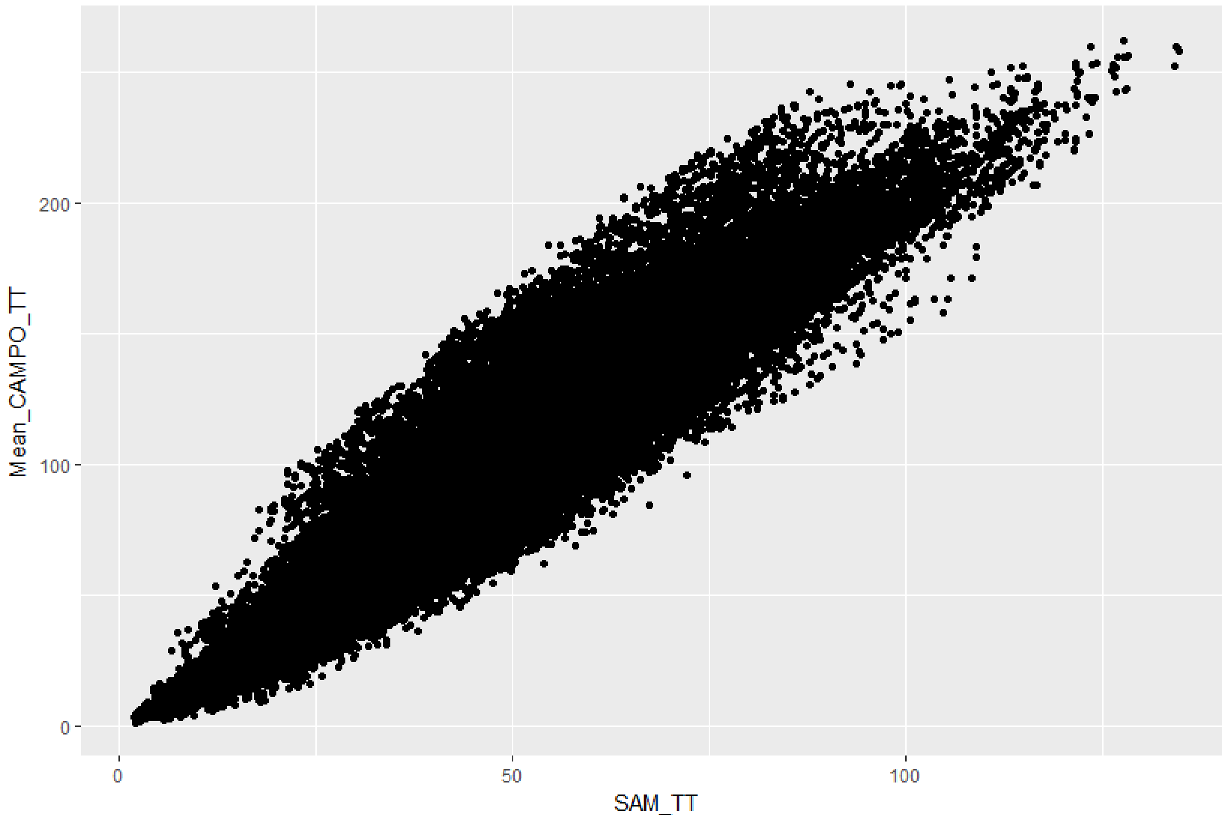


Figure 19 Variation of travel time in CAMPO model with respect to SAM

To quantify the correction factor, a line with zero-intercept was fit. The slope determined from the regression analysis is 1.54, i.e., on an average CAMPO travel time is 1.54 times greater than SAM travel time between any two zones. The adjusted R-squared value for the predicted correction factor is 0.981, which indicates a very good fit. The total absolute error in travel time, after applying correction factors to all zones within the CAMPO region lead to a 66.78% reduction in total travel time error. Thus, this correction factor can be used to improve the travel time predicted by SAM for evaluating future projects.

The correction factor method is better than the simple override method because it calculates a single factor to update SAM demand and travel time, which can then be applied to correct SAM demand and travel time towards that of the MPO. Thus, a project requiring an evaluation a few years into the future will not require an updated run of the MPO model to override SAM demand and travel time for the future year; instead, the correction factor obtained from the previous runs can be used to model this impact. The disadvantage of the correction factor method is that it can cause internal inconsistency within the SAM model, where the updated demand and travel time values may not satisfy the trip distribution and traffic-assignment equilibrium criteria. As described earlier, this inconsistency is generated because the SAM model is not re-run from scratch using these updated values.

The inconsistencies within SAM this method generated represent 222,839.41 trips and 2,643,749.89 minutes. The mean percentage errors within SAM were 21.76% and 69.53% (for demand and travel time, respectively.)

4.3 Correction regressions

The objective of this method is to develop regression equations that can predict changes in the input/output of SAM with respect to parameters of SAM itself (i.e., without relying on the demand and travel time information from the MPO model). Similar to correction factors, we can develop separate regression equations for improving the inputs and the outputs.

The regression models for improving OD pair travel time predictions generated by SAM and the CAMPO model can be a function of different input parameters. Two types of regression equations are developed, which vary in the amount of input required for each of them: single input regression and multi-input regression

4.3.1 Single-input regression model

This model carries a simpler framework. Similar to the correction factor method, the input used for this regression is the travel time or demand from SAM. The hypothesis is that the error in the travel times or demand can be explained just by looking at its magnitude. This hypothesis is logical for the travel time case because for the CAMPO testbed, SAM was consistently predicting lower travel times and the error in the travel time depended on the magnitude of the observed SAM travel time. For the demand case, no apparent correlation was found within SAM and CAMPO demand, yet the regression model was built. The results shed more insight into this lack of correlation.

The regression equations are developed by fitting a linear regression model between the predicted values from the CAMPO model and SAM model. The CAMPO model's predictions are considered the true predictions that SAM should have reached. There are 72,630 OD pairs in SAM that overlap with the CAMPO model. The travel time and demand between each OD pair was made available from SAM. For the CAMPO model, the travel time and demand between those OD pairs was estimated using the aggregation methods described in Chapter 3. Of those OD pairs, 90% were randomly selected and were used to develop the regression model and the remaining 10% (7263 data points) were used to validate the model. The unit of travel time in both models is seconds while of demand is number of vehicles.

Equations 1 and 2 show the regression equation parameters for travel time and demand respectively.

Table 5 shows the statistics of residual errors evaluated after applying the obtained regression equations on the validation data, which are defined as the difference between predicted value using the regression model and the original value obtained through the CAMPO model:

$$SAM\ corrected\ travel\ time = -1.688 + 1.565 * SAM\ travel\ time \qquad (1)$$

$$SAM\ corrected\ demand = 6.176 + 0.777 * SAM\ demand \qquad (2)$$

Table 5 Single-input regression model summary

Residuals summary (travel time in seconds)				
Min	**1st quartile**	**Median**	**3rd quartile**	**Max**
-59.330	-8.050	-0.954	6.613	64.677
Coefficients				
		Estimate	Std. Error	t-value
(Intercept)		-1.688	0.118	-14.23
SAM_TT		1.566	0.002	850.36
	Adjusted R-squared		0.92	
Residuals summary (demand)				
Min	**1st quartile**	**Median**	**3rd quartile**	**Max**
-1816.9	-6.200	-6.100	-4.600	5030.1
Coefficients				
		Estimate	Std. Error	t-value
(Intercept)		6.176	0.262	23.55
SAM_demand		0.777	0.003	244.65
	Adjusted R-squared		0.48	

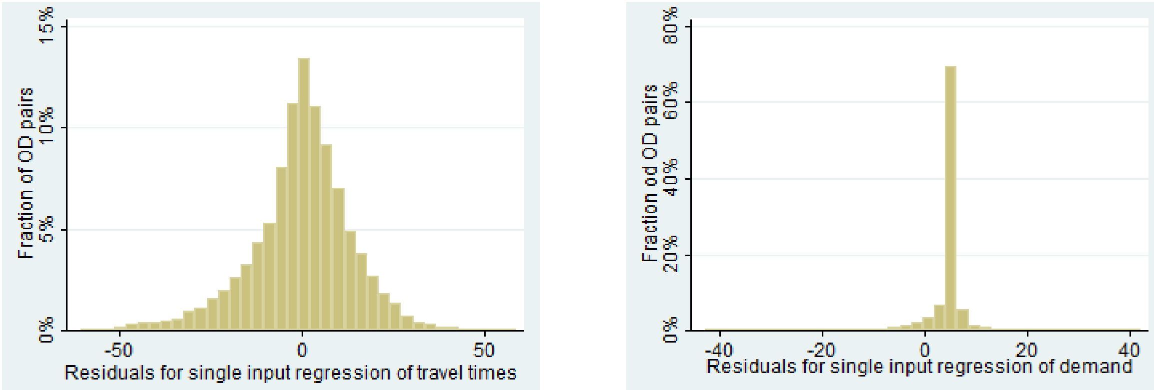
As observed, a high *t*-statistic for the SAM_TT variable indicates that it is significant in the regression model and a high value for adjusted R-squared indicates a good fit. The distribution of residuals around zero is also reasonable with the first and third quartile values being reasonably close to the median value. For the demand case, the R-squared value is low, indicating a poor fit.

The histogram plot of the residual errors of the validation dataset is shown in Figure 20. The model predictions for travel time are within a reasonable range to the true predictions of the CAMPO model ranging within an absolute difference of 50 seconds. For the demand case, the residuals have a high spike near -6.1.

The coefficients for the travel time regression indicate that corrected travel time is approximately 1.5 times the original SAM travel time, which is consistent with the travel time correction factor. The total absolute error in travel time after applying the single input regression were found to reduce to 12,300 hours, leading to a percentage improvement in consistency of 66.95%. This model can thus be used to correct travel times produced by SAM to that of the CAMPO model.

Conversely, the total absolute error in demand was found to increase to 1,080,000 trips, which is a 23.98% increase in inconsistency. This increase and the skewed distribution of residual errors in Figure 20 show that regression equations are not useful to correct SAM demand to that of CAMPO demand. This is because of the inconsistent relation between the demand of SAM and the CAMPO model. This issue may not be there for other MPOs, in which case the regression equations can be used.

Another disadvantage in using a regression model is that it requires building separate regression models for each MPO's region. The equations may not be transferable from one MPO to the other as MPOs develop their planning models separately. We next explore multi-input regression models to identify other variables that may influence the variation of travel time or demand.



(a) *(b)*

Figure 20 Single-input regression model: histogram counts of residual errors on validation data for (a) travel time and (b) demand

4.3.2 Multi-input regression model

For this model, we predict the error in travel time and demand, defined as the difference between the values from CAMPO and SAM model, as a function of different inputs characteristics of SAM. We use the following inputs (with the shorthand notation for each of them inside the parentheses):

1. Free-flow travel time between the OD (SAM_freeflowTT)
2. Total demand originating from the origin zone (origin_production)
3. Total demand destined at the destination zone (dest_attraction)
4. Total length of lanes in miles weighted by capacity of the link for all links inside the origin zone (origin_lane_miles)
5. Total length of lanes in miles weighted by capacity of the link for all links inside the destination zone (dest_lane_miles)
6. An indicator variable indicating if either origin or destination zone is at the boundary. If yes, then the variable takes the value 1, else 0 (is_boundary)

The variables were chosen because of the following observations:

1. As the distance between SAM zones increases, the difference between travel times produced by SAM and the CAMPO model increased. Thus, free-flow travel time was chosen as a proxy variable for the distance between the zones.
2. The errors in travel time and demand were more pronounced if the origin or destination nodes were located at the city centers. Thus, the total number of trips originating and terminating in each zone was used.
3. The models displayed some counter-intuitive behaviors. There were OD pairs where SAM predicted higher demand levels than the CAMPO model, but produced lower travel times. This behavior was attributed to the error in network aggregation. Thus, to quantify this difference in network aggregation, we included lane-miles as the network property for both the origin and the destination zone in the regression model.
4. We also used an indicator variable for the boundary location of the CAMPO model's region to account for differences in network or demand aggregation at the boundary of CAMPO model.

The results in this section consider all six variables for the regression model. These variables were obtained directly from SAM or were calculated using basic processing of the data. Variables origin_lane_miles and dest_lane_miles were estimated using the method described in Section 3.1.2.2. Similar to the single-input case, 90% of the data points were randomly selected and used to fit the model. The other 10% were used to validate the model.

Equation 3 and 4 show the regression equations:

$$\begin{aligned} Corrected\ SAM\ TT &= -9.433 + 2.251 * SAM\_FreeFlowTT - 0.00023 \\ &* origin\_production + 0.0009 * dest\_attraction + 0.000067 \\ &* origin\_lane\_miles - 0.000070 * dest\_lane\_\_miles - 2.596 \\ &* isBoundary \end{aligned} \tag{3}$$

$$\begin{aligned} Corrected\ SAM\ Demand &= 20.95 - 0.861 * SAM\_FreeFlowTT + 0.002 \\ &* origin\_production + 0.003 * dest\_attraction + 0.00018 \\ &* origin\_lane\_miles + -0.0001 * dest\_lane\_\_miles + 6.214 \\ &* isBoundary \end{aligned} \tag{4}$$

The residual error statistics is shown in Table 6.

Table 6 Multi-input regression model summary

Residuals summary (travel time)				
Min	**1st quartile**	**Median**	**3rd quartile**	**Max**
-63.636	-8.987	-1.243	6.89	67.577
Coefficients				
		Estimate	**Std. Error**	**t-value**
(Intercept)		-9.433	0.168	-56.140
SAM_freeFlowTT		2.251	0.003	717.670
origin_production		0.000	0.000	-18.190
dest_attraction		0.001	0.000	85.670
origin_lane_miles		0.000	0.000	48.750
dest_lane_miles		0.000	0.000	-39.780
factor(isBoundary)1		-2.596	0.142	-18.300
	Adjusted R-squared		0.900	
Residuals summary (demand)				
Min	**1st quartile**	**Median**	**3rd quartile**	**Max**
-141.4	-22.3	-7.9	7.6	4540.8
Coefficients				
		Estimate	**Std. Error**	**t-value**
(Intercept)		20.950	0.925	22.650
SAM_freeFlowTT		-0.861	0.017	-49.900
origin_production		0.002	0.000	34.070
dest_attraction		0.003	0.000	53.060
origin_lane_miles		0.000	0.000	17.850
dest_lane_miles		0.000	0.000	10.460
factor(isBoundary)1		6.214	0.781	7.960
	Adjusted R-squared		0.130	

As observed, the demand regression equation has a very low R-squared value, indicating a poor fit and thus the results are not reliable in predicting corrected SAM demand using these input variables. For the travel time case, all the variables have high *t*-statistics, indicating that they are all significant in the regression model. The large difference in the magnitude of the estimated coefficients is due to the difference in the order of the magnitude of those variables and the travel time.

The variables with positive coefficient estimates lead to increase in travel time with increase in the variable value. This is true for free-flow travel time variable, which is consistent with our observation. Regions with high origin and destination demand have higher values of travel time between them. The location of zones at the boundary leads to a 2.5-second reduction in the travel time error, which is very minor. The increase in lane miles at the origin and destination (or equivalently, denser concentration of roads near the origin and destination) increase the travel time between zones.

The residual errors for the validation data for the travel time case is shown in Figure 21. The histogram is similar to the one obtained for the single regression model, indicating a good performance of the regression model on the validation dataset.

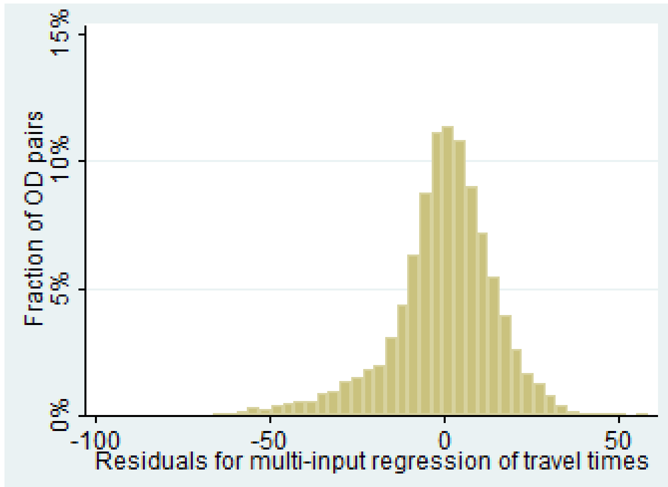


Figure 21 Multi-input regression model on travel times: histogram counts of residual errors on validation data

The total absolute error in travel time is found to reduce by 64.3%. This reduction in inconsistency is lower than the one obtained from single input regression indicating that having more inputs is not further useful in predicting SAM travel time as compared to a single input. For the demand case, the total absolute error in demand is found to increase by 135.8%, which is because of the poor fit of data to the choice of explanatory variables.

In addition to the disadvantage of repeating the efforts of developing regression models for different MPOs, the multi-input regression model is more complicated to estimate as it requires significant preprocessing of the network and demand data to extract the values for the explanatory variables. Given its poor performance against the single-input regression and the simplicity of the single-input regression, we recommend using single input regression for predicting SAM travel time. For the demand case, the correction factor method performs the best and thus its use is recommended.

4.4 Inputting MPO demands into SAM

The simple override method, as stated previously, is based on the idea of relying on the higher-resolution model wherever this is possible—mainly where there is geographic overlap.

However, given that the travel times between zones can be seen as a function of the demand in the four-step modelling framework, another consistency-improving alternative is to use the demand matrix obtained during the simple override method and feed it into SAM. The assumption is that we are reducing the discrepancies between SAM and the MPO model by using demand matrices that are more similar to each other in each model's assignment procedure. This will likely produce more consistent travel times between the MPO and SAM models.

Figure 22 is a histogram illustrating the distribution of the errors after applying the demand input procedure.

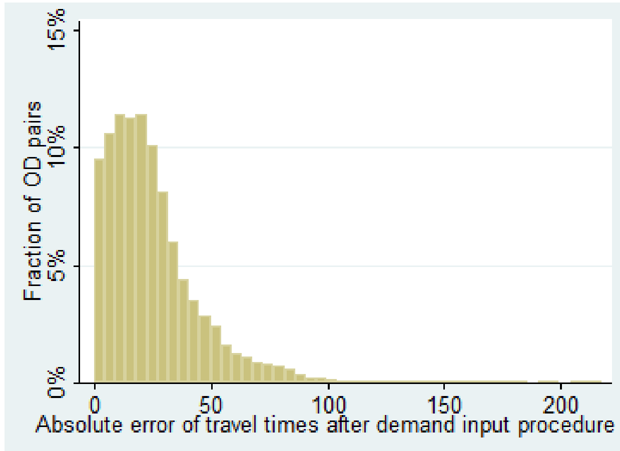


Figure 22 Error distribution of travel times after demand input procedure

Figure 22 displays a clear improvement in consistency after the demand input procedure when compared to the histogram presented in Figure 13—the errors are more tightly concentrated around zero after the procedure is applied.

After feeding the new demand matrix into SAM and running the assignment procedure, the total absolute error reduced to 30,688 hours (17.77% reduction) and the average mean percentage error reduced to 27.41% (reduction of approximately 6.78 percentage points)

Even though this consistency improvement is lower than that of previous procedures, this method is more robust regarding its implementation. In other words, while the first three methods mostly focus on treating data and finding relationships between the different models, this method allows for inputting those changes back into SAM. Also, when there are significant changes to the network (e.g., construction of new highways), the correction factors and regressions will likely have to be recalculated, while this method will not. Both levels (the MPO model and SAM) will have to incorporate the information of the new infrastructure, but the procedure itself will be the same. Furthermore, this method eliminates inconsistencies within SAM.

4.5 Changing input parameters

MPO and SAM models are usually implemented in TransCAD, with specialized procedures that expect files formatted a specific way. Although these models implement the traditional four-step planning scheme, they have different requirements and perform these tasks in substantially different ways. Figure 23 illustrates the main interfaces for the CAMPO and SAM models.

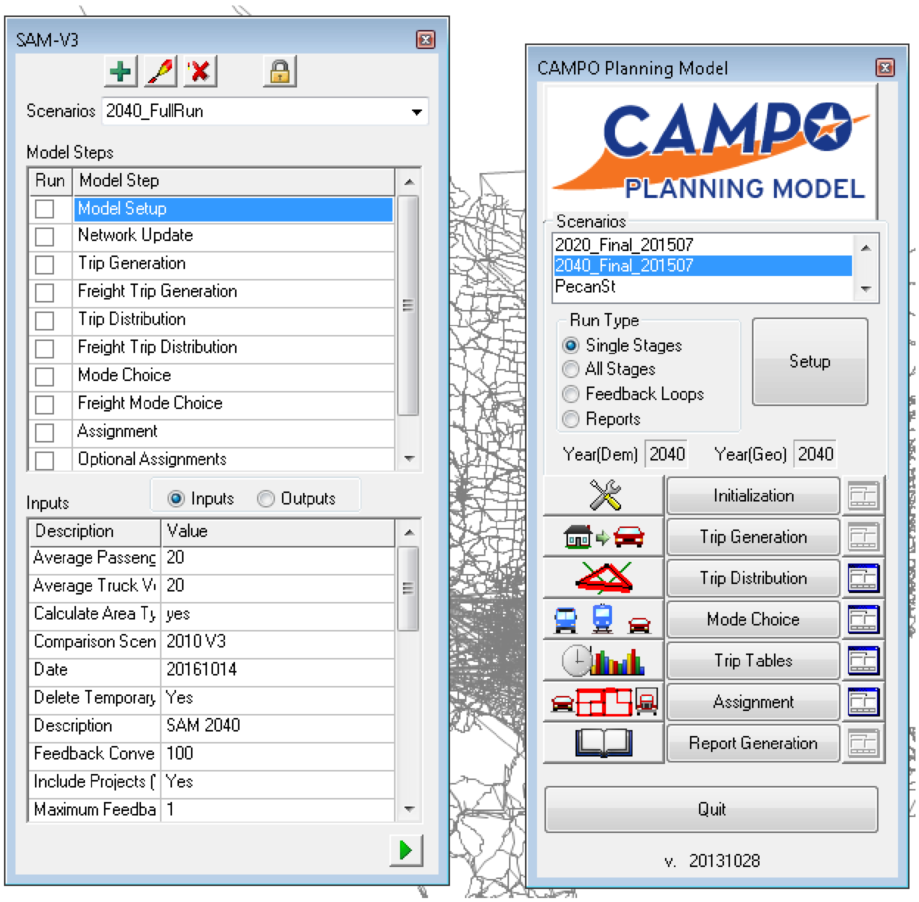


Figure 23 Comparison of SAM (left) and CAMPO (right) model interfaces

One way to improve consistency is to alter the high-level model parameters. It is not explicitly clear how these parameters should be adjusted to improve consistency, since the two models implement the four-step process differently. However, properly chosen adjustments to these parameters may be successful in improving consistency.

In the next sub-sections, we examine what high-level model parameters are available to adjust to improve result-consistency between CAMPO and SAM.

4.5.1 High-level parameters in CAMPO

CAMPO allows users to specify any combination of the demographics and network years by the use of master multi-year network and TAZ files, as well as the option to develop alternative networks or demographics to define a scenario. There are also pre-loaded scenarios with all required information readily available. These high-level parameters are available in each stage:

1. **Trip Generation Stage Parameters:** This section involves five parameters, which are shown in the parameters tab of the model scenario manager dialog box (Figure 24). These parameters are all scalars, and include the number of internal zones (*M*), the total number of zones including externals (*N*), the number of sectors, the number of generation areas (Area Types), and the Consumer Price Index based on 1967.

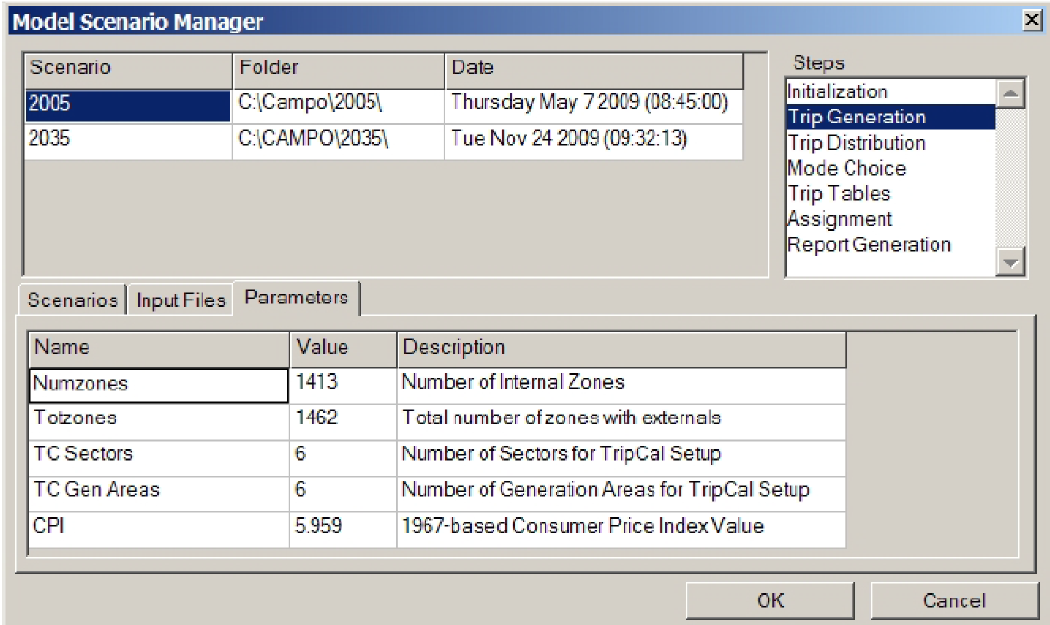


Figure 24 Model scenario manager for Trip Generation Stage

2. **Trip Distribution Stage Parameters:** This section involves one parameter: a flag field to activate the warm start option as shown in Figure 25, which is optional for the Trip Distribution stage. If warm start is selected under the Initialization stage, then a value of 1 as a distribution parameter will cause the initial skims to use loaded values. A value of 0 starts the skims with free-flow time.

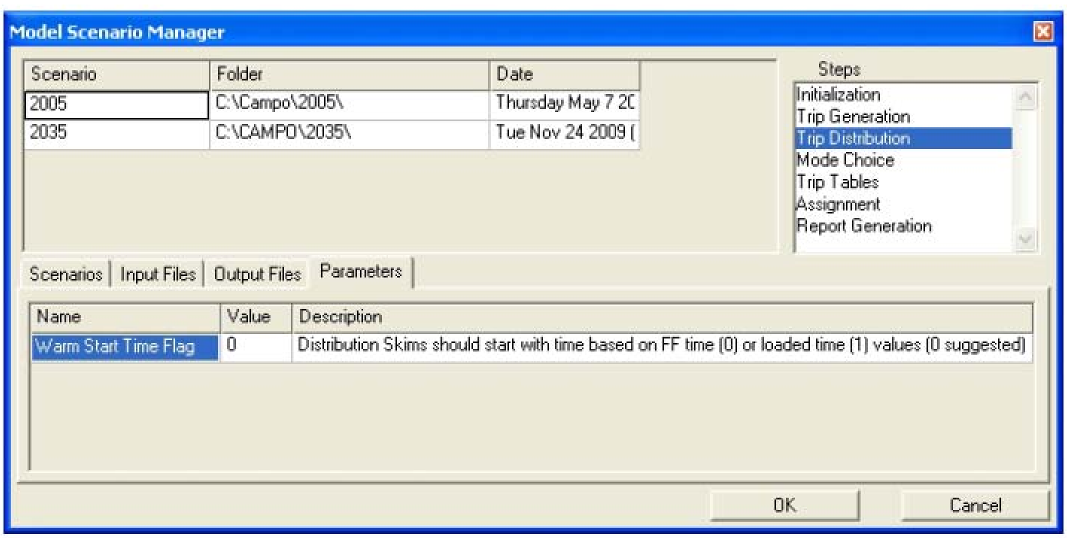


Figure 25 Model scenario manager for Trip Distribution Stage

3. **Mode Choice Stage Parameters:** The parameters tab does not exist for the Mode Choice section. Instead, the parameters can be accessed through the mode choice parameters input file "Parameters.bin". It is possible to modify the parameters (coefficients) for mode choice

variables such as in-vehicle travel time, parking cost, and average cost-per-mile based on previous studies.

4. **Trip Tables Stage Parameters:** The Trip Tables section (Figure 26) has two parameters: *Austin-San Antonio external zone ID* for which commuter rail trips are subtracted from or added to IH 35, and *Combine Flag*, which reflects how the highway OD vehicle trips are to be tabulated: 1-Merge All Purposes, 2-Separate Purposes, 3-Combine to HBW, HBNW, and NHB. These parameters are mostly related to how results are displayed and seem to have little impact on the whole.

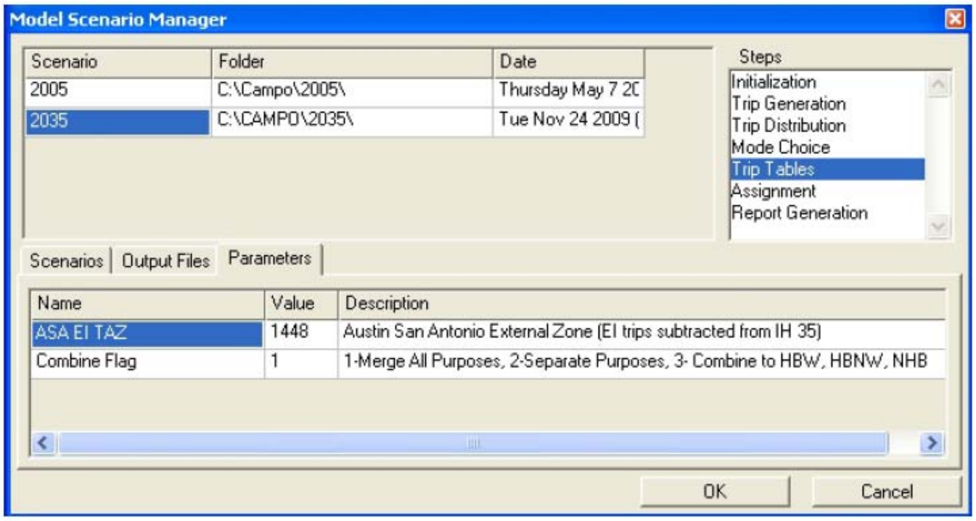


Figure 26 Model scenario manager for Trip Tables Stage

5. **Assignment Stage Parameters:** The Assignment section has nine parameters that are operational in the CAMPO Planning Model (Figure 27). Seven of these parameters are toll-based parameters and the remaining two parameters are functions of the multi-class assignment model stopping criteria, which contain the maximum number of iterations and convergence criterion for the assignment step. All of these parameters are used directly in the highway assignment procedure. Specifying a different convergence criterion might lead to results closer to SAM and similarly toll-based parameters might affect the traffic induced on toll roads rather than arterials and could provide results closer to the aggregate analysis of SAM.

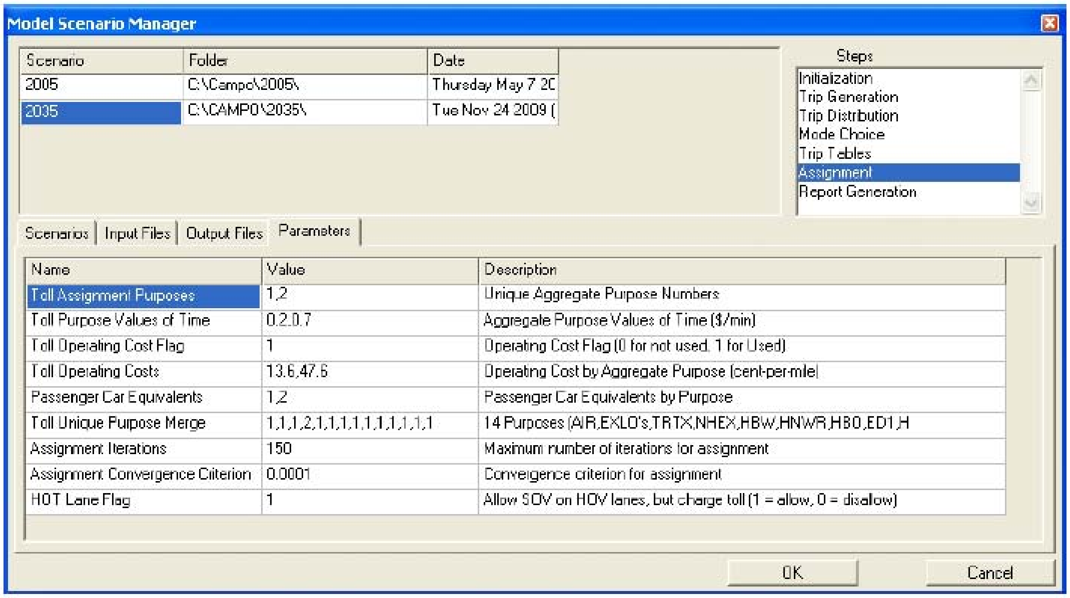


Figure 27 Model scenario manager for the Assignment Stage

4.5.2 High-level parameters in SAM

The SAM-V3 is a traditional four-step travel demand model that includes a feedback loop between the traffic assignment step and trip distribution. The model interface in SAM is pre-loaded with base and forecast scenarios, which cannot be modified unless new ones are created. In any new scenario created we can fine-tune the following parameters to get results closer to that of CAMPO:

- Average Passenger Vehicle Mileage
- Average Truck Vehicle Mileage
- Maximum Feedback Iterations
- Time Period AM End MD Start
- Time Period MD End PM Start
- Time Period NT End AM Start
- Time Period PM End NT Start

4.5.3 Results

Extending this method to the whole state of Texas would involve dealing with the models of multiple MPOs, and it is unlikely that the parameters in SAM could be changed in a way to simultaneously reduce inconsistencies with all of the MPO models. Therefore, the strategy undertaken for this measure was to perform changes to the MPO model and quantify how these changes reduced overall inconsistencies.

Changing the parameters related to the trip distribution and assignment stages proved to yield more positive results out of several preliminary tests that were run. The results for this method are summarized in Table 7.

The changes made to the trip distribution parameters included activating the warm start. This led to an increase of 0.35% in the travel time's absolute error as well as a 0.16% increase in the demand's absolute error.

Similarly, changing the passenger car equivalents for commercial vehicles from 2 to 2.5 and allowing the use of single-occupant vehicles on high-occupancy vehicle lanes (charging tolls) decreases the travel time's absolute error by 1.00% and the demand's absolute error by 18.00%.

When reducing the maximum number of iterations required for convergence and, simultaneously, increasing the tolerance for the convergence criterion, we observed decreases of 1.45% and 25.00% in the travel time's and the demand's absolute errors, respectively.

The final attempt included changing the toll-based parameters (high-occupancy toll lane flag and car equivalents) parameters as well as the convergence criteria parameters (maximum number of iterations and convergence tolerance). In this case, the decreases in the travel time's and demand's absolute errors were, respectively, 2.35% and 24.97%.

Changing the assignment parameters causes significant changes in the demand because the new costs (which include tolls) affect the initial costs between OD pairs, which will in turn affect the distribution stage and, therefore, change the final OD matrix.

Table 7 Changing high-level parameters—results of multiple runs

Changes made in the CAMPO model		**Absolute error in Demand** (% change in absolute error)	**Absolute error in Travel Time** (% change in absolute error)
Before making any changes		871,686.51	2,239,211.92
Changing parameters in distribution stage		873,078.64 +0.16 %	2,247,062.60 +0.35 %
Changing parameters in Assignment Stage	Changing toll based parameters	2,216,782.41 -1.00 %	713,554.43 -18.14 %
	Changing assignment/ stopping parameters	2,206,689.02 -1.45 %	653,732.85 -25.00 %
	Changing both parameters	2,186,502.22 -2.35 %	654,030.23 -24.97 %

4.6 Efficient aggregation techniques

An alternative method to address inconsistencies is to identify network aggregation schemes that result in a statewide model that better reflects constituent MPO models. Specifically, the objective is to provide an approach for network aggregation that allows the state to estimate the resulting inconsistency and correct for the estimated errors. This is a more significant departure from the existing SAM setup, and would require reconstructing the statewide model in a different way. A portion of the Austin network highlighted in Figure 28 was used to evaluate alternative aggregation schemes.

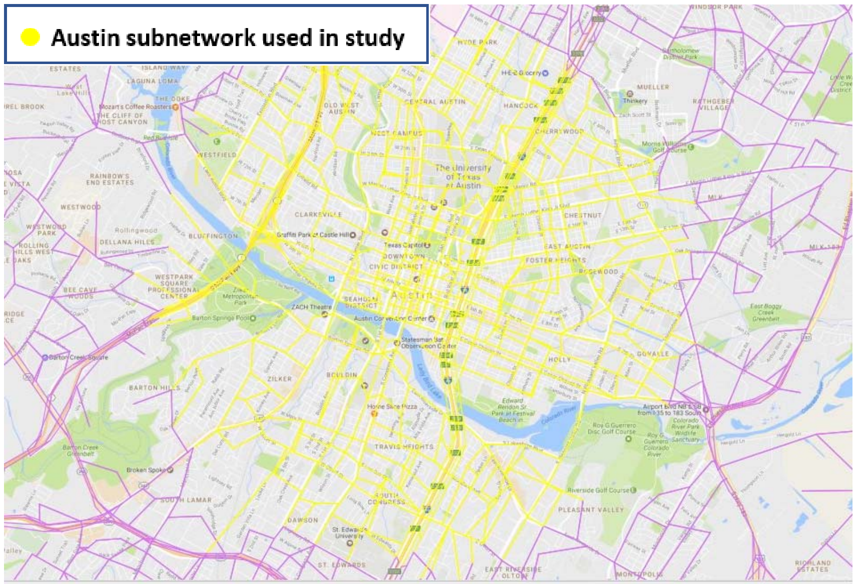


Figure 28 Portion of the Austin network used for testing aggregation schemes

Network aggregation may lead to errors on link flow values in the statewide aggregate network. This procedure involves removing links that belong to lower functional classes upon aggregation. Therefore, vehicles using the lower class links in the disaggregate network would shift to alternative links in the aggregated model. Measuring the average link flow bias that results from network aggregation provides an estimate on the correction factor needed to obtain the flow in the disaggregate network. This section evaluates different aggregation schemes that could be used by the state to construct the statewide network model and to calculate the average bias in link flows.

Bovy and Jensen (1983) compared assignment results from three network levels (fine, medium, and coarse) with traffic count data and empirically evaluated the difference in link flows between abstracted links and their disaggregate counterparts in a test network. It was shown that the relative error between assignment results and count data for primary roads was reduced from 87% to 45% when the medium level network was used instead of the coarse network. This is due to shifting vehicles that originally used disaggregate links to the aggregate links.

4.6.1 Link aggregation: extraction

Network extraction is a hierarchical aggregation approach in which links of a lower functional class are removed from the network. This method maintains the characteristics of the links such that the links in the abstracted network are identical to their counterparts in the disaggregate network. Figure 29 shows link extraction implemented for a portion of the Austin network. The links in blue represent the links in the abstracted network. Meanwhile, the links in blue and orange combined represent the full disaggregate network. In other words, the link extraction was implemented by removing the orange links (lower functional class) from the network. The lower class links were identified by assessing the speed limits in the network. Links with lower speed limits typically belong to lower functional classes.

The impact of link extraction on the link flows was obtained by constructing hypothetical OD pairs. However, the subsequent approach for measuring the bias on the link flows could be used for any OD matrix. The origins are shown in Figure 30, and the destinations include multiple nodes within the considered section and near its periphery.

A traffic assignment algorithm was used to obtain the link flows in the disaggregate and the abstracted networks. The percentage error between the link flows after removing outliers is shown in Figure 31. This corresponds to an average percent error of 6.5%, which implies that the link flows in the abstracted network were, on average, 6.5% greater than their counterparts in the disaggregate network.

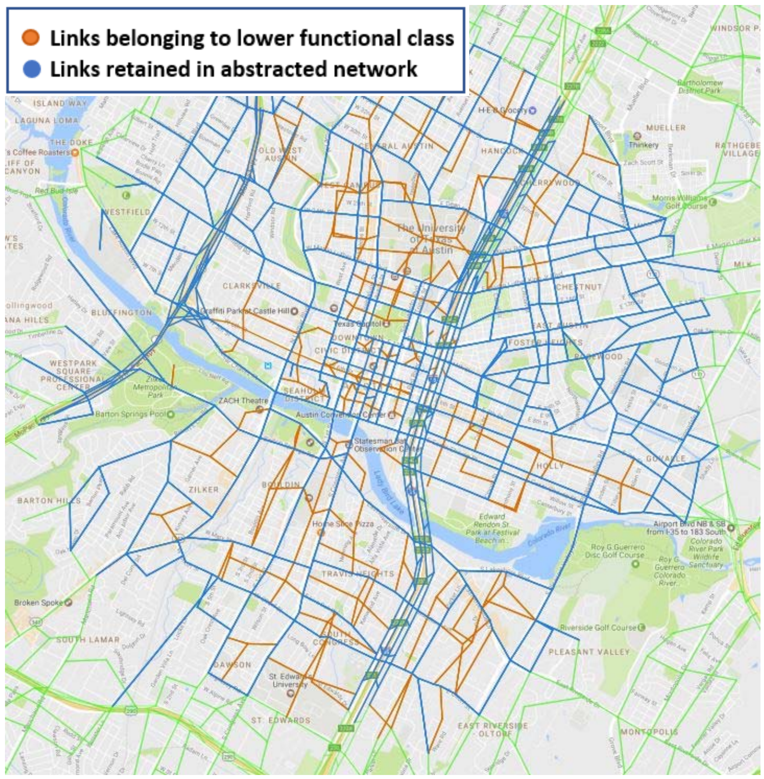


Figure 29 Link extraction for a section of the Austin network

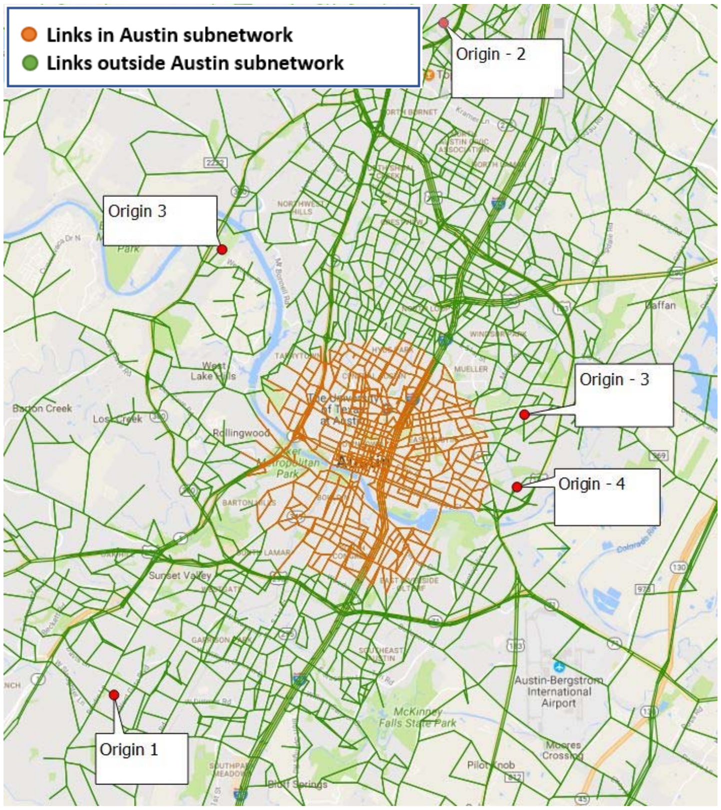


Figure 30 Location of origins used for testing aggregation schemes

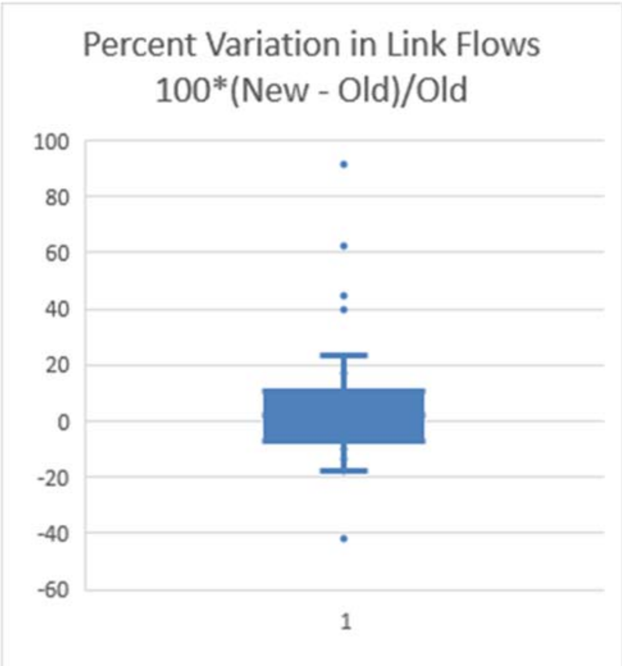


Figure 31 Variation in link flows: link extraction

4.6.2 Link aggregation: abstraction

The same analysis was repeated for an alternative aggregation scheme referred to as link abstraction. The aim of this aggregation scheme is to preserve the level of service between zones in the aggregate network (Chan, 1976). The level of service could be measured using the travel time, which is obtained after running the traffic assignment on the aggregate network. However, modifying the aggregate link characteristics to obtain a specific value of travel time (after running traffic assignment) is challenging due to the dependence of the routing procedure on alternative paths. An alternative approach could be to improve the capacity on aggregate links that are adjacent to the removed disaggregate links.

For example, as shown in Figure 32, the capacity on San Antonio Street in the north-south direction within the black circle would be added to the capacities on Guadalupe and Rio Grande, and the capacity on West 17th Street would be distributed to Martin Luther King Boulevard and West 15th Street. This is motivated by the observation of Bovy and Jensen (1983) that the network loses capacity after the aggregation process due to shifting vehicles that originally used disaggregate links to the aggregate links. The aggregation results did not indicate a significant difference as compared to link extraction (approximately 6.5% bias in link flows). This is due to the low values of OD demand assumed earlier. However, the method could be applied for different combinations of OD demand to test the bias in link flows associated with each OD matrix variation.

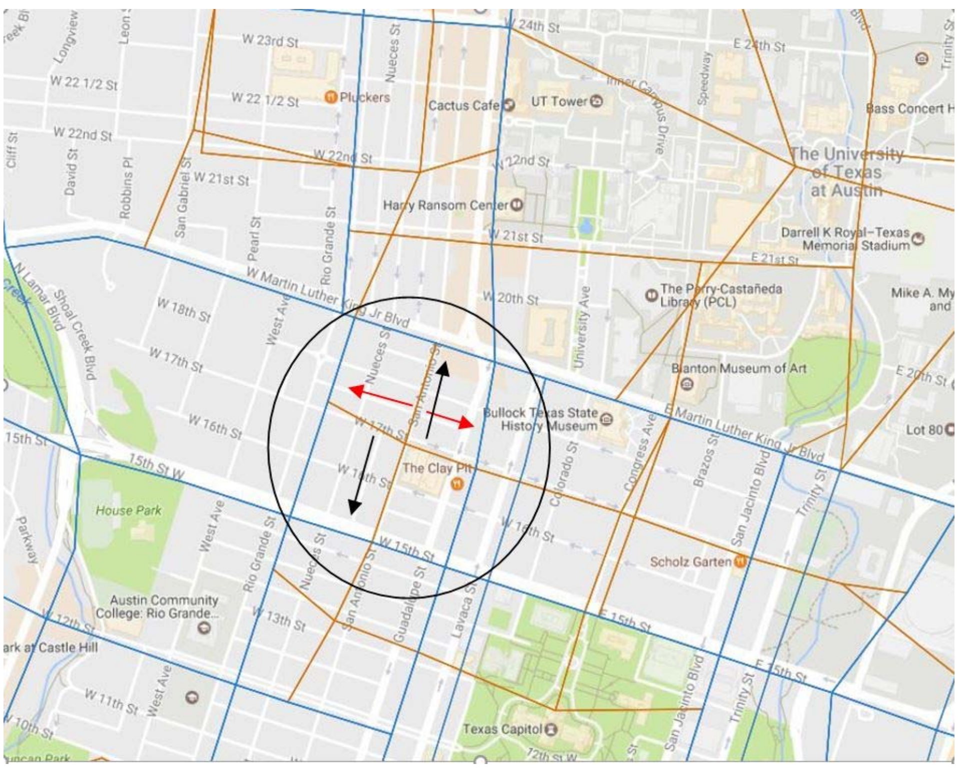


Figure 32 Distribution of capacity to aggregate links

This section described two different link aggregation strategies: link extraction and link abstraction. The percent error on the aggregated link flows in a portion of the Austin network was obtained to be approximately 6.5% for both aggregation methods. However, this value corresponds to a hypothetical OD demand matrix. In practice, TxDOT could follow the same procedure using a different OD matrix to measure aggregation errors resulting from the aggregation techniques. This will give an indication of which aggregation method is best (i.e., less error). The percent error on link flows could also serve as a correction factor for link flows obtained from the aggregate network. Note that constructing the OD matrix in the abstracted network requires aggregating demand by zones. In other words, this refers to adding the demand from the disaggregate zones to form an aggregate zone, and connecting the aggregated demand to the abstracted network. This process is shown in Figure 33.

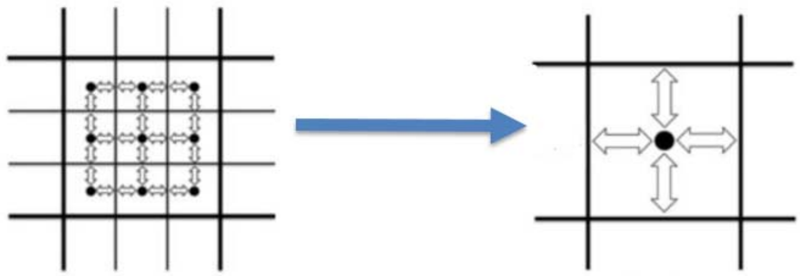


Figure 33 Zone aggregation (Jeon, 2012)

4.7 Decentralized implementation

A decentralized implementation of traffic assignment, called DSTAP and described in Jafari et al. (2017), is used for solving traffic assignment problems on large-scale networks such as the Texas statewide model. Decentralized implementation replaces the MPO models in a statewide model with their aggregated version, where the aggregation is done using the user equilibrium sensitivity analysis. In a decentralized implementation, the MPOs will have their own independent functionality, and the aggregated statewide network communicates with the MPO models to solve the traffic asignment problem. There are two types of data exchnage between the MPOs and statewide model. First, the information from the output of MPO models will be used to update the aggregated statewide network. This ensures that the statewide network is up to date with the current MPO models. Second, the output of the statewide model, mainly flow assignment, will be used to update the external trips to the MPOs. These update steps are performed iteratively after the occurrence of any change in MPO models or the statewideP model. The direct result of the decentralized implementation in conjunction with these updates would be a consistent model with an acceptable run time that still preserves the independent operation of the MPOs.

This section evaluates the properties of the proposed decentralized algorithm on planning networks. Due to lack of sufficient data from all MPOs in Texas, we implemented DSTAP on a subnetwork representing Central Texas. This subnetwork includes the Austin regional network (the "full network"), which has 6349 nodes, 18,696 links, 1117 zones, 231,497 OD pairs, and total demand of 687,690 vehicles. This extracted subnetwork includes three counties: Williamson County, Travis County, and Hays County. In the following discussion, we refer to the Austin regional network as the *full network*, the aggregated version of the Austin regional network as the *statewide network*, and the southern and northern partitions as *southern* and *northern* MPOs.

Williamson County and Hays County are tightly coupled with Travis County with a clear partitioning at the Colorado River. Because of this special topology, we partitioned the network into two subnetworks: the northern subnetwork (Williamson County and the part of Travis County to the north of the Colorado River) and southern subnetwork (Hays County and the part Travis

County to the south of the Colorado River). Figure 34 shows the extracted subnetwork and the selected partitions. Each subnetwork has 20 boundary nodes, and there are a total of 27 links connecting these 2 subnetworks through boundary nodes. There are no regional nodes in the proposed network decomposition.

Table 8 provides the statistics for the extracted network, Austin regional network (full network), statewide network, and subnetworks introduced in the DSTAP algorithm.

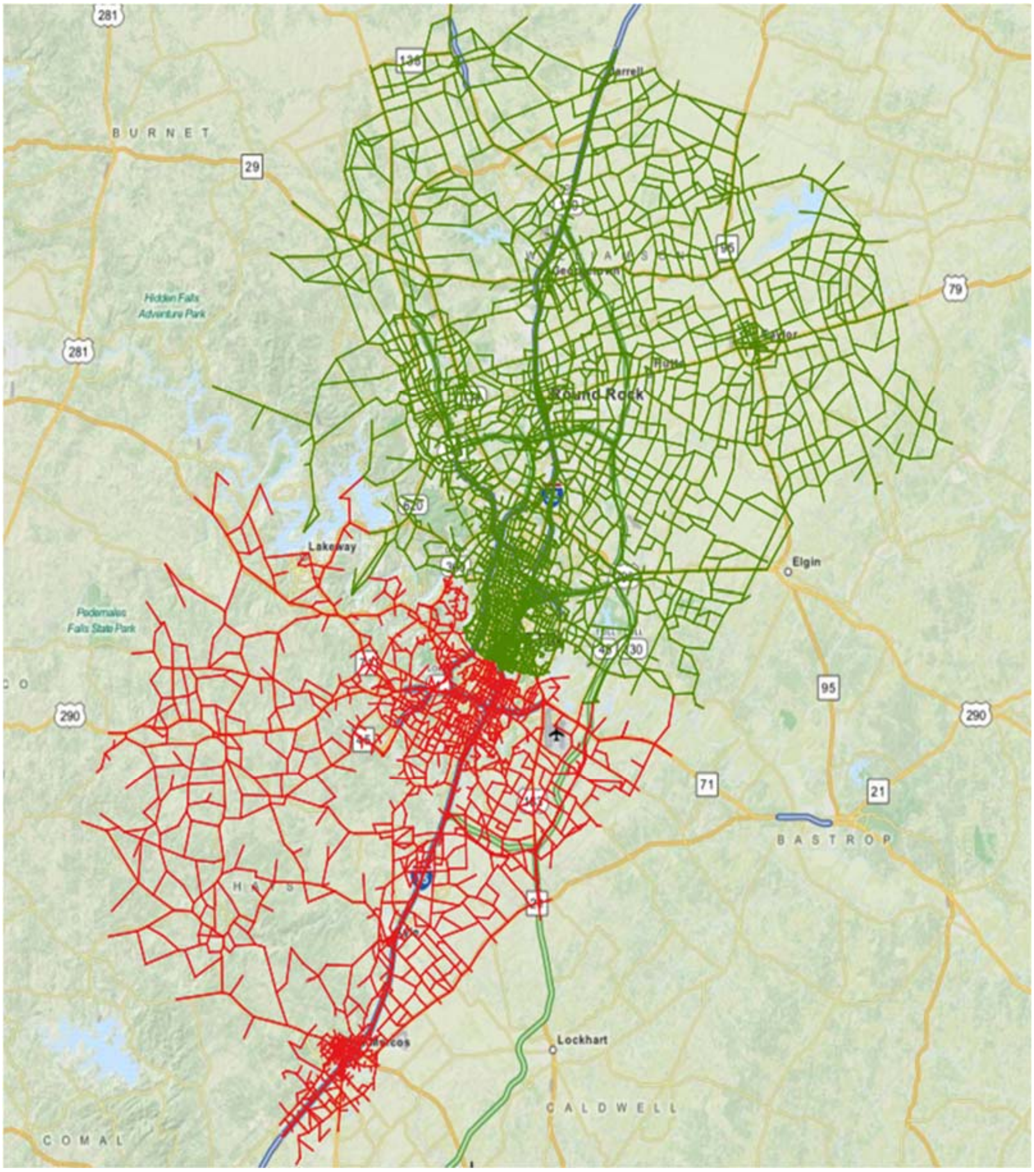


Figure 34 Austin network decomposed into two subnetworks: northern and southern subnetworks

Table 8 Statistics of the Austin network solved in centralized approach and DSTAP statewide network and subnetworks

Network	Nodes	Zones	OD pairs	Demand	Physical links	Artificial links
Austin regional network	6349	1117	231497	687690	18696	0
Statewide network	1854	907	67329	127695	27	24536
Southern subnetwork	3283	490	57557	185979	6863	0
Northern subnetwork	3966	627	106611	374016	11806	0

4.7.1 Implementation

Although convergence of the DSTAP algorithm was shown in Jafari et al. (2017), efficient performance on practical networks requires further implementation choices to be made. This subsection discusses our findings based on the experiments we performed in the Austin network. All tests were run on a 3.3 GHz Linux machine with 8 GB RAM.

In our implementations, better performance was obtained when the convergence criterion ϵ_{od} was decreased gradually. Obtaining highly converged solutions in the initial iterations does not appear to be an efficient use of computational time, which is intuitive. For the Austin network, we started with maximum excess cost value of 5 minutes for the subproblems and simply decreased it by a factor of 0.9 every iteration. This improves the convergence rate by solving the subnetworks faster, especially at the first iterations where solution from iteration to iteration may change significantly. For termination criterion in the master problem (problem dealing with the statewide network), we selected maximum excess cost of 1 minute.

The master problem starts with the flow assigned to the statewide network at previous iteration, and re-equilibrates this flow based on the new artificial regional link parameters to obtain the new flow assignment. In addition, after solving the statewide network at each iteration and updating the subnetwork OD demands (external demand to the MPOs), the subproblems need not be solved from scratch. Warm-starting the subproblems with the solution from the previous iteration—proportionally inflating or deflating the path flows for OD pairs whose demand changed—provided solutions with a good initial gap and a better convergence rate.

4.7.2 Convergence properties

Figure 35 plots the maximum excess cost values for the statewide network, northern and southern subnetworks, and also the excess cost on the Austin network in a logarithmic scale for a termination criterion of 0.8 minute, and initial step size of 0.2. The maximum excess cost for the Austin regional network was calculated by constructing a feasible path flow solution on the Austin network from the DSTAP path flow solution. The DSTAP algorithm converged in 90 iterations with a maximum excess cost of 0.76 minute on the statewide network, and $4.28\text{E}-4$ minute and $1.74\text{E}-4$ minute on southern and northern subnetworks, respectively. The maximum excess cost on the full network was always within 10% of that of the statewide network, and upon convergence, the full network had a maximum excess cost of 0.816 minute.

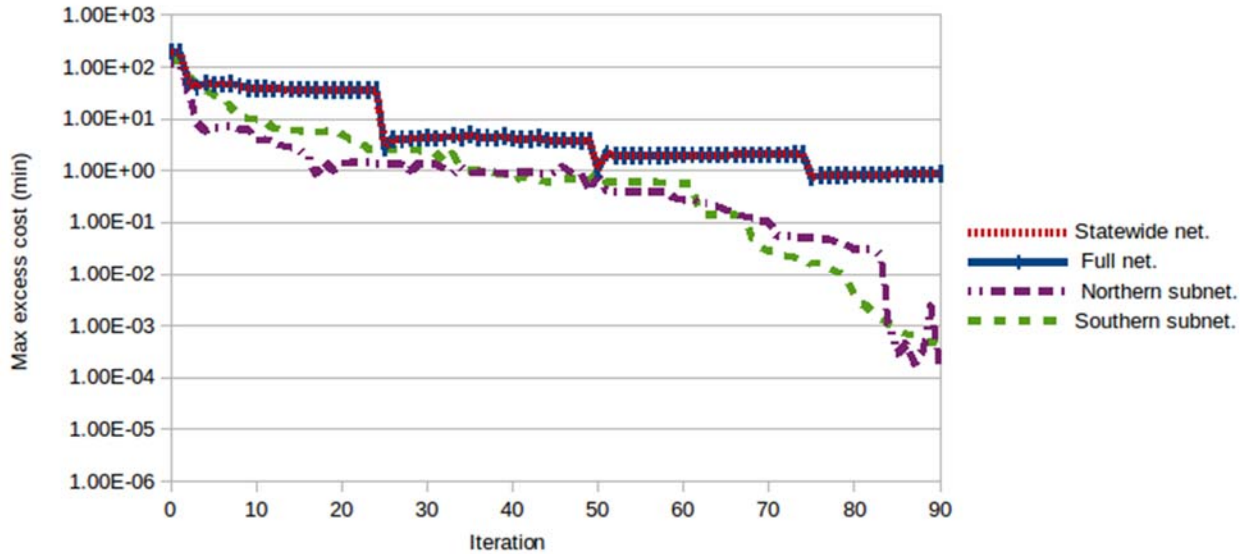


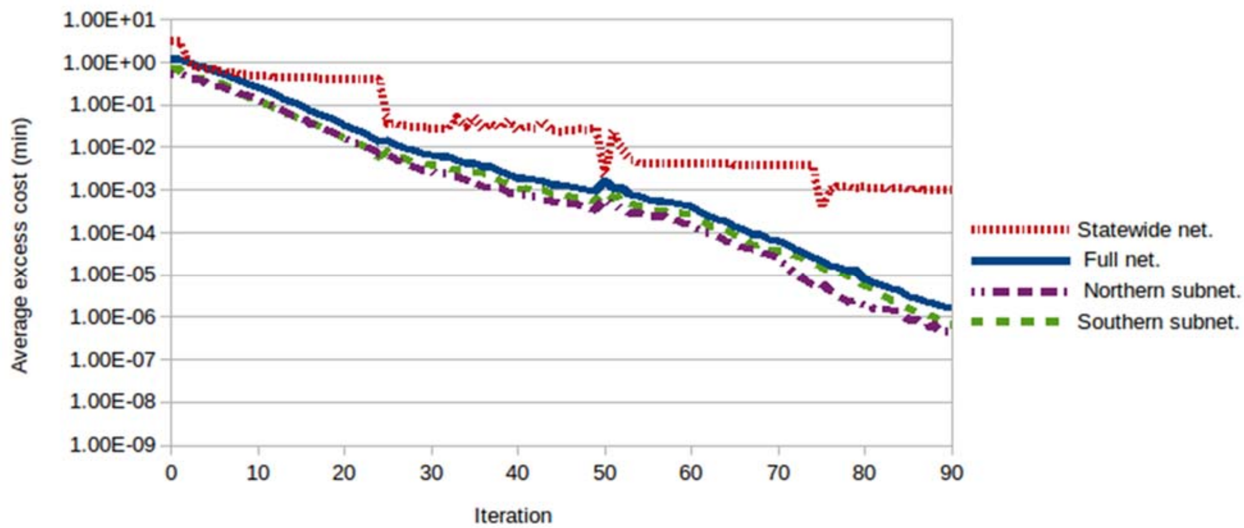
Figure 35 The maximum excess cost of the full network (blue), statewide network (red), and the subnetworks (green and purple)

Figure 36 shows the average excess cost and relative gap values for the Austin network, statewide network, and northern and southern subnetworks. For any general network u with set of OD pairs W_u, the average excess cost and relative gap measures may be defined as:

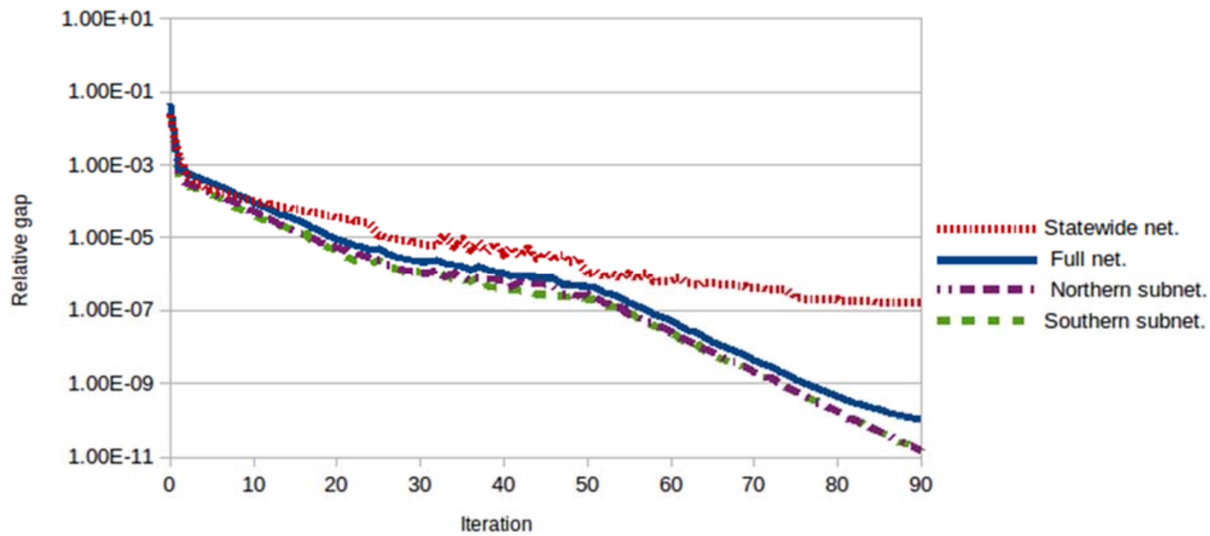
$$\text{Average excess cost}=\frac{\sum_{w\in W_u}\sum_{\pi\in p_w} f_\pi(T_\pi - T_{b_w})}{\sum_{w\in W_u} d_w}$$

$$\text{Relative gap}=\frac{\sum_{w\in W_u}\sum_{\pi\in p_w} f_\pi(T_\pi - T_{b_w})}{\sum_{w\in W_u}\sum_{\pi\in p_w} f_\pi T_\pi}$$

where T_{b_w} is cost of the shortest path for OD pair w. Upon convergence, the average excess cost and gap value of the DSTAP solution applied to Austin network were $1.16\text{E}{-6}$ and $8.74\text{E}{-11}$, respectively.



(a) Average excess cost



(b) Relative gap

Figure 36 (a) The average excess cost (b) and relative gap of the full network, statewide network, and the northern and southern subnetworks

4.7.3 Correctness

To examine the accuracy of the DSTAP algorithm, we solved for equilibrium on the Austin network using the traditional gradient projection method, to a gap value of $1\text{E}{-}10$, and measured the percentage error in the equilibrium OD travel times as:

$$\epsilon_t(w) = \frac{|t_D(w) - t_C(w)|}{t_C(w)}, \quad \forall\, w \in W$$

where $\epsilon_t(w)$ is the relative error in travel time of OD pair w, and $t_D(w)$ and $t_C(w)$ are respectively the equilibrium travel times from DSTAP and the centralized method, computed as the average travel time of all used paths at equilibrium. Figure 37 shows the average percentage OD travel time error $\frac{\sum_{w \in W} \epsilon_t(w)}{|W|}$ against the iteration number of DSTAP algorithm in the final assignment.

The average travel time error, expressed in Figure 37, decreases and has a value of 0.006% upon termination.

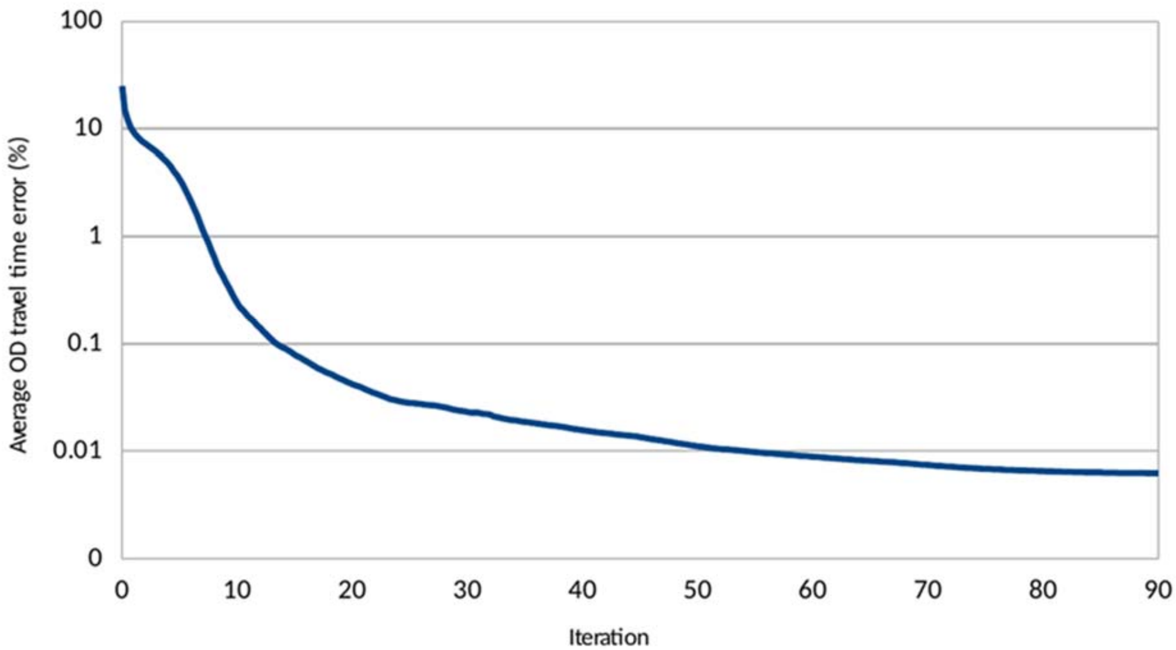


Figure 37 The average percentage error in OD travel times of DSTAP compared to centralized algorithm solution

A similar measure was proposed to evaluate the accuracy of the link flows. Let $\epsilon_f(a)$ denote the percentage error in flow of link a given by:

$$\epsilon_f(a) = \frac{|x_D(a) - x_C(a)|}{x_C(a)}, \quad \forall\, a \in A$$

where $x_D(a)$ and $x_D(a)$ denote the flow assigned to link a in the DSTAP and centralized methods, respectively. The average link flow error is plotted in Figure 38. The DSTAP algorithm terminated with an average link flow error of 0.067%, and more than 98.9% of links had an error less than 1%.

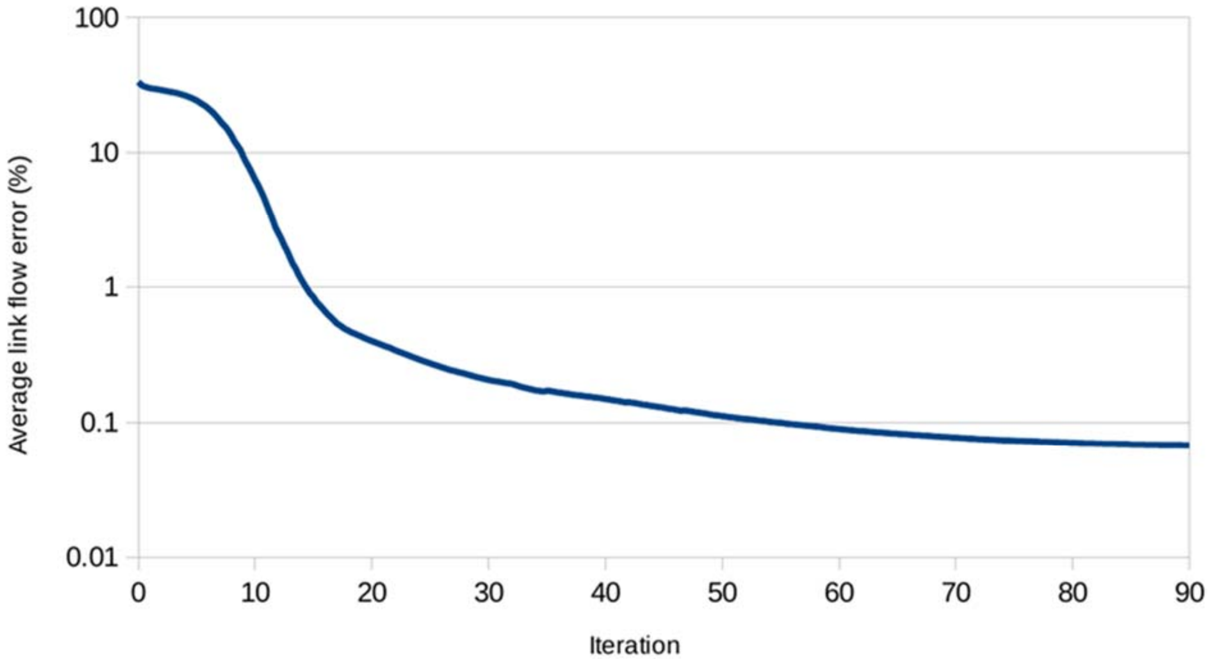


Figure 38 The average percentage error in flows assigned to links in DSTAP compared to centralized algorithm

4.7.4 Computational effort

This section investigates the computational requirements of the DSTAP algorithm, compared with the centralized approaches. Here we used relative gap as the measure of convergence, and both the DSTAP and centralized approaches were used to solve the network to a relative gap of $1\text{E}{-5}$. The simulations were implemented on one machine and the Thread class in Java was used to solve the subproblems simultaneously. More specifically, one thread is created for each subproblem and if one of the threads ends earlier, it waits for the other thread to finish before calling the next task. The traditional, centralized approach resulted in a run time of 1780 seconds while the proposed DSTAP algorithm, with described parallel implementation, could solve the Austin network to the same level of relative gap in 1128 seconds: a savings of almost 36%.

To get a broader understanding of the computational performance of DSTAP, we conducted a sensitivity analysis of the overall demand level in the network, scaling the OD matrix by factors ranging from 0.2 to 2. Figure 39 plots the runtime of DSTAP algorithm (statewide network in red and parallelized subnetworks in green) compared to a centralized approach (black). Figure 39 shows that the computational savings of DSTAP are more significant in absolute terms for congested networks: more than 8500 seconds when demand is doubled. Almost independent of the demand level, roughly four times as much computational time is expended on the subproblems as on the master problem.

Figure 40 plots the percentage time saving for different demand levels. For low congestion cases, the saving varies between $35\% - 55\%$, increasing slightly as demand increases: the savings are almost 70% when OD demands are doubled. Also note that in our simulations, the time spent to perform the sensitivity analysis and estimate the artificial links for each subnetwork is between $15\% - 20\%$ of total subnetwork computational time.

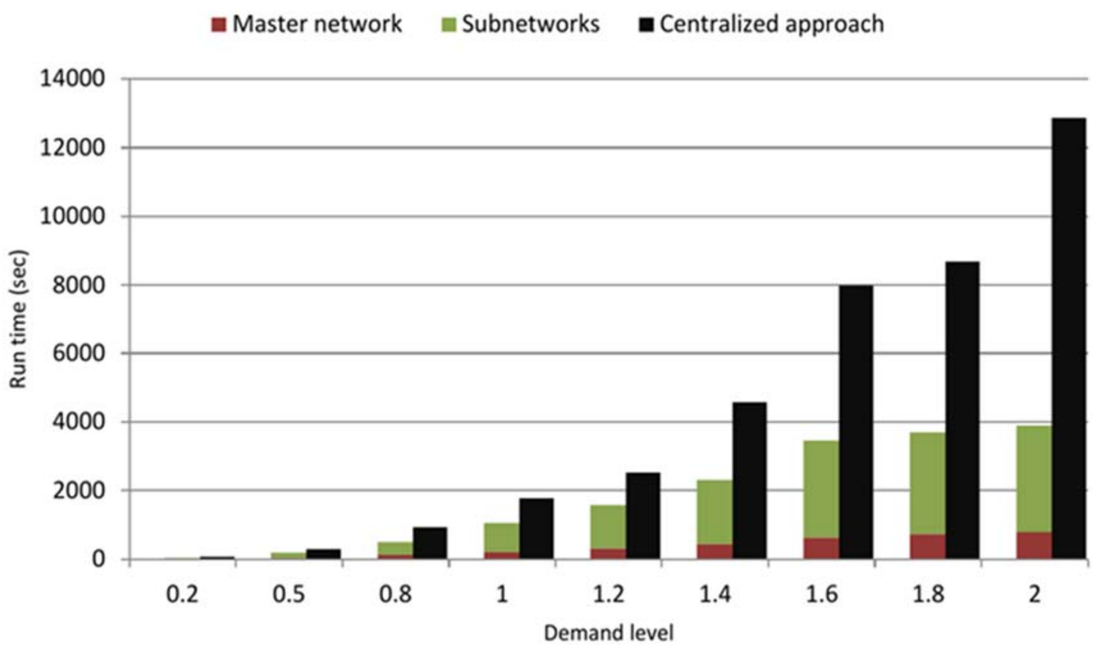


Figure 39 Computational time of the master (red) and subnetworks (green) in DSTAP compared to centralized run time (black) for different demand levels

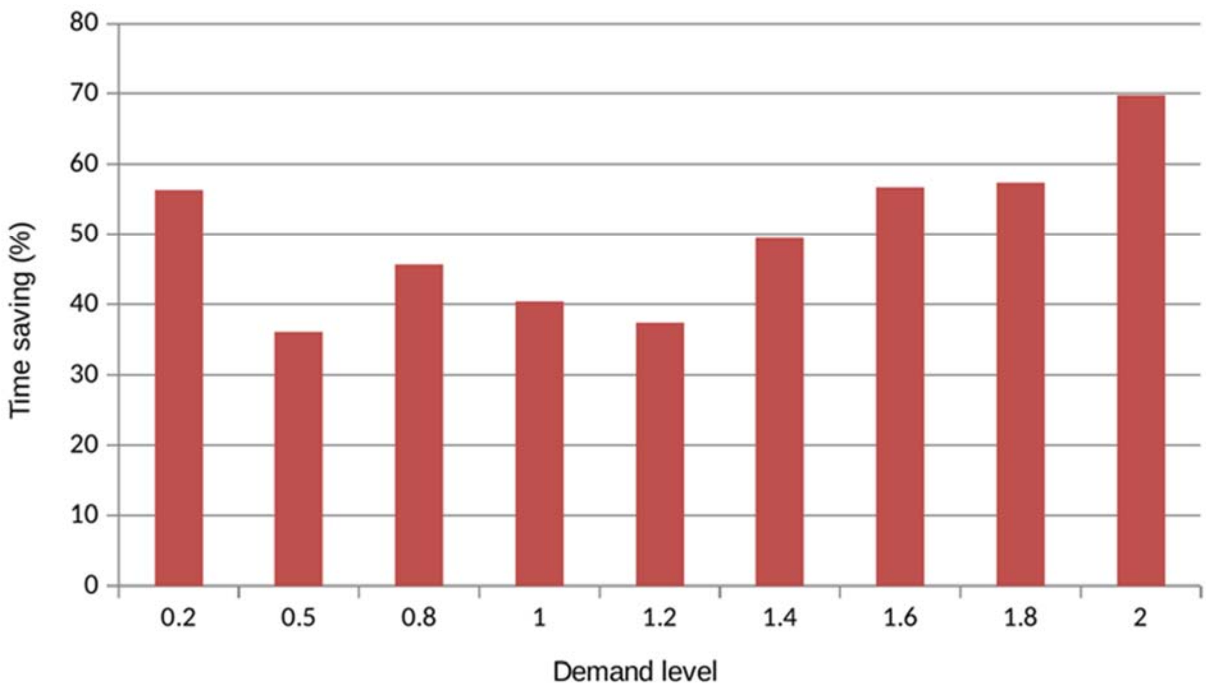


Figure 40 Computational savings of DSTAP algorithm

4.7.5 Concluding remarks on decentralized implementation

Here we implemented the proposed spatial decomposition approach for the traffic assignment problem from Jafari et al. (2017) on a subnetwork extracted from the Texas SAM. The DSTAP algorithm distributed the assignment task between the statewide network, an equilibrium assignment over a simplified version of the full network, and subproblems, each solving for equilibrium on a smaller subnetwork (MPO models).

Artificial regional and subnetwork links were created based on linear approximations obtained through sensitivity analysis. These artificial links essentially carried out the network aggregation task and were critical components of the algorithm, because they allow for both the statewide network and subproblems to anticipate the response from the other networks they interact with.

The subproblems (MPO models) were modeled in the statewide network using some artificial regional links, which were updated each iteration. The assigned regional demand to these artificial regional links was then used to update the OD demands in subproblems (external demand to MPO models). This exchange of information between the statewide and subproblems was implemented in an abstract way to ensure an accurate and fast assignment process. Experiments on the Austin network showed the computational advantages of DSTAP, and its convergence to the correct equilibrium solution.

Chapter 5. Summary and Recommendations

In this research we have highlighted seven different procedures for improving consistency between SAM and MPO models and quantified the improvement as best as possible using measures established in previous tech memos.

The simple override method, although almost eliminating the input and output inconsistencies between SAM and the CAMPO model, creates inconsistencies between SAM's demand and travel times. The data required from each MPO for this method are the OD pair demands and travel times and the geographic TAZ data. Even though it is the least complex of the methods proposed, the effort required in implementing the simple override is not negligible.

The correction factor and regression methods give the planner tools that allow for the correction of demands and travel times after a single run of SAM and the MPO model. After obtaining the equation describing this relationship, the MPO model need not be run further in order to acquire estimates of the corrected OD pair demands and/or travel times. Similarly to the simple override method, though, these approaches also generate SAM-SAM inconsistencies. They also require the same information as the simple override method, but involve more effort due to finding the best regression specification.

The inputting demand procedure attempts to solve a part of the problem of generating inconsistencies within SAM by aligning both models' demands where they overlap and then re-running SAM. This did indeed produce an improvement in consistency, and had the benefit of not generating SAM-SAM inconsistency. There is, however, added complexity here due to difficulties with handling the software in which SAM was developed.

Table 9, Table 10, and Table 11 summarize the main results of these first methods.

Table 9 Reduction of inconsistencies between SAM and the CAMPO model—Demand

Method	Demand Errors			
	Average Percent Error	**Median Percent Error**	**Absolute Error**	**Change**
Original Model	9020%	87.81%	871,200	---
Simple Override	1.74%	0.00%	0.05	-100.00%
Correction Factor	7070%	88.47%	830,800	-4.69%
Regression	2558000%	1057%	1,080,000	+23.98%
Inputting MPO demand into SAM	1.74%	0.00%	0.05	-100.00%

Table 10 Reduction of inconsistencies between SAM and the CAMPO model—Travel Time

Method	Travel Time Errors			
	Average Percent Error	Median Percent Error	Absolute Error	Change
Original Model	32.93%	33.61%	2,239,000	---
Simple Override	0	0.00%	0.07	-100.00%
Correction Factor	13.83%	10.34%	743,900	-66.78%
Regression	13.39%	10.22%	740,100	-66.95%
Inputting MPO demand into SAM	27.41%	27.59%	1,842,000	-17.77%

Table 11 Inconsistencies generated within SAM

Method	SAM-SAM Inconsistency			
	Demand Absolute	Demand Average %	Travel Time Absolute	Travel Time Average %
Simple Override	871,700	399.5%	1,841,000	39.65%
Correction Factor	222,800	21.76%	2,643,000	69.53%
Regression	548,900	2267%	1,936,000	21.79%
Inputting MPO demand into SAM	0.00	0.00%	0.00	0.00%

The method of altering the high-level parameters of both models produced minor improvements in the demand inconsistency (approximately 2%) while considerably reducing the travel-time inconsistency (approximately 25%). This method, however, involves a substantial effort by TxDOT, mainly due to the fact that it requires running all of the MPOs' models multiple times in order to find which make all of the models consistent. This method requires access to all over the MPO models within the state.

In an attempt to bring both statewide and MPO models closer on a more fundamental level, the efficient aggregation and decentralized implementation methods propose changes to how SAM is structured. Even though they are the most complex procedures presented and will take the longest to develop, they hold the keys to the greatest improvements in consistency. These methods require not only the OD pair demands and travel times for all the MPOs' models, but also their networks.

It should be noted here that the results presented in this research are specific to the relationship between SAM and the CAMPO model. The effectiveness of each of these methods might be different for other MPOs' models.

Chapter 6. Conclusion

Statewide models have undergone heavy development in the last decade. They are being developed and used in 40 states across the US and serve multiple purposes, such as intercity corridor planning, statewide system planning, and bypass studies. Transportation models, however, are not just developed on the state level. Many MPOs develop smaller-scale models in order to address local transportation-related issues.

The difference in scope between the statewide models and the MPO models can generate different outcomes for analysis of the impact of the same project or can lead to conflicting political agendas depending on which one is used for decision-making. Identifying these inconsistencies and developing methods to evaluate and remove them are the primary focus of this research.

Statewide travel demand models usually include the areas covered by several MPO models within the state and involve some kind of interaction with these MPO models. These interactions can be the statewide model providing the internal-external or external-external traffic volumes to the MPO models as well as the statewide models using the aggregation of the networks in MPO models to construct the statewide network.

Generally, statewide models and MPO models are complementary: while the MPO models usually account for shorter distance trips, statewide models can be used to model longer distance trips as well as freight movement. Statewide models account for planning at the larger scale, and tend to incorporate MPO models in either of two ways: a) the stitch approach, where the MPO models are connected to form the statewide model; and (b) the aggregation approach, in which the network and demand of the MPO model is aggregately represented in the statewide model.

The passenger travel components of statewide models usually follow the MPO models in structure, relying heavily on the traditional four-step model with segregated trip purposes. Some states, like Oregon and Ohio, have shifted to using an integrated land use and economic activity model along with the four-step model. These shifts are governed by the purposes for which the statewide models are used. The freight component of statewide models is usually performed in one of two ways: commodity based or direct vehicle based. More than three-fourths of the states with statewide models incorporate freight modeling using the commodity-based approach, as it makes accurate use of the available databases.

It is recommended across different literatures that statewide and MPO models should be developed in a coordinated fashion, under the cooperation of both state and MPO agencies. This coordination usually goes beyond the mere consistency of data being used. Rather, the coordination should also be in the development of the network itself, the software in which the networks are modeled, and the methods and internal procedures used.

The methodology of integrating the statewide and the MPO models has been another focus of this report. Given the difficulties of integrating the two planning levels (statewide and MPO), efforts have been put into the development of multi-resolution modeling. This consists of a unifying framework under which different parts of a system are described at different levels of detail. This approach is a trade-off between the model accuracy and complexity. In it, urban areas are represented in a simple and easily set-up fashion. Currently, a majority of US states rely on aggregation-based approaches to MPO models within the statewide model.

We presented several ways to measure inconsistency, divided into three categories: network, input, and output inconsistencies. We also showed that the both SAM and the CAMPO model present significant levels of inconsistency.

Furthermore, we proposed seven methods to reduce inconsistency, each of them with their own data requirements and implementation complexities. These methods were divided into three groups of ascending complexity.

The first three methods (simple override, correction factors, and correction regressions) are the simplest to implement and are effective in reducing inconsistencies between the two models, but generated inconsistencies within SAM.

In the second group, changing high-level parameters seemed promising for travel-time improvement. Its results with respect to demand inconsistencies, however, were lacking and proved to be somewhat cumbersome, especially considering the application of this technique for all MPOs' models. Still in the second group, the method of inputting aggregated MPO demand into SAM yielded positive results and also eliminated the inconsistencies within SAM.

The third and last group of methods proposed involve a substantial amount of effort from TxDOT but will likely generate the largest benefits in terms of consistency.

The most relevant conclusion drawn from this study is that there are no one-size-fits-all solutions for inconsistencies, and the relationship between SAM and the MPO models should be studies on a case-by-case basis. Furthermore, it would be advantageous to both MPOs and TxDOT if their network modeling efforts were combined and performed in a collaborative fashion. One example of this would be if, for the regions where there is overlap with an MPO, SAM focused on the external-to-external and external-to-internal trips, while the MPO focused on the internal-to-internal and internal-to-external trips. This information about these trips would then be exchanged between the MPO and TxDOT. In this way, inconsistencies would be solved by a different approach: each model focuses on different types of trips, therefore eliminating the chance of inconsistencies arising in the first place.

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