PROJECT REPORT

SANDAG TRAVEL MODEL ENHANCEMENTS TO SUPPORT 2021 LONG-RANGE TRANSPORTATION PLAN

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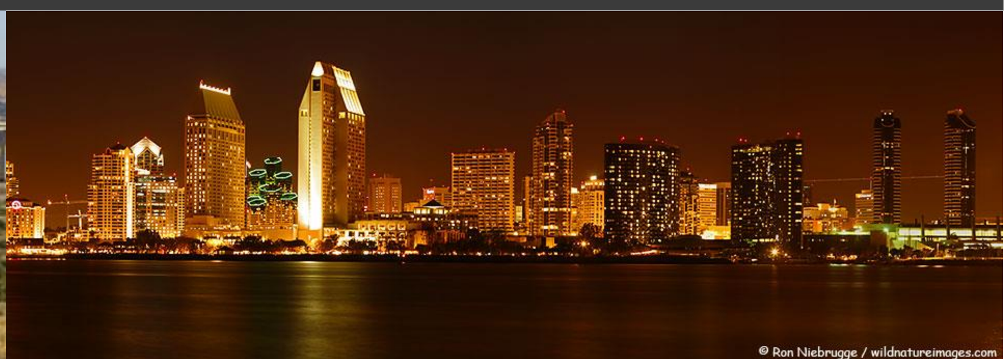

Model Enhancements to Support 2021 Regional Transportation Plan

PREPARED FOR:
SAN DIEGO ASSOCIATION OF GOVERNMENTS

SANDAG

SUBMITTED BY:
RSG

55 Railroad Row
White River Junction, VT 05001
802.295.4999
www.rsginc.com

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1.0 INTRODUCTION

This report describes the work undertaken under the SANDAG On-Call Modeling Services Contract, Task Order 1 for model support, to enhance the San Diego Association of Governments (SANDAG) activity-based model functionality for application to the Five Big Moves planning effort. The SANDAG activity-based model is a member of the Coordinated Travel – Regional Activity-based Modeling Platform (CT-RAMP) family of models in use by many large Metropolitan Planning Organizations in the United States. The model system includes a detailed representation of space, stop-to-stop transit utility calculations, and was recently updated to include an all-streets representation of walk and bike accessibilities (Davidson et al, 2010). The model is applied to a fully-attributed synthetic population of San Diego residents and includes disaggregate tour-based model components for non-resident overnight visitors, Mexican residents, internal-external trips, and airport trips.

This project focused on enhancements related specifically to the following functionality:

- Telecommuting
- Autonomous vehicles
- Transportation Networking Companies (TNC)
- Micromobility (e-scooters)
- Tolling
- Transponder Ownership Model

The following document describes the enhancements related to this functionality in terms of impacts on model structure, explanatory variables, and sensitivities. The document also describes the re-calibration of the model to represent existing TNC and e-scooter demand. The results of sensitivity tests are available separately.

2.0 TELECOMMUTING

In order to more accurately test the effects of changes in telecommuting assumptions on travel behavior, a telecommute model was estimated from 2017 household travel survey data and implemented in the resident travel demand models. The outcome of the telecommute model are reflected in adjustments made to the Coordinated Daily Activity Pattern (CDAP) model, the mandatory tour generation model, and the non-mandatory tour frequency model.

The dependent variable in the telecommute model is a person-level variable collected during the recruitment phase indicating the telecommute frequency for persons with job type other than 'work at home'. The frequency of response to this question is shown in Table 1. A careful analysis of actual commute frequency for each response category (not shown) indicated that most of the variation in actual commute frequency can be explained with fewer categories of telecommute frequency. The analysis involved cross tabulating the share of workers who actually worked on days surveyed by reported telecommute frequency. An interesting aspect of the data analysis indicated the importance of equally representing all days of the week in expanded survey days; otherwise, a disproportionate share of survey days on Tuesdays through Thursdays can indicate a higher than expected commute frequency for telecommuters, since the likelihood of telecommuting is higher on Mondays and Fridays (and telecommuters are more likely to travel to work on other days of the week than non-telecommuters, all else being equal).

TABLE 1: WORKERS BY TYPICAL TELECOMMUTE FREQUENCY

TYPICAL TELECOMMUTE FREQUENCY	FREQ.	PERCENT
6-7 days a week	28	1%
5 days a week	29	1%
4 days a week	52	1%
2-3 days a week	312	6%
1 day a week	323	6%
9 days every 2 weeks	11	0%
1-3 days per month	456	8%
Less than monthly	832	15%
Never	3,598	64%
Total	**5,641**	**100%**

The final stratification of telecommute frequency is shown in Table 2.

TABLE 2: RAW AND EXPANDED WORKERS BY FINAL TELECOMMUTE FREQUENCY

TELECOMMUTE FREQUENCY	RAW		EXPANDED	
	Freq.	Percent	Freq.	Percent
Never or less than 4 days per month	4,889	87%	983,812	92%
1 day per week	323	6%	42,735	4%
2-3 days per week	312	6%	35,798	3%
4 or more days per week	120	2%	9,218	1%
Total	**5,644**	**100%**	**1,071,564**	**100%**

A multinomial logit model was estimated to predict telecommute frequency based on household and person variables. Estimation results are shown in Table 3. An ordered logit model was also attempted; however, the specification was discarded due to illogical coefficients. this finding is consistent with other literature.[1] Occupation, household size and structure, income, work and student status, number of vehicles, and distance to work are significant. Note that the number of significant explanatory variables decreases as telecommute frequency increases. this may be due in part to the limited number of observations for which more frequent telecommuting is observed, but may also be caused by limits in available explanatory variables. For example, some workers in the technology sector may be more able to telecommute than others, due to their job responsibilities. This unobserved variation in the factors that lead to telecommuting suggest that future model predictions should be treated with care. Nonetheless, the addition of this model provides a useful lever for SANDAG staff to test the effects of changes in telecommute frequency on travel behavior.

[1] See Mannering, Jill S. Mokhtarian, Patricia L. Modeling the Choice of Telecommuting Frequency in California: An Exploratory Analysis, The University of California Transportation Center, University of California Berkeley, CA 1995.

TABLE 3: TELECOMMUTE FREQUENCY MODEL ESTIMATION RESULTS

Alternative\Variable	Coef.	Std. Err.	z
Never_or_less_than_4_days_month - base alternative			
1_day_per_week			
Services	-1.624	0.512	-3.17
SalesOffice	-0.620	0.262	-2.37
ResourceConstruct	-1.570	1.012	-1.55
TransportMat	-14.747	738.148	-0.02
adlts1	0.177	0.182	0.97
pay_park	0.457	0.266	1.72
inc60k_100k	0.560	0.260	2.16
inc100k_150k	0.644	0.262	2.46
inc150k_plus	0.920	0.266	3.46
wdist	0.016	0.008	2.12
_cons	-3.579	0.256	-14
2_3_days_per_week			
Services	-0.651	0.350	-1.86
SalesOffice	-0.738	0.300	-2.46
haskids_6_12	0.517	0.227	2.28
adlts1	-0.066	0.208	-0.32
parttime	0.425	0.243	1.75
college	0.600	0.363	1.65
inc60k_100k	0.389	0.260	1.5
inc100k_150k	0.193	0.279	0.69
inc150k_plus	0.765	0.273	2.8
veh0	0.407	0.430	0.95
veh3	-0.730	0.242	-3.02
_cons	-3.752	0.299	-12.57
4_or_more_days_per_week			
SalesOffice	-0.894	0.526	-1.7
haskids_0_5	-0.864	0.371	-2.33
haskids_6_12	-0.810	0.406	-1.99
adlts1	-0.043	0.324	-0.13
parttime	1.112	0.321	3.46
_cons	-3.303	0.490	-6.74

Figure 1 shows workers classified by daily activity pattern type and telecommute frequency. There are three broad daily activity pattern types predicted by the CDAP model:

- M=Mandatory; at least one work or school tour
- N=Non-Mandatory; no work or school tours, at least one other out-of-home activity
- H=Home; no travel

Note that all three activity pattern types could include some telecommuting. The figure shows that the likelihood of mandatory travel decreases as telecommute frequency increases, while a 'rebound' effect can be observed where non-mandatory travel increases. This effect is also well-documented in the literature.

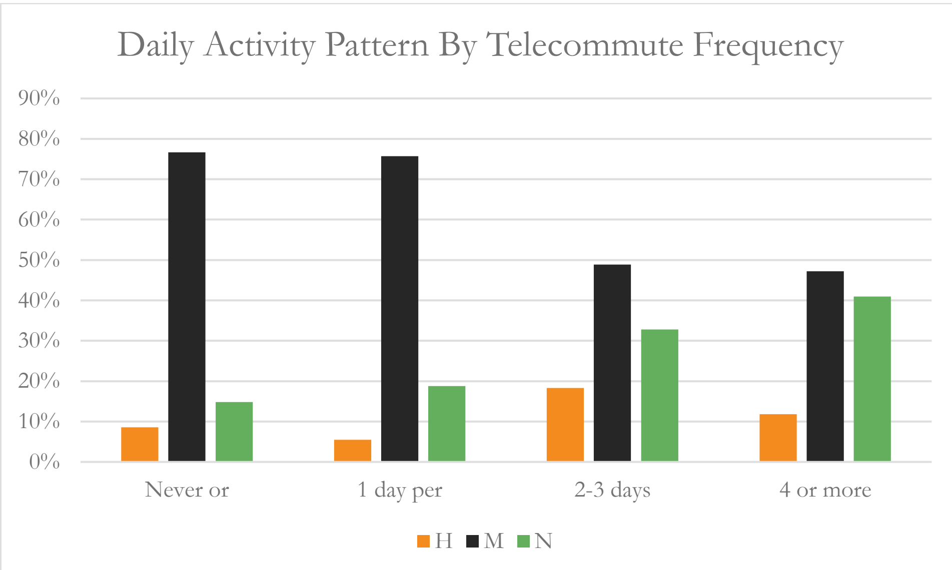

FIGURE 1: DAILY ACTIVITY PATTERN BY TELECOMMUTE FREQUENCY

Figure 2 and Figure 3 show the relationship between telecommute frequency and individual non-mandatory and joint non-mandatory tours respectively. It can be seen that the frequency of days with no non-mandatory tours generally increases with respect to telecommute frequency, while the number of days with one individual non-mandatory tour generally decreases. However, it can be seen from Figure 3 that the number of fully-joint tours generally increases with telecommute frequency. This may be an indicator of the coordination of telecommuters work schedules with other household members such that they can engage in out-of-home activities together. Such activities may include discretionary as well as maintenance activities, such as bringing children to doctors appointments.

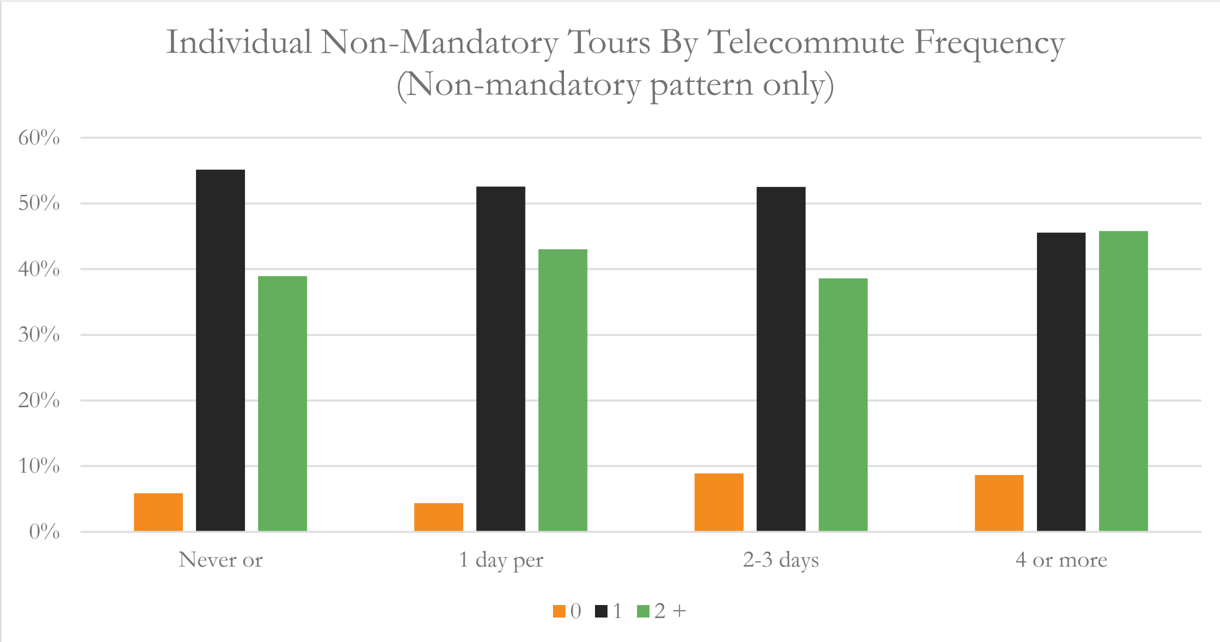

FIGURE 2: INDIVIDUAL NON-MANDATORY TOUR FREQUENCY BY TELECOMMUTE FREQUENCY

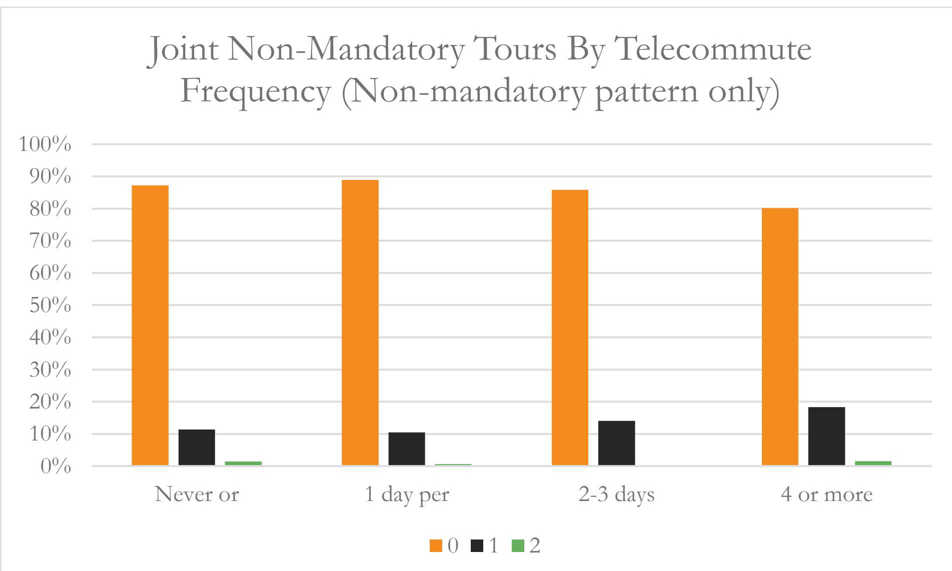

FIGURE 3: JOINT NON-MANDATORY TOUR FREQUENCY BY TELECOMMUTE FREQUENCY

In order to represent telecommute effects in the downstream daily activity pattern and tour frequency models shown above, models were re-estimated with variables similar to the ones currently implemented in the model transferred to the implemented model. Table 4 shows the telecommute coefficients for the CDAP model., indicating that after controlling for other explanatory variables (person type, gender, occupation, income, day of week, household size, presence of children by age, number of vehicles) increasing telecommute frequency increases participation in non-mandatory and home activity patterns. Note that full model estimation results are not shown.

TABLE 4: TELECOMMUTE FREQUENCY COEFFICIENTS FOR COORDINATED DAILY ACTIVITY PATTERN MODEL

TELECOMMUTE FREQUENCY	M	N	H
Less than 1 day per week	Base	Base	
1 day per week		0.526	0.496
2-3 days per week		1.387	1.584
4 or more days per week		1.848	1.711

Table 5 shows telecommute frequency coefficients when interacted with number of individual non-mandatory tours, after accounting for person type, gender, occupation, income, day of week, household size, presence of children by age, and number of vehicles. The results show that telecommuting 1 day per week or 4+ days per week results in fewer patterns with one or more tours, while telecommuting 2-3 days per week results in a higher frequency of one non-mandatory tour but a lower frequency of 2+ tours.

TABLE 5: TELECOMMUTE FREQUENCY COEFFICIENTS FOR INDIVIDUAL NON-MANDATORY TOUR FREQUENCY

TELECOMMUTE FREQUENCY	0 TOURS	1 TOURS	2+ TOURS
Less than 1 day per week	Base	Base	
1 day per week		-0.005	-0.348
2-3 days per week		0.142	-0.041
4 or more days per week		-0.406	-0.447

The effects of telecommute frequency were also analyzed with respect to non-mandatory tour complexity (number of stops), after controlling for person type, gender, income, day of week, household size, presence of children by age, and number of vehicles – see Table 6.. Note that it was not possible to estimate the effects by tour purpose, due to the low number of observations. However, it can be observed that across all tour purposes, the complexity of non-mandatory tours decreases as telecommute frequency increases. This suggests that telecommuters may be attempting to maximize their at-home time in order to increase their productivity.

TABLE 6: TELECOMMUTE FREQUENCY COEFFICIENTS FOR STOP FREQUENCY

TELECOMMUTE FREQUENCY	0 STOPS	1 STOP	2-3 STOPS	4+ STOPS
Less than 1 day per week	Base	Base		

TELECOMMUTE FREQUENCY	0 STOPS	1 STOP	2-3 STOPS	4+ STOPS
1 day per week		-0.126	-0.301	-0.611
2-3 days per week		-0.149	-0.768	-0.909
4 or more days per week		-0.158	-0.473	-1.470

In summary, workers who telecommute one or more day per week are:

- Less likely to go to work; more likely to stay home or engage in non-mandatory travel (roughly equally)
- Somewhat less likely to engage in multiple individual non-mandatory tours
- Less likely to make intermediate stops on non-mandatory tours

Note that we also tested for distance and duration effects on non-mandatory tours but the results were inconclusive.

Since the telecommute frequency coefficients were introduced into the CDAP, non-mandatory tour frequency models, and stop frequency models, these models were adjusted in calibration to match their initial targets, as described below.

3.0 AUTONOMOUS VEHICLES AND TRANSPORTATION NETWORKING COMPANIES

RSG recently added Autonomous Vehicle (AV) and Mobility-As-A-Service (MaaS) functionality to the San Diego Association of Governments (SANDAG) activity-based travel demand models. Several new components were introduced into the CT-RAMP model in ABM2+ to explicitly model the ownership and availability of autonomous vehicles and shared mobility services. First, the auto ownership model was extended to consider autonomous (AV) versus human-controlled (HV) vehicles. Second, a simulation model was added that determines for each AV-owning household whether an AV is available for each tour. Third, the tour and trip mode choice models were extended to consider new mobility-as-a-service modes and coefficients were modified to represent AV-scenario assumptions. Fourth, software was modified to explicitly track whether an AV was chosen for each tour and trip and to provide the capability to assign AVs as a separate vehicle class. Finally, a vehicle routing model was developed to represent taxi and TNC routing, and an intra-household AV sharing algorithm was developed to represent repositioning trips between household members.

3.1 | AUTO OWNERSHIP ENHANCEMENTS

As shown in Figure 4, the model is nested with a choice between 0 and 1+ vehicles at the top, followed by a choice of 1, 2, or 3_+ vehicles. As shown in the figure, the model was extended to consider number of AVs versus HVs for each auto-owning choice, with an asserted nesting coefficient of 0.3. It was assumed that a household owning 4 vehicles would likely not own any autonomous vehicles and future scenarios that assume high levels of AV ownership would significantly reduce or even eliminate the share of 4+ vehicle owning households.

Table 7 shows the coefficients added to the auto ownership model to capture likely socio-economic and mobility attributes related to AV ownership. The exponentiated values are also shown in order to illustrate the effect of the coefficient on the probability of AV ownership. These coefficients were adopted from recent AV scenario testing conducted by RSG using the Jacksonville DaySim model. They assume that younger and more wealthy households are more likely to own AVs, all else being equal. They also assume that households with longer work commutes would be more likely to own an AV. Although they are informed by current literature, there is no way to statistically estimate these variables since there are no AV-owning households currently.

There is an additional variable that reflects the accessibility to non-mandatory activities by TNC modes, that can be used to decrease auto ownership for households in zones with relatively good TNC access. The accessibility is built using auto travel time and distance skims and takes into account an average wait time for TNC based on the density of the zone, as described more fully below. The coefficient for this variable is borrowed from the coefficient for home TAZ transit accessibility, multiplied by the natural log of the ratio of the TNC share of resident trips to non-mandatory activities divided by the transit share of resident trips to non-mandatory activities. This has the effect of scaling the sensitivity to TNC accessibility to be consistent with transit accessibility. Ultimately re-estimating the auto ownership model with this variable would be desirable.

TABLE 7: AUTO OWNERSHIP VARIABLES AND COEFFIECIENTS RELATED TO AUTONOMOUS VEHICLES AND TNCS

VARIABLE	COEFFICIENT	EXP (COEFFICIENT)
Household Income under $50k	-1.0000	0.37
Household Income 100k+	1.0000	2.72
Younger household (Number of persons 18 to 35 >= Number of Persons 65+	0.5000	1.65
Older household (Number of persons 18 to 35 < Number of Persons 65+	-1.0000	0.37
Hours of travel by auto for work, summed across all workers in household	0.2500	1.28
Home TAZ Maas Accessibility	TBD	TBD

In addition to these variables, a set of alternative-specific constants was applied and calibrated to reflect different levels of AV ownership according to scenario-specific targets. A spreadsheet was developed to calculate the target for each auto ownership choice based on a user-specified average vehicle ownership and a user-specified AV percentage of privately-owned vehicles. These constants have been calibrated for 20% and 50% AV ownership scenarios to be tested during sensitivity testing.

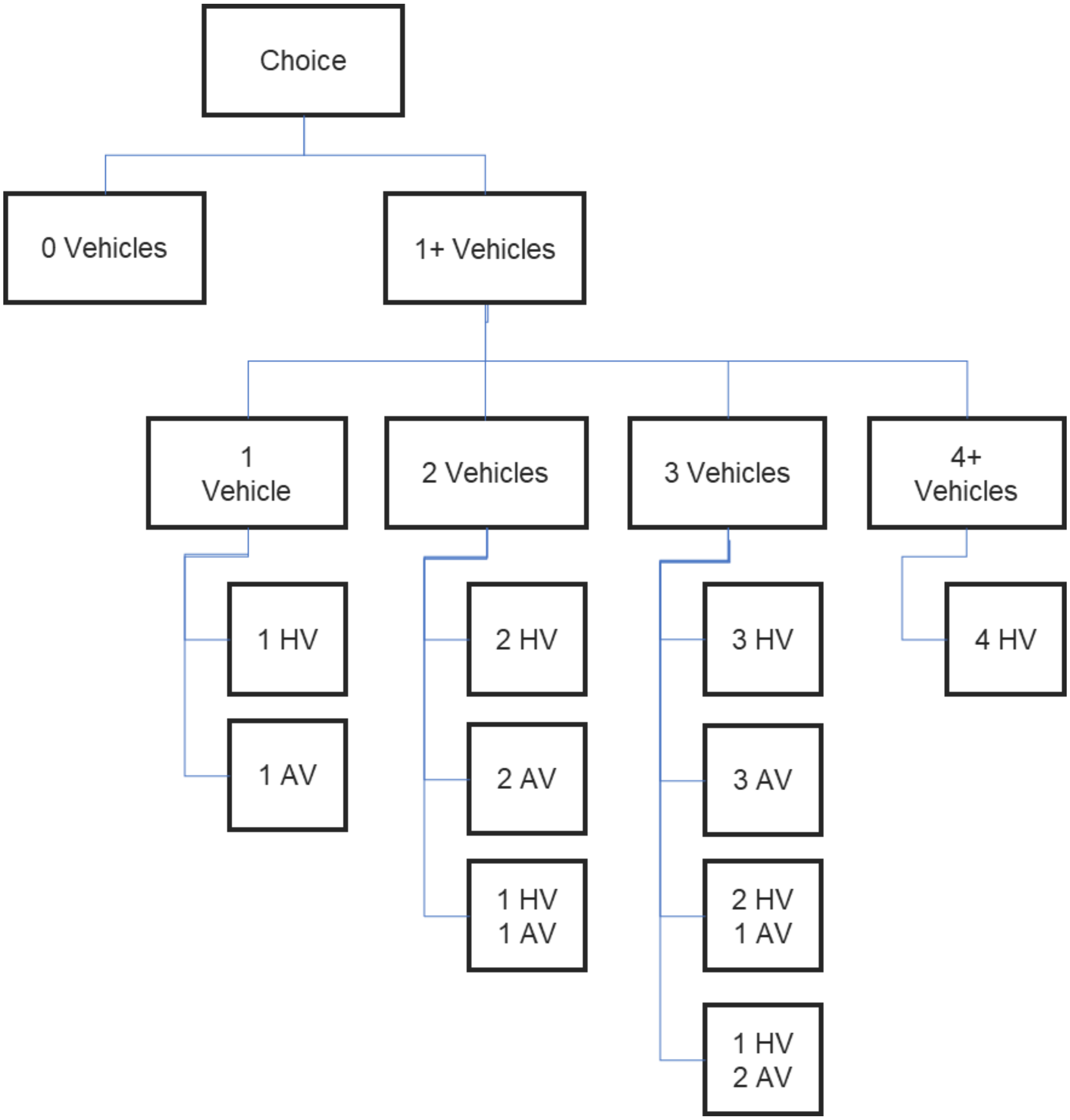

FIGURE 4: AUTO OWNERSHIP MODEL WITH AV CHOICE

3.2 | AV TOUR AVAILABILITY

Households that own at least one of each type of vehicle (HV and AV) have a choice of which vehicle to use for each tour, which is taken into account not only when auto is the chosen mode but also when evaluating other modal options (walk, bike, transit, etc.). ABM2+ was enhanced to make this decision explicit, without introducing a full vehicle allocation model that would result in a much more complicated system. Instead, the AV availability model assumes that the starting point for the probability of an AV being available for the tour is equal to the share of AVs to total vehicles owned by the household. Since it is likely that the probability of an AV might be higher than the proportion of AVs owned by the household due to the flexibility offered by AVs in terms of repositioning, the user can set "probability boosts" based on the ratio of autos to drivers.

Currently the probability boost is set to 1.2 (20% higher) when autos is less than drivers and 1.1 (10% higher) when autos is greater than or equal to drivers.

3.3 | MODE CHOICE ENHANCEMENTS

SANDAG tour and trip-based mode choice models were modified to explicitly represent the choice of mobility-as-a-service modes. A new "Taxi\TNC" nest was added with sub-alternatives for traditional taxi versus new Transportation Networking Company (TNC) modes including single-passenger TNC such as UberX and shared-passenger TNC such as UberPool. The kiss-and-ride (KNR) to transit alternative was extended to represent privately-owned vehicle KNR versus TNC-KNR (first/last mile transit service).

Table 8 shows the utility components associated with Taxi and TNC modes.

TABLE 8: TAXI AND TNC UTILITY COMPONENTS

UTILITY COMPONENT	VARIABLE - TAXI	VARIABLE - TNC SINGLE	VARIABLE - TNC SHARED	COEFFICIENT
In-vehicle time	GP time	GP time	GP time * 1.25 (to represent out-direction travel and pickup/dropoff time)	In-vehicle time coefficient
Wait time	Simulated from distribution	Simulated from distribution	Simulated from distribution	1.5 * IVT coefficient
Tolls	Not allowed	Not allowed	Not allowed	N.A.
Fare	Initial cost + cost per mile * distance + cost per minute * time	Max(minCost, Initial cost + cost per mile * distance + cost per minute * time)	Max(minCost, Initial cost + cost per mile * distance + cost per minute * time)	Cost coefficient
Alternative-specific constant	Base year = calibrated Future-year = User-defined	Base year = unavailable Future-year = User-defined	Base year = unavailable Future-year = User-defined	N.A.

Taxi and TNC mode wait times are simulated from distributions that were estimated based on a survey of actual taxi and TNC wait times conducted in the Portland region in 2015[1]. The survey data was limited to call-initiated pickups (no pre-planned pickups were included). Lognormal distributions were estimated from this observed data for each mode according to the land-use density of the tour or trip origin. Density is defined as (population + employment)/area (sq. mi.). There are five categories of density from high to low with breakpoints at 15000, 5000, 2000, and 500.

The wait time distributions for taxi trips are shown in Figure 5, and wait time distributions for TNCs are shown in Figure 6, with average wait times shown in Table 9. As shown in the figures and tables, the ranges of wait time and standard deviation for taxi are much higher for taxis than for TNCs. Even so, the average wait time for a TNC for trips starting in the lowest density bin was over 10 minutes in 2015. This wait time may decrease in the future as demand for TNCs increase. Therefore, the average and standard deviation of each lognormal distribution are user-defined properties and can be varied with respect to specific scenarios.

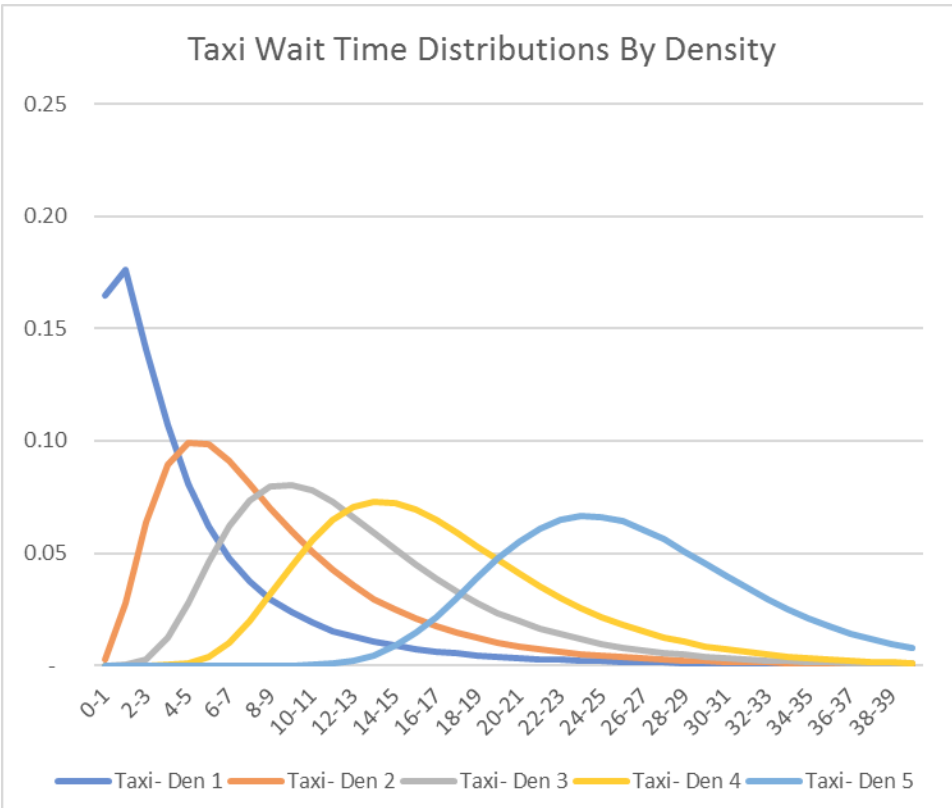

FIGURE 5: TAXI WAIT TIME DISTRIBUTIONS

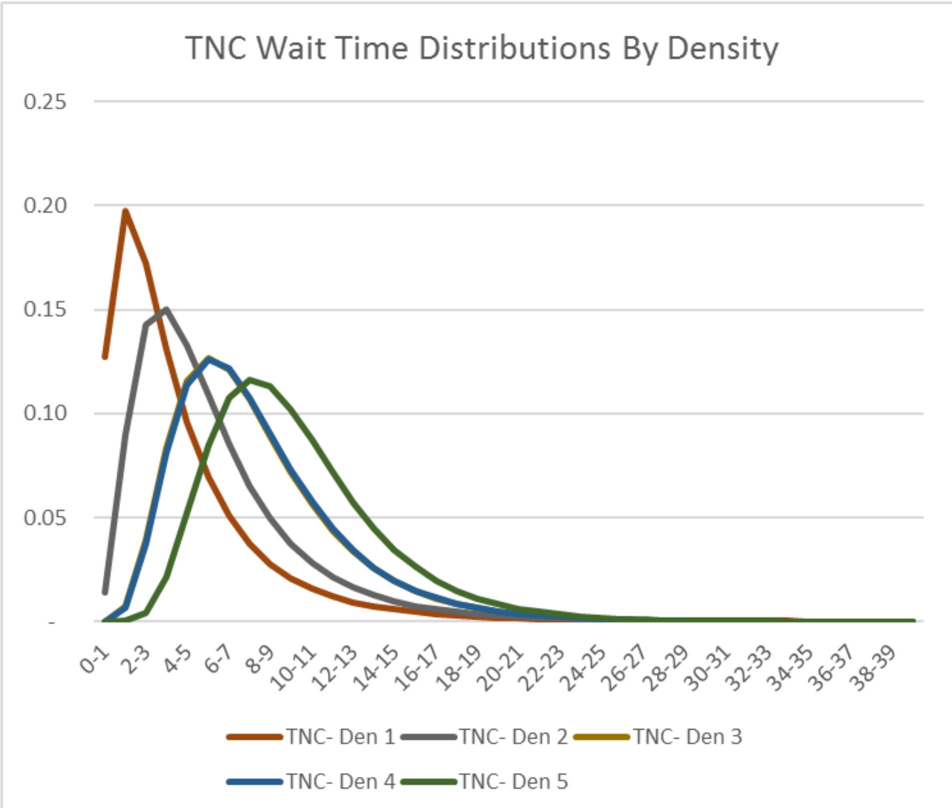

FIGURE 6: TNC WAITIM TIME DISTRIBUTION

TABLE 9: AVERAGE WAIT TIMES FOR TAXI AND TNC BY DENSITY

DENSITY RANGE		AVERAGE WAIT TIME (MIN)		
High	Low	Taxi	TNC- Single	TNC – Shared
100000000	15000	5.5	4.7	7
15000	5000	9.5	6.3	8
5000	2000	13.3	8.4	11
2000	500	17.3	8.5	15
500	0	26.5	10.3	15

TNC and taxi cost variables are also set in user-defined properties, with base-year values set based on publicly available data[2]. The base-year costs are shown in Table 10. Note that the average wait times in Table 9 and costs in Table 10 for shared TNC are currently asserted. All of these values will be re-calculated from observed TNC survey data once it is available.

TABLE 10: TAXI AND TNC COSTS

COST COMPONENT	TAXI	TNC- SINGLE	TNC – SHARED
Base fare	$2.20	$2.20	$2.20
Cost Per Mile	$2.30	$1.33	$0.44
Cost Per Minute	$0.10	$0.24	$0.08
Minimum Cost	0	$7.20	$3.00

In addition to the new modes, if the AV Tour Availability model indicates that an AV is available for the tour, a set of coefficient modifiers are applied to reflect differences in the actual or perceived travel time and cost of driving. These modifiers are specified for in-vehicle time, auto operating cost, parking cost, and terminal time, and are user-defined in the SANDAG properties file.

Their base values are shown in Table 11. The in-vehicle time modifier is currently set to 0.75 to reflect the assumed increased comfort, productivity and reliability of driving in an AV. Parking cost is eliminated as it is assumed the vehicle would be sent to a free remote site for the duration of the activity or else sent home (the vehicle deadheading model reflects the actual decision). Auto operating cost modifier is 0.75 to reflect the increased fuel efficiency of an AV, and terminal time is eliminated from the utility of driving since it is assumed that an AV would provide curbside pick-up/drop-off service. All of these parameters can be modified by the user to test the effect of different assumptions regarding the operation and use of AVs.

TABLE 11: COEFFICIENT MODIFIERS

COEFFICIENT	MODIFIER
In-vehicle time	0.75
Parking cost	0
Auto operating cost	0.75
Terminal time	0

3.4 | MOBILITY-AS-A-SERVICE VEHICLE ROUTING MODEL

The above model enhancements focus specifically on the *demand* for TNCs and AVs. Model outputs include trips by mode, including taxi, TNC-single, and TNC-shared, as well as an indicator that describes whether an AV was available for drive alone, shared 2, and shared 3+ trips. A vehicle routing model was developed to represent both linking of shared-TNC trips across the population, as well as the relocation of vehicles to serve passengers (passenger-less trips). The algorithm was developed with the following features:

- Reasonable approximation of real-world shared AV routing algorithms
- Capability to estimate vehicle fleet size required to serve passenger demand
- Takes trip lists from SANDAG activity-based travel model as an input

- Outputs a vehicle trip list that can be assigned to transport network to estimate impacts (congestion, VMT, etc.)
- Generates empty vehicles
- Rapid development, reasonable runtime

We took inspiration for our algorithm from the Lyft Engineering Blog on Lyft Line[3]. The first cut of their algorithm was a greedy haversine matchmaking system. A greedy system is one that takes the first match found that satisfies constraints, as opposed to system-optimal solution. The constraints include the time requesting ride, a maximum detour time, and the eventual elimination of backtracking (this was added in a later version). Their approach was evolutionary. Eventually they implemented a less greedy algorithm by introducing route swapping (passengers are swapped with faster route if the swap can be made before pickup). Additional rules were added, including the number of additional pickups per passenger, and rules regarding the sequence of pickups and drop-offs. Over time, hundreds of rules were added. New features were added as well, such as HotSpots, where passengers are requested to walk to a designated pickup spot to optimize the vehicle route taking into account passenger delay.

We have insufficient resources to design, implement, test, and run a complicated algorithm like Lyft's for planning purposes, and we believe such an effort would be overkill. As noted, one of the key objectives of our work is to ensure that our algorithm is fast as it needs to run for an entire simulation day and potentially 10-15 million trips in a reasonable time (1-2 hours). We developed a heuristic greedy algorithm that satisfies this constraint and results in a plausible set of routes.

The algorithm works as follows:

- In each increment of time
    - Find a person trip (auto only) that needs a ride at random
    - Find nearest empty vehicle to serve the passenger. If there isn't one, generate one at the origin. If there is one, generate a trip from last location to the pickup zone.
    - For all zones within max diversion distance of the first passenger, in order from closest to furthest:
        - Find passengers who need a ride subject to constraints:
            - Their origin and destination have to be within max diversion time of first passenger
            - Their pick-up & drop-off location has to be in the same direction as first passenger (no backtracking)
        - Stop adding passengers if max vehicle capacity reached
    - Route the vehicle through passenger pick-up and drop-off locations
        - Assume pickups and drop-offs occur according to location from closest to furthest
    - Update vehicle availability queue (vehicle available after last drop-off according to travel time skim)

Currently the model runs at a 5-minute time resolution. Note that the algorithm is a bit simplistic, in that the selection of additional passengers in a ride-sharing vehicle is constrained by the destination of the first passenger. In an actual ride-share, the vehicle can be continuously routed if intermediate passengers are dropped off after the first passenger. However, implementation of this level of complexity is beyond the scope of the project. One potential simplistic enhancement is to select the first passenger based on trip distance. This has not been implemented yet.

Recent enhancements to the algorithm include HotSpots and vehicle refueling. HotSpots are defined as the micro-zone (MAZ) within each TAZ with the most ride-sharing passengers in each time increment. Any ride-sharing passenger departing in the same time increment within a maximum walk distance are relocated to that HotSpot. This enhancement reduces the number of short intra-zonal vehicle relocations to pick up additional passengers in high-demand TAZs. Vehicle refueling stops simulate the trip to gas stations or charging stations. The user can specify the maximum distance across all vehicle trips before a refueling stop is required (currently set to 300 miles), and the time required for refueling (currently set to 15 minutes). Upon reaching the maximum distance, the vehicle is routed to the closest refueling station. Currently, MAZs with refueling stations are based on SANDAG's land-use parcel data, and stored as a field in the input MAZ file (refuel_stations).

The algorithm also serves and routes single-ride TNCs and traditional taxi trips. Currently it is assumed that all vehicles can serve both single-ride trips and shared ride trips, so the estimated vehicle fleet size takes into account both types of riders. In the case of a single ride trip, only the requesting trip is served with no pickups of any additional passengers other than those included in the first passengers travel party (joint trips and visitor\airport\Mexican resident travel parties).

The model outputs a taxi and TNC trip list which identifies the vehicle number, trip number, occupancy, origin, destination, period, and passenger(s) picked up and dropped off at the origin and destination of the trip.

The model also outputs a trip table which is added to non-taxi\TNC trips prior to auto assignment, including passenger-less TNCs and TNCs with passengers. In the case of an AV scenario (a scenario where the AV share is greater than zero), we assume that all TNCs are driverless; therefore both zero- passenger and one-passenger vehicles are added to the SOV trip tables prior to assignment, whereas 2-person and 3+ person TNCs are added to shared-2 and shared 3+ vehicle trip tables respectively. In the case of a non-AV scenario, the zero-passenger vehicles are added to the SOV trip tables, the one-passenger vehicles are added to the shared-2 trip tables, and the two and higher passenger vehicles are added to shared 3+ trip tables. We assume that all taxi and TNC trips are in the 'high' value-of-time bin. In the future, we may wish to assign AVs as a separate vehicle class, but this is not currently implemented.

3.5 | INTRA-HOUSEHOLD AV ROUTING ALGORITHM

The vehicle routing algorithm described above represents mobility as a service trip modes. However, in an autonomous vehicle scenario, privately-owned AVs may also be relocated to serve trips made by household members. This algorithm is somewhat different than a shared-ride vehicle routing algorithm, as the demand for single and shared ride TNC trips arises from the CT-RAMP model, which already takes into account travel time, wait time and cost. In the case of intra-household vehicle routing, a new model must be used that also take into account trip attributes such as parking cost (an AV trip to a zone with parking costs is likely to send the vehicle to a remote location or home rather than pay for parking), the cost required to relocate the vehicle (including tolls as a possible strategy to reduce congestion), and other potential attributes.

In order to represent this choice process, we implement a greedy algorithm coupled with a utility maximization model. The model runs in two passes; first, vehicles are allocated to household trips. Next, vehicle parking location is chosen for destinations in parking-constrained areas.

The model works as follows:

1. AV-eligible auto trips are sorted by person, and the time between trips (30-minute resolution) is calculated for each trip by each person. This is a useful variable to capture the likelihood of a particular traveler to keep possession of a vehicle for trips with a short duration
2. Trips are re-sorted by household. Trips departing in the same time period are assumed in order by activity purpose (mandatory, non-mandatory).
3. Each trip chooses a household autonomous vehicle i (up to 3 AVs are considered, see auto ownership choice model above) according to a multinomial logit model based on the following variables:
    a. The utility of travel to reposition vehicle i from the last known vehicle location (destination of last trip served by vehicle i or home location if no trips served)
    b. A utility 'benefit' based on the duration of the activity, conditioned on whether the traveler is already with vehicle i, which starts at 60 equivalent minutes of in-vehicle time for activities of 30 minutes or less, and decreases to 0 for activities over 1.5 hours.
4. Each trip to a parking-constrained destination chooses a parking location (stay with person, remote parking, return home) according to a multinomial logit model based on the following variables:
    a. Stay with vehicle: The parking cost at the destination based on the duration until the next trip served (employer reimbursement is taken into account)
    b. Stay with vehicle: The utility benefit for staying with the vehicle, based on the duration of the activity (see 3.b. above)
    c. Remote parking: The cost of remote parking, specified in the input file, based on the duration until the next trip served
    d. Remote parking: The utility of travel to the remote parking lot, specified as the closest remote parking lot to the current vehicle location
    e. Remote parking: The utility of travel from the remote parking lot to the next trip served
    f. Home: The utility of travel to the home location
    g. Home: The utility of travel from the home location to the next trip served
5. After the models are run, vehicle trips are created from the results and written to a file which includes the origin and destination MAZ, purpose, occupancy, and trip served (if relevant).
6. Empty vehicle trips are aggregated into origin-destination skims by period which are added to SOV trip tables from the travel models prior to assignment. We assume the AVs are in the 'high' value of time category.

4.0 MICROMOBILITY

Micro-mobility refers to modes such as e-scooters and dockless bike-share. These modes can be currently identified by the following characteristics:

- Powered by electric motors with a limited range
- Operate at speeds roughly equivalent to fast walk or bike, thus competing primarily with active modes
- Generally shared rather than privately owned
- Availability at trip origin depends upon the location/placement of the vehicles after charging
- Pay-as-you-go payment model (though in the future a monthly subscription payment plan may be offered)

According to recent data[2], the City of San Diego had approximately 222,000 e-scooter rentals over a two-week period from October 1 to October 14, 2019, or approximately 15,000 daily trips. This represented a 50% decrease from a two-week period in July 2019. This decline in usage may be related to decrease in tourism from July to October, but also potentially due to changes in the City regulatory environment; both Jump (Uber) and Skip have withdrawn from the San Diego market. Note that according to 2016 SANDAG household travel survey data, there are approximately 1M walk trips per day made by San Diego residents, so the share of e-scooters compared to walk trips is very low (1.4%).

The SANDAG travel demand model system was modified to incorporate micro-mobility modes in the following way:

- Micro-mobility mode accessibility, speed, and cost are taken into account when calculating perceived walk times for each origin-destination MGRA. We use a generalized cost equation to convert a generic micro-mobility mode cost into equivalent minutes of time. We then assume an all-or-nothing choice in which we take the minimum time of either walk time or micro-mobility generalized cost time.
- We replace walk time with the minimum time described above in the relevant parts of the SANDAG CT-RAMP model, including the time between microzones used for short-distance walk trips (MGRA-MGRA walk time), the time between transportation analysis zones used for long-distance walk trips (TAZ-TAZ walk time), and the time between microzones and transit access points used for transit access and egress time (MGRA-TAP walk time).
- We apply a post-processing procedure to determine, for each traveler choosing walk mode or walk as an access or egress transit mode, their probability of choosing walk or micro-mobility as the actual mode, and use Monte Carlo simulation to make a choice from that probability.

The following sections of this document describe the generalized time equation used for calculating equivalent minutes of micro-mobility time and the post-processing procedure for calculating walk versus micro-mobility mode and the data used for calibration.

[2] https://www.sandiegouniontribune.com/news/transportation/story/2019-10-24/e-scooter-ridership-plummets-in-san-diego

4.1 | MICRO-MOBILITY GENERALIZED TIME

The micro-mobility generalized time calculation requires the analyst to specify attributes for a 'generic' micro-mobility mode. It is possible to extend this procedure to consider multiple micro-mobility modes, but we wish to keep data requirements to a minimum at this time. Micro-mobility generalized time attributes are specified, with defaults indicated, in Table 12.

TABLE 12: MICRO-MOBILITY GENERALIZED COST ATTRIBUTES

ATTRIBUTE (CONTROL FILE TOKEN)	DESCRIPTION	UNITS	DEFAULT
active.micromobility.speed	Average speed	Miles per hour	12
active.micromobility.variableCost	Variable cost	Dollars per minute	0.20
active.micromobility.fixedCost	Fixed cost	Dollars	1.00
active.micromobility.rentalTime	Rental time	Minutes	1
active.micromobility.constant	Non-included attributes	Minutes	5 (min asserted, note calibrated is much higher)
active.micromobility.vot	Value of time	Dollars per hour	15
MicroAccessTime (MGRA file attribute)	Search/access time	Minutes	Variable by origin MGRA

The variable and fixed cost for micro-mobility modes is based on an average of rental costs in San Diego for Lime and Bird scooters in October 2019. Lime cost was $1 to unlock and $0.24 minute to ride, while the cost of a Bird scooter was $1 to unlock and $0.15 to ride. The top speed of e-scooters is 15 MPH; we assert an average speed of 12 MPH lacking any available data. We assert a rental time (time to unlock the e-scooter with mobile device) of 1 minute. We assert average availability times by origin MGRA; this is the time required to walk to an available, charged micro-mobility device. We also assert a non-included attribute penalty of 5 minutes. This is the penalty of not having the app on the phone, general attitudes towards e-scooters, and other potential disbenefits that account for the relatively low share of micro-mobility trips compared to the walk mode.

The generalized time calculated for the generic micro-mobility mode for a given origin o and destination d is:

$$\begin{aligned} GenTime = {} & \frac{Length_{od} * 60}{Speed} + rentalTime + microAccessTime_{o} + constant \\ & + \left(variableCost * \frac{Length_{od} * 60}{Speed} + fixedCost \right) * 60/VOT \end{aligned}$$

The generalized cost of micro-mobility is calculated in equivalent minutes of time for each MGRA-MGRA pair and MGRA-TAP pair, in a post-processing procedure written in Python. The procedure also reads the 'actual' walk time calculated by Java, and replaces the 'actual' walk time with the minimum of the micro-mobility generalized time or the walk time[3]. Figure 7 shows the result of the micro-mobility generalized time equation compared to walk time for a sample origin MGRA with an access time of 4 minutes. As can be seen, the walk time is lower than the micro-mobility equivalent time up to a distance of approximately 1.1 miles, due to the fixed time associated with accessing the micro-mobility vehicle, the time required for rental, the non-included attributes penalty, and the equivalent minutes of fixed cost. After 1.1 miles, the micro-mobility mode is more attractive.

The dashed line shows the minimum perceived time that will be used in demand models. Given that the micro-mobility time is lower for trips over 1.1 mile, the effect would be an increase in walk trips over this threshold.

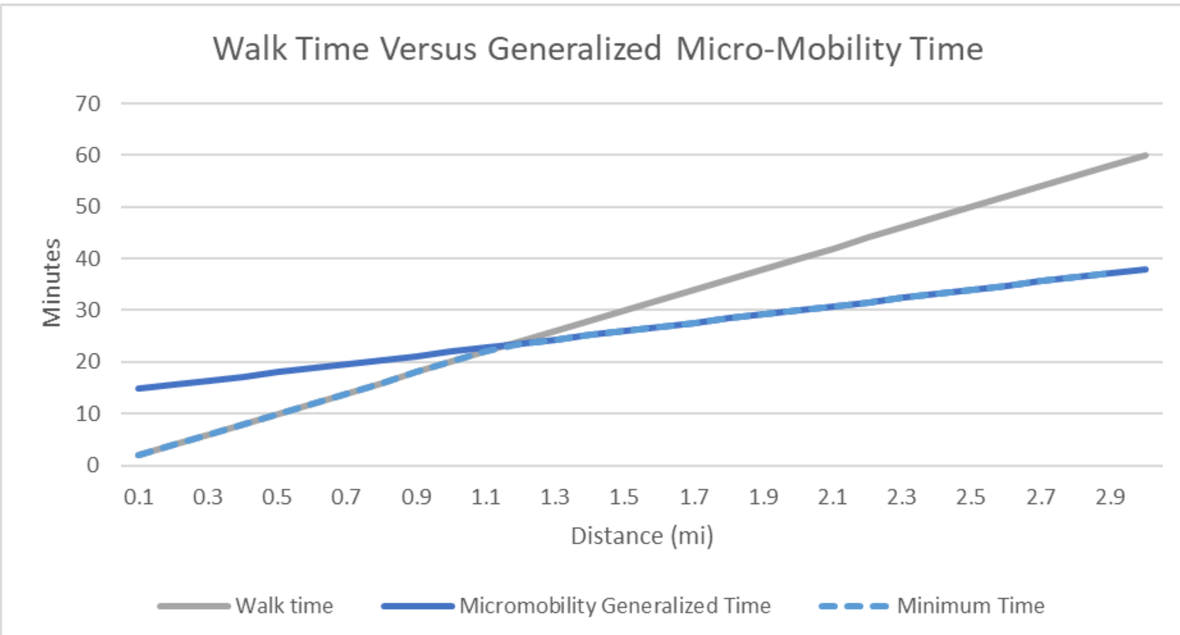

FIGURE 7: WALK TIME VERSUS GENERALIZED MICRO-MOBILITY TIME BY DISTANCE

4.2 | IMPLEMENTATION OF GENERALIZED TIME CALCULATION

The active walk network path procedure writes two files; the walk time between MGRAs within the maximum walk mode distance threshold and the walk time between MGRAs and TAPs within the maximum transit access/egress walk distance threshold. The distance thresholds are currently 3.0 miles and 1.0 mile respectively). Based on an analysis of Lime trips by distance from Salt Lake City (see below), we see no reason to extend the walk thresholds currently in place.

The two files are indicated by the sandag_abm.properties file tokens active.logsum.matrix.file.walk.mgra (=walkMgraEquivMinutes.csv) and active.logsum.matrix.file.walk.mgratap (= walkMgraTapEquivMinutes.csv). The Python code will read these tokens from the properties file, as well as the additional tokens specified in Table 12. The Python code will also read the MGRA file specified in the MGRA file token from the properties file mgra.socec.file (= input/mgra13_based_input2016.csv), and store

[3] Note: The walk files have both 'actual' and 'perceived' times. In the Java CT-RAMP code, only 'actual' times are currently used.

the MicroAccessTime field and the MAZ number in a DataTable. The code will read each active file output by Java and calculate the generalized micro-mobility time using the parameters provided in the properties file. The code will read the perceived walk time from the file and replace it with the minimum of the perceived walk time and the micro-mobility generalized time.

4.3 | MICROMOBILITY TRIP MODE CHOICE

A logit choice model will determine walk versus micromobility mode for walk trips and walk as an access/egress mode to transit. Utility equations for walk mode and micromobility mode are shown below.

$Utility_{walk} = Beta_{time} * \text{walk time}$

$Utility_{Micromobility} = Beta_{time} * \text{micromobility time} + Beta_{cost,income} * \text{cost} + Constant_{micromobility}$

The time and cost coefficient will be transferred from the trip mode choice mode, and scaled in calibration such that the observed trip length distribution shown in Figure 8. Calibration targets will be summarized from the recently-conducted Transportation Networking Company (TNC) survey, and compared to the 15,000 daily micromobility trips implied from the October 2019 data cited above for San Diego. If the TNC survey is not consistent with the City of San Diego data, the team will decide which targets to adopt for calibration. According to a 2018 E-scooter survey conducted by the City of Portland (Table 13), 14% of e-scooter riders would have driven if an e-scooter was not available, while 34% would have taken taxi, Uber, or Lyft, and another 35% would have walked. These percentages can be used to calculate a reduction in existing auto, walk, bike, transit, and TNC modes in order to calculate calibration target values for walk and micro-mobility modes.

The choice model is implemented in Java and applied to resident and visitor trips prior to writing trip files to disk.

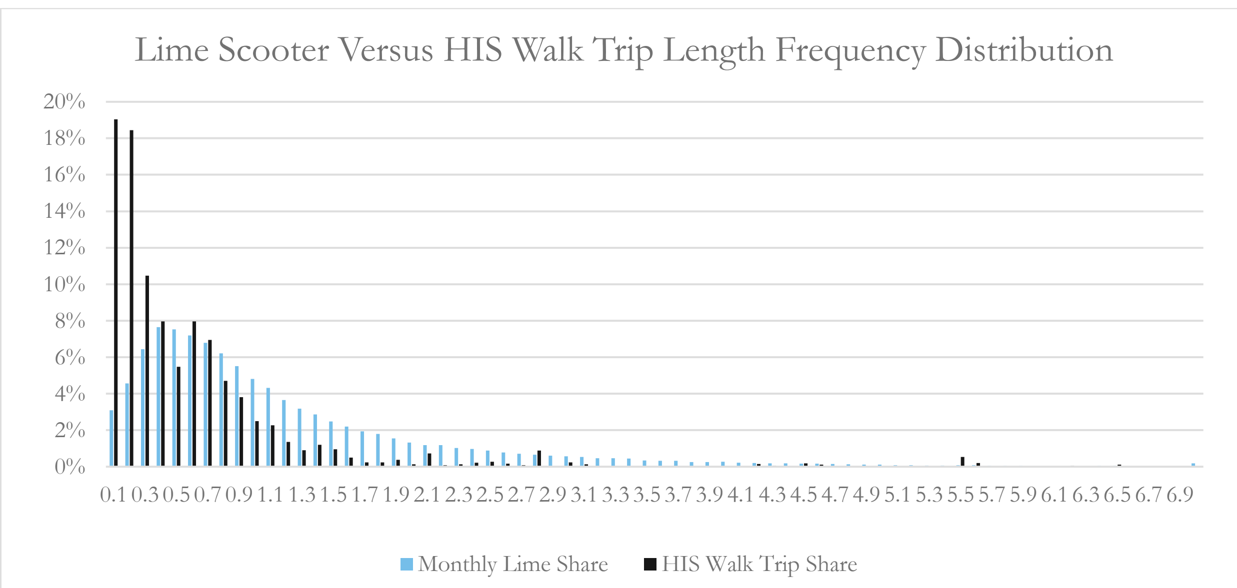

FIGURE 8: TRIP LENGTH FREQUENCY DISTRIBUTION COMPARISONS FOR SALT LAKE CITY LIME SCOOTER TRIPS VERSUS SANDAG HOUSEHOLD TRAVEL SURVEY WALK TRIPS

TABLE 13: MODE CHOICE IF E-SCOOTER NOT AVAILABLE

THINK ABOUT YOUR LAST RIDE ON AN E-SCOOTER IN PORTLAND. IF A SHARED E-SCOOTER HAD NOT BEEN AVAILABLE, HOW WOULD YOU HAVE GOTTEN AROUND? (SELECT ONLY ONE.)	PERCENT
Driven a personal vehicle, carshare vehicle, or other motor vehicle	14.33%
Other (please specify below)	1.04%
Ridden a personal bike	0.76%
Ridden a personal e-scooter	0.28%
Ridden as a passenger in a vehicle and dropped off by a friend, family member, or other person	1.80%
Ridden BIKETOWN	3.13%
Taken a Bus/ MAX/ Streetcar	3.89%
Taken a taxi, Uber, or Lyft	34.25%
Walked	35.48%
Would not have taken trip	5.03%
Grand Total	**100.00%**

Source: 2018 E-Scooter Pilot User Survey Results, Portland Bureau of Transportation, City of Portland 2018

5.0 TOLLING

The team performed a successful test where toll and non-toll choices were collapsed into one category and let the highway skimming and assignment determine the toll versus non-toll path choice. The goal was to simplify the mode structure in the demand models and reduce number of vehicle classes in highway skimming and assignment. The simplification offered significant benefits on both the demand and the supply side. In the java demand models, this resulted in less memory footprint, less skims to read, and less utility calculates, therefore resulting in significant time savings. The supply side also received runtime benefits due to fewer vehicle classes that made the highway skimming and assignment steps run faster. The fewer vehicle classes also created some room to add more vehicle classes in future (ex. AV demand) with relatively lower burden on overall runtime.

The collapsing of toll classes not only improved the model run time and lowered memory requirements; it also significantly improved the flows on the SR-125 toll facility. The improved flows on the toll facility further reinforced the argument for a need to simplify the toll choice in the model system. Convinced with these results, the team went ahead and made the simplification in the model system.

The following sections first describe model changes and then present results by comparing before and after flows.

5.1 | MODEL CHANGES

The toll choice simplification required changes to both mode choice structure in the demand models and vehicle classes in highway assignment and skimming.

MODE CHOICE

Table 14 presents new collapsed modes and how they are related to the initial modes. The collapsed modes reduced the mode choice alternatives by 3 – from 16 initial to 13 collapsed.

TABLE 14: INITIAL VS COLLAPSED MODES

<table>
<tr><th>NO.</th><th>INITIAL</th><th>NO.</th><th>COLLAPSED</th></tr>
<tr><td>1</td><td>Drive Alone Free</td><td rowspan="2">1</td><td rowspan="2">Drive Alone[4]</td></tr>
<tr><td>2</td><td>Drive Alone Pay</td></tr>
<tr><td>3</td><td>Shared Ride 2 Free</td><td rowspan="2">2</td><td rowspan="2">Shared Ride 2</td></tr>
<tr><td>4</td><td>Shared Ride 2 Pay</td></tr>
<tr><td>5</td><td>Shared Ride 3 Free</td><td rowspan="2">3</td><td rowspan="2">Shared Ride 3</td></tr>
<tr><td>6</td><td>Shared Ride 3 Pay</td></tr>
</table>

[4] There is one drive-alone mode; however, drive-alone trip tables are segmented by transponder ownership, since use of I-15 managed lanes requires a transponder for single-occupant vehicles.

NO.	INITIAL	NO.	COLLAPSED
7	Walk	4	Walk
8	Bike	5	Bike
9	Walk to Transit	6	Walk to Transit
10	Park and Ride to Transit	7	Park and Ride to Transit
11	Kiss and Ride to Transit	8	Kiss and Ride to Transit
12	TNC to Transit	9	TNC to Transit
13	Taxi	10	Taxi
14	TNC Single	11	TNC Single
15	TNC Shared	12	TNC Shared
16	School Bus	13	School Bus

The truck models (heavy truck model and commercial vehicle model) were also modified to eliminate toll versus non-toll segmentation and produce travel by truck class only. The models retained the toll-eligible skims so that they can consider toll cost in travel choices, should toll facility be included in the path based on their value-of-time. The revised mode choice model structure is shown in Figure 9.

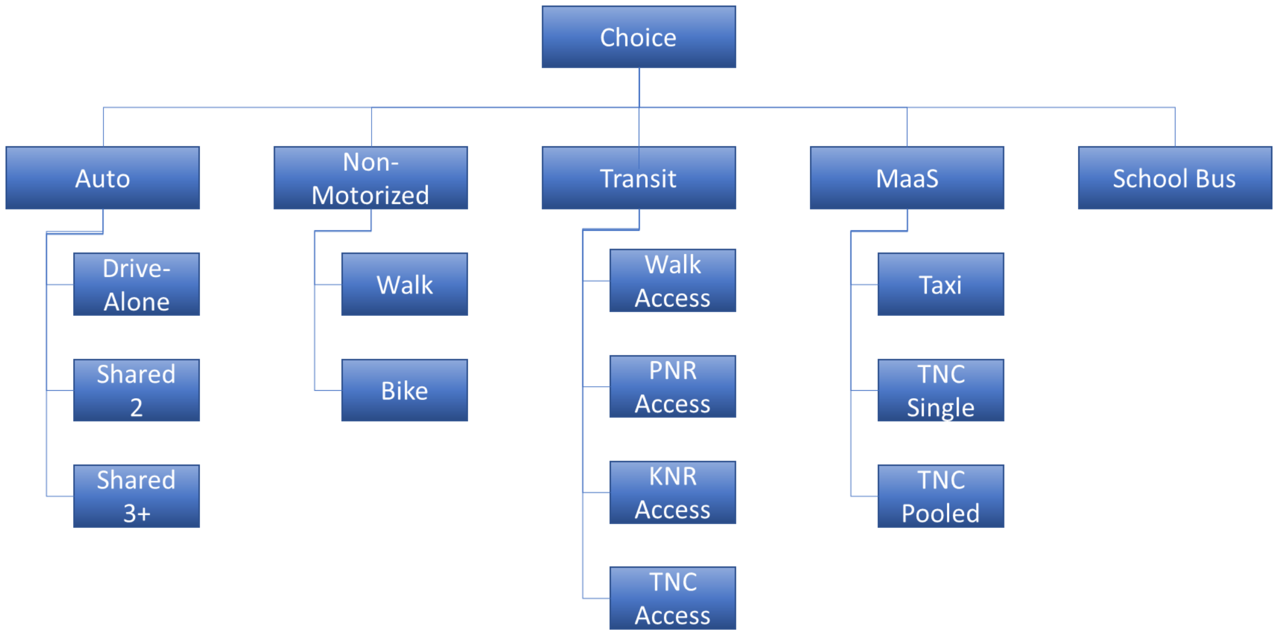

FIGURE 9: REVISED MODE CHOICE MODEL STRUCTURE

HIGHWAY ASSIGNMENT

Similar to mode choice alternatives, the assignment classes were also collapsed by combining free and toll vehicle classes into one. Further, the drive alone demand is segmented by transponder availability. The transponder ownership model predicts transponder ownership of for the San Diego households. The ownership information is carried over to the trip level to segment residents' travel by SOV in two classes: no transponder and transponder. It is assumed that if a household owns a transponder then all trips made by the household members have it available for use.

The transponder segmentation is used to determine SOV demand eligibility for using the 1-15 managed lane facility. The SOV demand with transponder are allowed to use the managed lane facility. The SOV demand without transponder are prohibited. HOV2 and HOV3 trips travel free on the facility, regardless of transponder availability. The SR125 toll facility has a cash option, therefore, the facility is allowed for all classes but applied with a toll if the facility is in the path.

Table 15 presents new collapsed assignment classes and their relation to the initial classes. The collapsing of toll choice reduced assignment classes by 9 - from 24 in regular to 15 in collapsed. Note that as could be interpreted from the table, for the SOV demand, no transponder and transponder classes do not directly relate to free and pay classes respectively. The new SOV classes are determined based on availability of a transponder for the trip.

TABLE 15: INITIAL VS COLLAPSED ASSIGNMENT CLASSES

<table>
<tr><th>NO.</th><th>INITIAL</th><th>NO.</th><th>COLLAPSED</th></tr>
<tr><td>1</td><td>SOV Free Low VOT</td><td>1</td><td>SOV Non-Transponder Low VOT</td></tr>
<tr><td>2</td><td>SOV Toll Low VOT</td><td>2</td><td>SOV Transponder Low VOT</td></tr>
<tr><td>3</td><td>HOV2 Free Low VOT</td><td rowspan="2">3</td><td rowspan="2">HOV2 Low VOT</td></tr>
<tr><td>4</td><td>HOV2 Toll Low VOT</td></tr>
<tr><td>5</td><td>HOV3 Free Low VOT</td><td rowspan="2">4</td><td rowspan="2">HOV3 Low VOT</td></tr>
<tr><td>6</td><td>HOV3 Toll Low VOT</td></tr>
<tr><td>7</td><td>SOV Free Medium VOT</td><td>5</td><td>SOV Non-Transponder Medium VOT</td></tr>
<tr><td>8</td><td>SOV Toll Medium VOT</td><td>6</td><td>SOV Transponder Medium VOT</td></tr>
<tr><td>9</td><td>HOV2 Free Medium VOT</td><td rowspan="2">7</td><td rowspan="2">HOV2 Medium VOT</td></tr>
<tr><td>10</td><td>HOV2 Toll Medium VOT</td></tr>
<tr><td>11</td><td>HOV3 Free Medium VOT</td><td rowspan="2">8</td><td rowspan="2">HOV3 Medium VOT</td></tr>
<tr><td>12</td><td>HOV3 Toll Medium VOT</td></tr>
<tr><td>13</td><td>SOV Free High VOT</td><td>9</td><td>SOV Non-Transponder High VOT</td></tr>
<tr><td>14</td><td>SOV Toll High VOT</td><td>10</td><td>SOV Transponder High VOT</td></tr>
<tr><td>15</td><td>HOV2 Free High VOT</td><td rowspan="2">11</td><td rowspan="2">HOV2 High VOT</td></tr>
<tr><td>16</td><td>HOV2 Toll High VOT</td></tr>
<tr><td>17</td><td>HOV3 Free High VOT</td><td rowspan="2">12</td><td rowspan="2">HOV3 High VOT</td></tr>
<tr><td>18</td><td>HOV3 Toll High VOT</td></tr>
<tr><td>19</td><td>Heavy-Heavy Truck Free</td><td rowspan="2">13</td><td rowspan="2">Heavy-Heavy Truck</td></tr>
<tr><td>20</td><td>Heavy-Heavy Truck Toll</td></tr>
<tr><td>21</td><td>Light-Heavy Truck Free</td><td>14</td><td>Light -Heavy Truck</td></tr>
</table>

NO.	INITIAL	NO.	COLLAPSED
22	Light -Heavy Truck Toll		
23	Medium-Heavy Truck Free	15	Medium -Heavy Truck
24	Medium -Heavy Truck Toll		

For the San Diego residents, the ownership of a transponder is available from the transponder ownership model. However, this information is not available for travel by other special markets (visitor, cross-border, internal-external, airport, and external-internal). Table 16 presents the assumptions used in segmenting SOV demand into transponder versus non-transponder classes. All trips from the Mexican resident (cross-border) and visitor models are assumed to have no access to transponders, whereas airport, internal-external, and external-internal models are assumed to have transponders available. Note that owning a transponder does not necessarily mean that I-15 managed lanes are used for trips generated by the household; actual facility use depends on if it is the trip path according to origin, destination, time of day, and value-of-time.

TABLE 16: SOV TRANSPONDER AVAILABILITY BY MARKET

MARKET	TRANSPONDER AVAILABILITY
CT-RAMP Resident	Transponder ownership model
Cross-Border	No
Visitor	No
Airport SAN	Yes
Airport CBX	Yes
Internal-External	Yes
External-Internal	Yes

HIGHWAY SKIMMING

The highway skimming was also updated to make it consistent with the highway assignment. One skim is generated for each vehicle class except two for SOV (transponder and non-transponder). The skimming process determines whether the mode choose a toll facility.

5.2 | RESULTS

This section compares flows from the before (regular classes) and the after (collapsed classes) models. The comparisons start with examining flows at the regional level and move on to assessing flows on I-15 managed lane and SR125 toll facilities due to them being directly related to the toll choice simplification. Note that results presented under this section use flows from an un-calibrated base year (2016) model.

REGIONAL

Figure 10 presents a scatter plot comparing before (regular classes) and after (collapsed classes) flows by link. The scatter plot is a good way to quickly identify magnitude of differences by link. A point in the plot represents x-value as before flow and y-axis as after flow. The reference line represents an ideal point location where both x and y values are the same. Results with most points closer to the reference line are considered as good. Generally, the plot shows good match of after flows with the before flows, except some links where after flow is higher than the before flows.

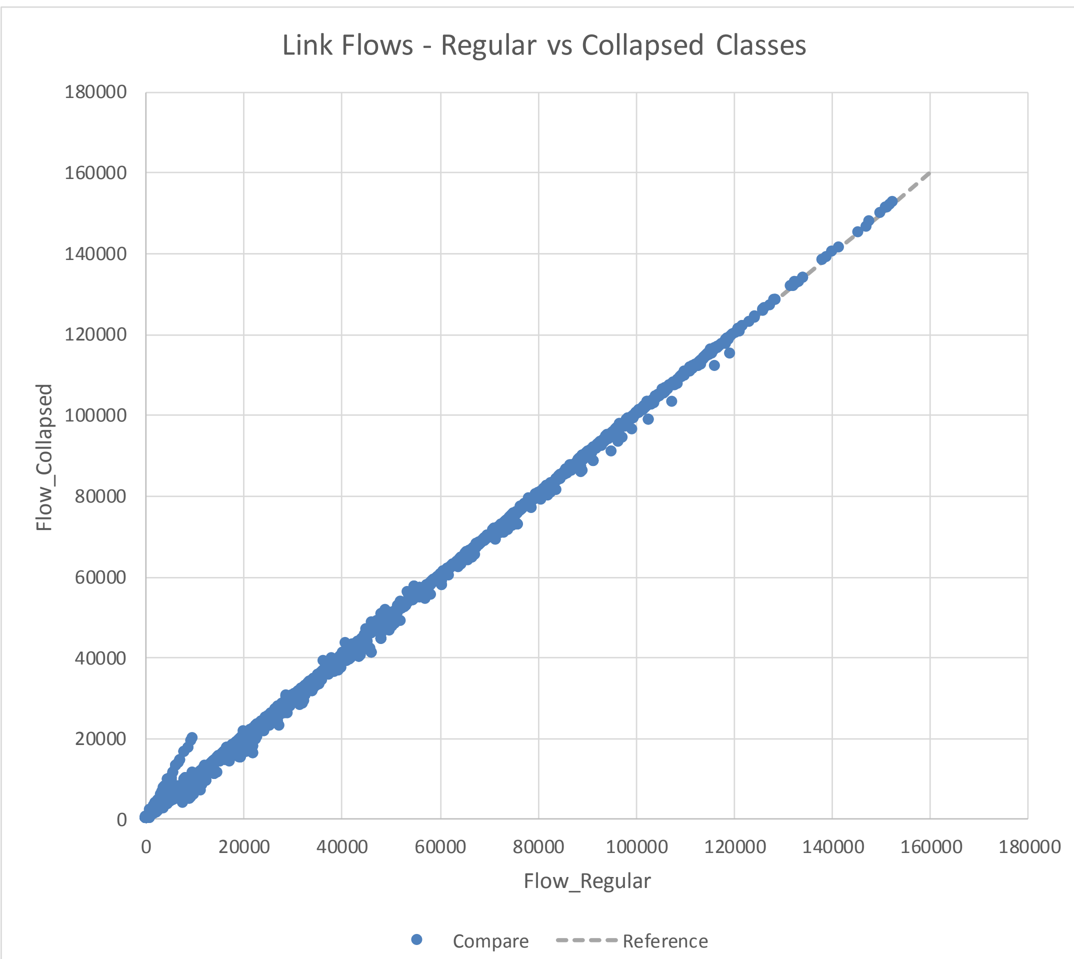

FIGURE 10: COMPARISON OF FLOW BY LINK – COLLAPSED TOLL CLASSES VS REGULAR CLASSES

A comparison of flows by facility type (general purpose or toll) shed more lights into the links with differences. As shown in Table 17, at the region level, before and after flows were very close. However, toll facilities showed higher flows with the collapsed classes. Other facilities, general purpose and managed lane, match pretty good.

TABLE 17: REGIONWIDE COMPARISON OF FLOWS ON ALL LINKS

FACILITY TYPE	REGULAR	COLLAPSED	DIFF	%DIFF
General Purpose	323,723,838	323,177,179	(546,659)	-0.2%
Managed Lanes (HOV2)	1,259,466	1,264,438	4,972	0.4%
Managed Lanes (HOV3)	-	-	-	0.0%
Toll Lanes	266,878	481,295	214,417	80.3%
TOTAL	**325,250,181**	**324,922,912**	**(327,269)**	**-0.1%**

I-15 MANAGED LANE FACILITY

Further, the flows on the I-15 managed lane and the SR-125 toll facilities were compared separately. Table 18 compares flows on the I-15 HOV lane facilities by direction – north bound (NB) and south bound (SB). The directional flows compare well as well.

TABLE 18: REGIONWIDE COMPARISON OF FLOWS – I15 MANAGED LANES

FACILITY NAME	REGULAR	COLLAPSED	DIFF	%DIFF
I-15 HOV NB	390,079	392,587	2,508	0.6%
I-15 HOV SB	282,134	282,307	173	0.1%
TOTAL	**672,213**	**674,894**	**2,681**	**0.4%**

Figure 11 and Figure 12 further examine I-15 HOV flows by comparing them by entry gate in the NB and SB direction respectively. In both plots, the X-axis shows entry gate and the Y-axis represents the corresponding flow. Before (regular) flows are represented by the red line and the after (collapsed) flows by the green line in either direction. For either direction, the collapsed flows match very close to the flows with regular classes further confirming very minimal impact of toll choice simplification on the use of the I-15 managed lane facility.

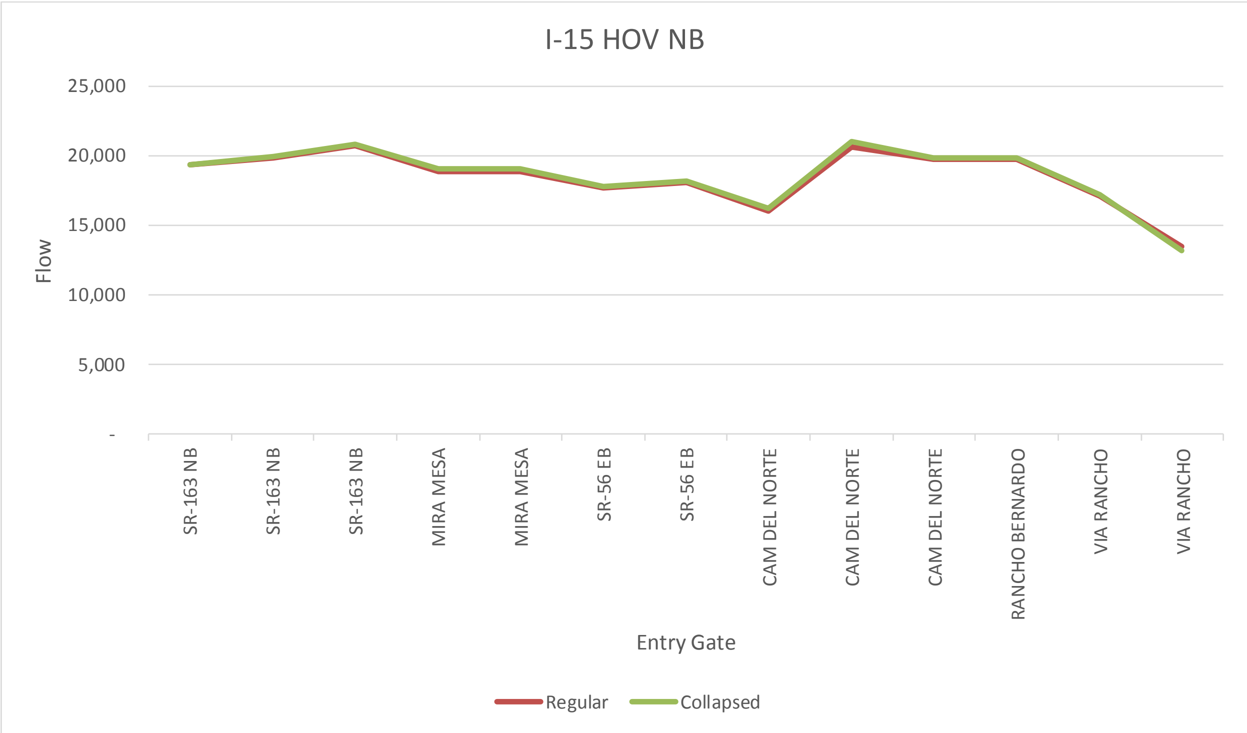

FIGURE 11: FLOW WITH REGULAR VS COLLAPSED CLASSES – I15 HOV NB

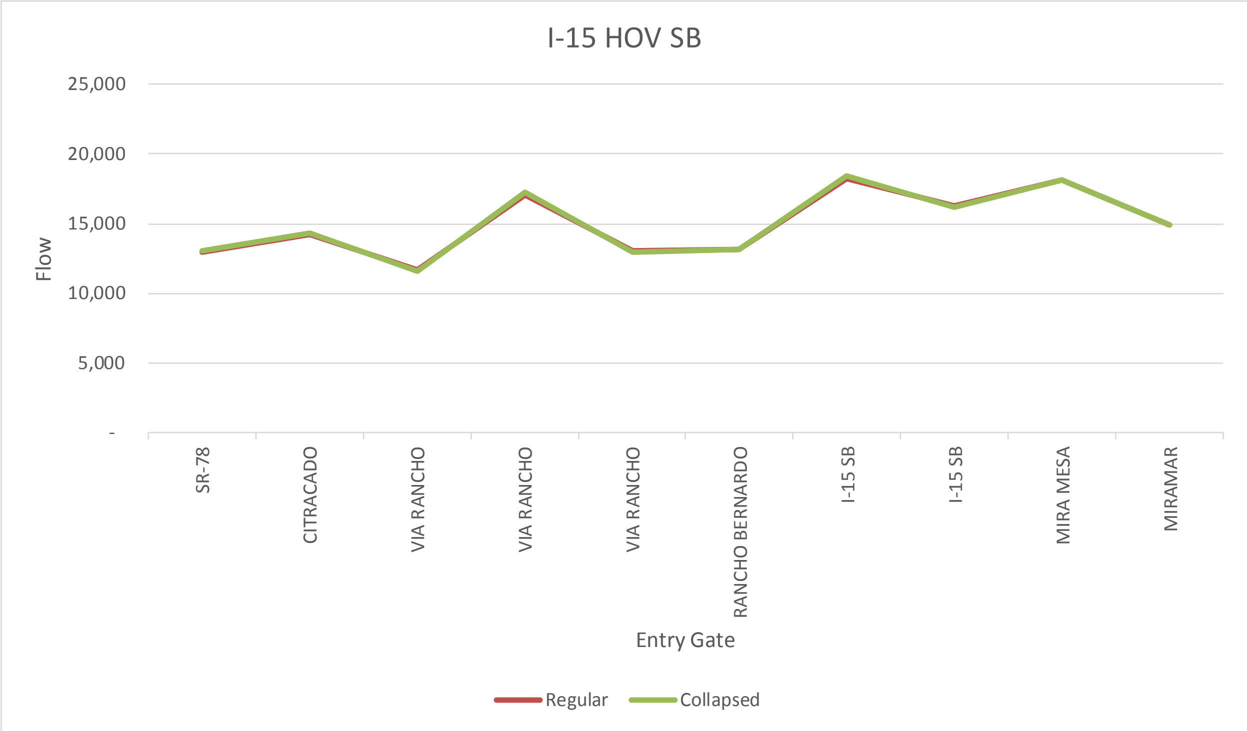

FIGURE 12: FLOW WITH REGULAR VS COLLAPSED CLASSES – I15 HOV SB

SR 125 TOLL FACILITY

The flows the SR-125 toll facilities were compared separately. compares flows on the SR-125 toll facility by direction – north bound (NB) and south bound (SB). Similar to the regional comparison, the directional flows show higher flows in the collapsed classes.

TABLE 19: REGIONWIDE COMPARISON OF FLOWS – SR125 TOLL LANES

DESCRIPTION	REGULAR	COLLAPSED	DIFF	%DIFF
SR-125 NB	122,839	220,577	97,738	79.6%
SR-125 SB	108,840	199,368	90,528	83.2%
TOTAL	**231,680**	**419,945**	**188,265**	**81.3%**

Figure 13 and Figure 14 further examine SR-125 toll flows by comparing them by entry gate in the NB and SB direction respectively. In both plots, the X-axis shows entry gate and the Y-axis represents the corresponding flow. The red columns represent before (regular) flows and the green columns after (collapsed) flows. The plots also include observed traffic counts in blue columns. As observed before, compared to the before (regular) flows, every entry gate saw more flows in the collapsed classes, however, increase in traffic flow resulted in better match with observed traffic counts, resolving the previous underestimation of flows on the SR-125 toll facility. Figure 39 and Figure 40 present corridor level comparison of estimated flows with the observed counts on SR-125 NB and SR-125 SB. Before, employing toll choice in both demand and supply models was perhaps over constraining travel on the toll facility – only toll trips were allowed to choose the toll facility in assignment. Now, in the collapsed classes, eliminating toll choice segmentation from the mode choice made all trips eligible to use the facility and assigned them to it based on congestion level and their value-of-time. This resulted in increased toll flows and a more realistic representation of travel on the facility.

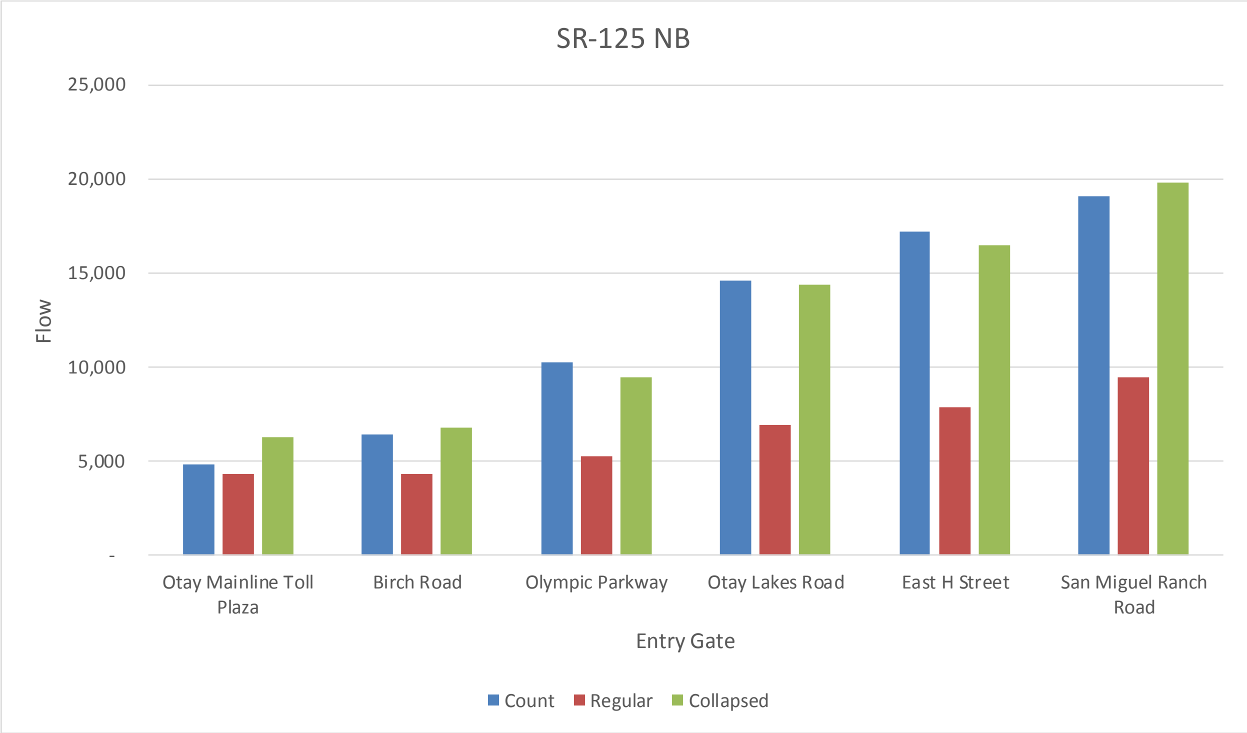

FIGURE 13: FLOW WITH REGULAR VS COLLAPSED CLASSES – SR125 NB

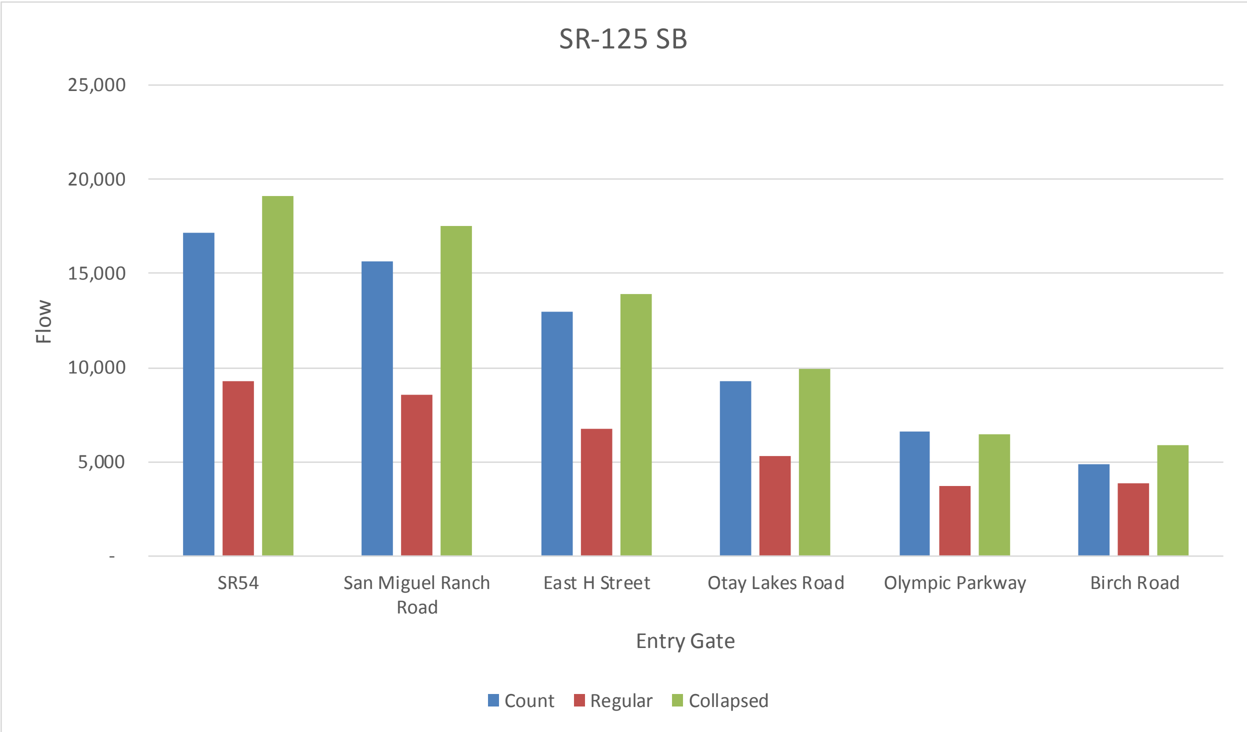

FIGURE 14: FLOW WITH REGULAR VS COLLAPSED CLASSES – SR125 SB

6.0 TRANSPONDER OWNERSHIP MODEL

The transponder ownership model requires zonal-level accessibilities as a key input. The accessibilities measure the usefulness of transponder ownership in terms of distance to the nearest managed lane (ML) facility, average travel time saving, and percent detour if no managed lane. The location of a ML facility greatly affects the accessibility attributes and thus, prediction of transponder ownership in the region. Future scenarios may see change in managed lane coding and therefore, required an automated creation of the transponder model accessibilities to have an appropriate response in the transponder ownership. As part of the model enhancements to support the 2021 Regional Transportation Plan update, procedures were developed to automatically calculate input accessibilities to the transponder ownership model. The new accessibilities showed more consistent and improved results compared to the old accessibilities which were held constant from values computed in the base year.

Note that to further help with future scenario testing, a property "tc.everyone.owns" is added to the properties file where, if set to 1, the non-transponder ownership alternative is turned off. Only 0-auto households would not own a transponder if set to 1.

The next sections first describe the methodology employed in calculating the accessibility attributes and then discuss the new results by comparing with the old accessibilities.

6.1 | METHODOLOGY

The generation of the transponder model accessibilities is implemented in Emme 4.4[5]. The output is a comma-separated value (CSV) file ("transponderModelAccesibilities.csv") that contains the following three accessibility attributes for each zone:

1. Distance (miles) to the nearest managed lane facility - DIST
2. Average travel time (mins) savings - AVGTTS
3. Percent detour - PCTDETOUR

The following sections describe calculation methodology for each of the three accessibility attributes.

DISTANCE TO THE NEAREST MANAGED LANE FACILITY

This attribute is calculated as straight line distance to the nearest managed lane facility (nearest link with a ML cost). It is a simple calculation of distance between each zone centroid to the nearest ML facility. The distance is calculated in miles.

Managed lane (ML) facility links are identified as network links that are freeway and (HOV2 or HOV3+) and has toll in either AM, MD, or PM period[6].

[5] Currently, the process is a stand-alone python script and will be integrated into the AB model system when migration to Emme 4.4 is complete.

[6] Network expression: (type = 1) and (lane_restriction = 2 or 3) and (toll_am + toll_md + toll_pm) >0

AVERAGE TRAVEL TIME SAVINGS

This attribute is average travel time savings for all households in each zone over all possible destination 'd'. The average is calculated using an expected value with the probabilities taken from a simplified destination choice model. The average travel time savings of a household in a zone 'z' is:

$$\frac{\sum_d (AutoTime_{zd} - TollTime_{zd}) \cdot Employment_d \cdot \exp\,(-0.01\ AutoTime_{zd})}{\sum_d Employment_d \cdot \exp\,(-0.01\ AutoTime_{zd})}$$

The times are calculated in minutes and include both the AM peak travel time to destination and the PM peak travel time returning from the destination. For *AutoTime*, the calculations use the non-transponder SOV skim for medium value-of-time bin (AM/PM_SOV_NT_M_TIME) and for *TollTime* the transponder SOV skim for medium value-of-time bin (AM/PM_SOV_TR_M_TIME).

$$AutoTime_{zd} = AM\_SOV\_NT\_M\_TIME_{od} + \ PM\_SOV\_NT\_M\_TIME_{do}$$

$$TollTime_{zd} = AM\_SOV\_TR\_M\_TIME_{od} + \ PM\_SOV\_TR\_M\_TIME_{do}$$

Employment in a zone is obtained from the MGRA file (field: "emp_total").

PERCENT DETOUR

The attribute is percent difference between the AM non-transponder travel time to sample zones and the AM non-transponder travel time to sample zones when the general purpose lanes parallel to all toll lanes requiring transponders were made unavailable in path-finder. It is calculated as:

$$\frac{Time\ Without\ Facility - Non\ Transponder\ Time}{Non\ Trasnponder\ Time}.$$

The nearest parallel GP facilities to ML facility links are identified using the following rules:

- Links within 100 ft of the flagged ML facility links
- Links that have approximately the same direction (within +/- 25 degrees angle) as ML facility links

The calculations use auto travel time without the reliability factor[7]. For a zone, the percent detour is an average over three sample destinations[8], see Table 20. For these zones, PCTDETOUR value is 0.

TABLE 20: SAMPLE DESTINATION ZONES

TAZ	DESCRIPTION
4027	Horton Plaza in San Diego Downtown
2563	Kearny Mesa
2258	Sorrento/UTC

[7] The shortest paths are calculated using the Shortest Paths toll available with Emme 4.4 only.
[8] Currently hard coded in the script. Would be moved to the properties file when the process is integrated into the model system.

Note that calculations of PCTDETOUR are more involved, however, the attribute is important in predicting transponder ownership correctly. According to the model estimation document, the model does not perform well without it. The estimation did not have disaggregate data so the average travel time savings (AVGTTS) variable doesn't do a very good job of expressing the likelihood of owning a transponder spatially since the amount of time savings (since its expressed across all jobs) is relatively low. Several zones NE of the I-15 Managed lane facility showed high time savings, which did not match the ownership data as well. The detour term (PCTDETOUR) is a more powerful spatial indicator since it stresses the visibility of the toll path. Eliminating this variable would have required re-estimation of the model and would probably have more spatial error in the model as a result. The below is excerpt from the model estimation explaining importance of this term:

"*The first two terms expressing the benefits of transponder ownership did not capture all of the benefits of transponder ownership because the expected travel time savings variable did not differentiate between those whose non-toll paths were still on I-15 and those who had options other than I-15 entirely. Those whose only good non-toll option is also on I-15 should be more likely to switch to owning a transponder because the alternative is more visible to them. Those who have a good non-toll option that does not use I-15 should be less likely to own a transponder even if the toll path would save time because they have more alternatives available to them. Therefore, we also included a third term expressing the percent difference between the AM non-toll travel time to downtown zone 3781 and the AM non-toll travel time to downtown when the general purpose lanes parallel to all toll lanes requiring transponders were made unavailable in the path-finder. Those who would tend to use I-15 even for non-toll paths would have much greater percent increase in travel time from detouring, while those with other options would have lower increases in travel time.*"

6.2 | RESULTS

Table 21 summarizes basic statistics for the three attributes in the old and new accessibilities files. Generally, distance to nearest ML facility (DIST) and average travel time savings (AVGTTS) are similar in the two accessibilities. This is not surprising given their calculations are very straight forward. However, percent detour (PCTDETOUR) exhibits larger differences due to more involved calculations. On average, the new accessibilities see higher detour (14%) compared to the old accessibilities (5%). The variation (Std. Dev.) across zones is also bigger. The maximum detour in the new accessibilities is 69% compared to 50% in the old accessibilities.

TABLE 21: STATISTICS OF OLD AND NEW INPUT ACCESSIBILITIES

STATISTIC	DIST (MILE)		AVGTTS (MIN)		PCTDETOUR	
	OLD	*NEW*	*OLD*	*NEW*	*OLD*	*NEW*
Mean	10.98	10.5	0.21	0.26	0.05	0.14
Median	10.12	9.8	0.08	0.01	-	0.01
Std. Dev.	7.21	7.18	0.59	0.82	0.1	0.18
Min	-	0.04	-	-	-	-

STATISTIC	DIST (MILE)		AVGTTS (MIN)		PCTDETOUR	
	OLD	*NEW*	*OLD*	*NEW*	*OLD*	*NEW*
Max	57.35	60.63	7	5.57	0.5	0.69

Figure 15 compares spatial distribution of distance to the nearest ML facility in the two accessibilities. The managed lanes facility is represented as the blue links. The value of DIST is showed with color gradient – a lower value (0-2 miles) is represented as yellow and a higher value (25 miles or more) is represented as dark red. The new accessibilities show a reasonable and consistent pattern of spatial change in distance to the ML links. The zones closer to the ML links are in light color and they get darker as they are located farther. The old accessibilities, somewhat, show a similar pattern, however, the map is patchy where several zones do not appear to have correct distance calculated for them. This could possibly be a result of the old accessibilities using an older network with unresolved network connectivity issues.

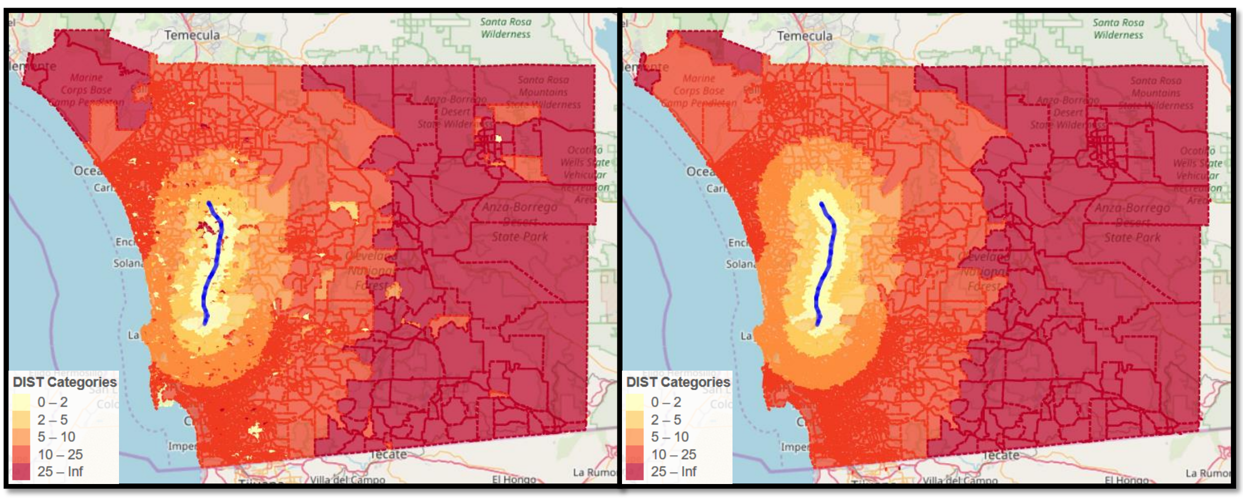

FIGURE 15: DISTANCE (MILE) TO CLOSEST ML FACILITY BY ZONE – OLD (LEFT) VS NEW (RIGHT)

A similar heat map as the attribute DIST is created for the average travel time savings (AVGTTS) attributes as well, see Figure 16. Clearly, the new accessibilities see more zones seeing higher travel time savings – in line with higher regional average of time savings as shows in Table 21. Those zones are in the NE of the ML links. The old accessibilities had larger time savings mostly contained around the ML facility. Also, there were more zones with travel time savings of 0, especially the yellow zones east of the ML facility.

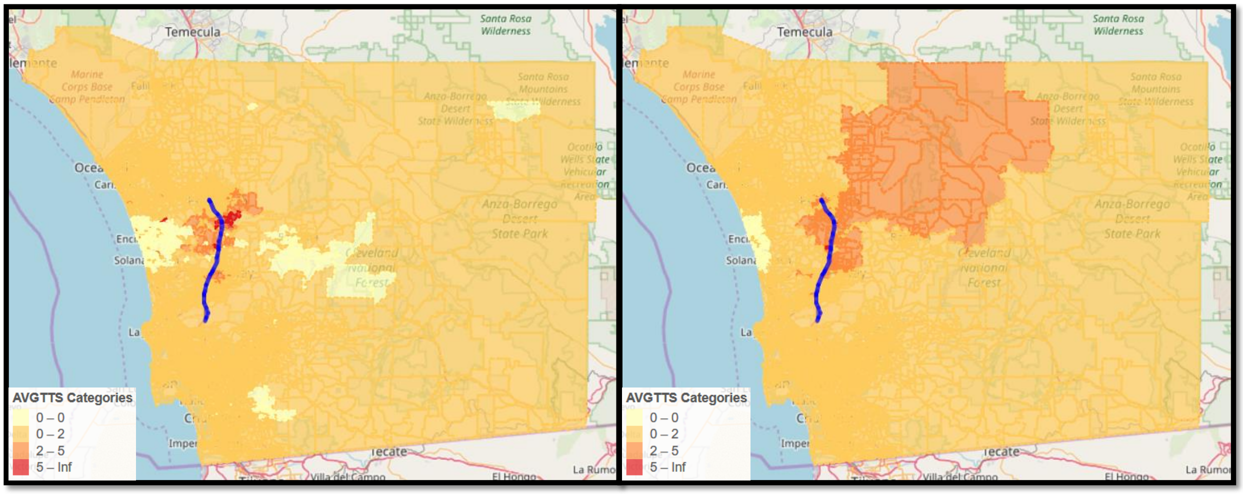

FIGURE 16: AVERAGE TRAVEL TIME (MIN) SAVING BY ZONE – OLD (LEFT) VS NEW (RIGHT)

Also seen in the summary statistics (see Table 21), the percent detour (PCTDETOUR) attribute shows more differences in the two accessibilities, see Figure 17. However, the pattern is similar where zones around and north of the ML facility experience larger detours. In general, the new accessibilities calculate higher detours for zones. The differences are mostly result of methodological differences in the two accessibility calculations. The new accessibilities calculate percent detour average over three sample destination zones (see Table 20) compared to only one destination (in downtown) in the old accessibilities.

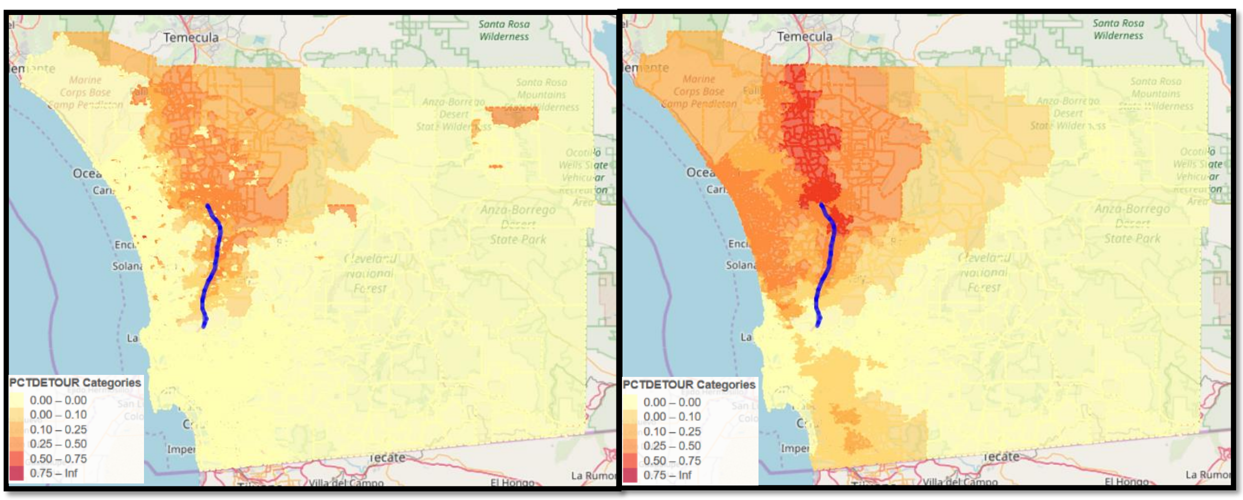

FIGURE 17: PERCENT DETOUR BY ZONE – OLD (LEFT) VS NEW (RIGHT)

Overall, the new accessibilities look more consistent and show improved results compared to the old accessibilities. Moreover, the automated generation of the transponder model accessibilities offers a new tool for future scenario testing.

7.0 MODEL CALIBRATION

Model calibration refers to the process of adjusting model parameters until the model replicates the travel patterns revealed by observed data (targets). The SANDAG ABM calibration is primarily based on targets derived from the 2016 Household Travel Survey, 2019 TNC Travel Survey and the 2015 Transit On-board Survey.

7.1 | CT-RAMP RESIDENT MODEL

PREPARING CALIBRATION TARGETS

The calibration targets for most of the model components during this exercise came from the last round of calibration. During the last calibration, targets were created using the 2016 Household Travel Survey and the 2015 Transit On-board Survey. During this calibration, another source of observed data was included, the 2019 TNC Survey. This survey was done specifically to look at the travel patterns of individuals who use TNCs (lyft/uber). This new survey was used to create tour mode choice and trip mode choice targets for the TNC modes in the travel demand model. Hence, the tour mode choice and trip mode choice targets during this calibration exercise came from the 2016 HTS, 2015 OBS and the 2019 TNC Survey.

The following paragraphs summarize the results from the model components calibrated after the TNCAV model enhancements were made. The models that were calibrated during this exercise were – Auto Ownership Model, Transponder Ownership Model, Telecommute Choice Model, Coordinated Daily Activity Pattern Model, Non-mandatory Tour Destination Choice Model, Tour Mode Choice Model, Trip Mode Choice Model and the Micro-mobility Choice Model. Calibration of each of these components are summarized below.

AUTO OWNERSHIP MODEL

The new auto ownership model has 11 categories which are combinations of HV (human-driven vehicle) and AV (autonomous vehicle). In the base year, there are no autonomous vehicles, hence the categories with AVs are equal to 0. The results are shown in Table 22 below. Figure 18 shows only 5 categories that are used in the base year model.

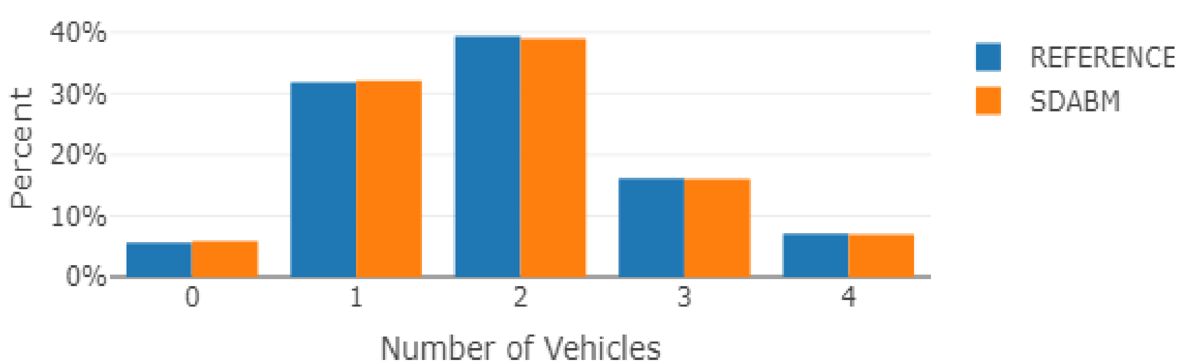

FIGURE 18: AUTO OWNERSHIP MODEL

TABLE 22: AUTO OWNERSHIP MODEL

	OBSERVED (CENSUS)		ESTIMATED (POST AO)	
AO Categories	# Households	Percentage	# Households	Percentage
0_CARS	63,477	5.7%	70,500	5.9%
1_CAR_1HV	356,176	32.0%	384,600	32.1%
1_CAR_1AV	-	0.0%	-	0.0%
2_CARS_2HV	437,225	39.3%	467,220	39.0%
2_CARS_2AV	-	0.0%	-	0.0%
2_CARS_1HV1AV	-	0.0%	-	0.0%
3_CARS_3HV	178,467	16.0%	191,320	16.0%
3_CARS_3AV	-	0.0%	-	0.0%
3_CARS_2HV1AV	-	0.0%	-	0.0%
3_CARS_1HV2AV	-	0.0%	-	0.0%
4_CARS_4HV	78,278	7.0%	83,480	7.0%
TOTAL	**1,113,624**	**100%**	**1,197,120**	**100.0%**

TRANSPONDER OWNERSHIP MODEL

The transponder ownership model was adjusted to match the calibration targets. Previously calibrated model results were used as the targets for this round of calibration. The results of the calibration are shown in Table 23. The model was calibrated to perfectly match the observed data.

TABLE 23: TRANSPONDER OWNERSHIP MODEL

OWN TRANSPONDER	TARGETS	%TARGET	MODEL	%MODEL
No	1,183,691	98.97%	1,184,760	98.97%
Yes	12,271	1.03%	12,360	1.03%

TELECOMMUTE CHOICE MODEL

The telecommute choice model was adjusted to match the calibration targets from the household travel survey, as shown above. The results of the calibration are shown in Table 24 and Figure 19.

TABLE 24: TELECOMMUTE CHOICE MODEL

TELECOMMUTE CHOICE	TARGETS	%TARGET	MODEL	%MODEL
Never	983,812	91.80%	1,312,160	91.70%
1 day/week	42,735	4.00%	57,720	4.00%
2-3 days/week	35,798	3.30%	47,000	3.30%
4 or more days/week	9,218	0.90%	13,340	0.90%

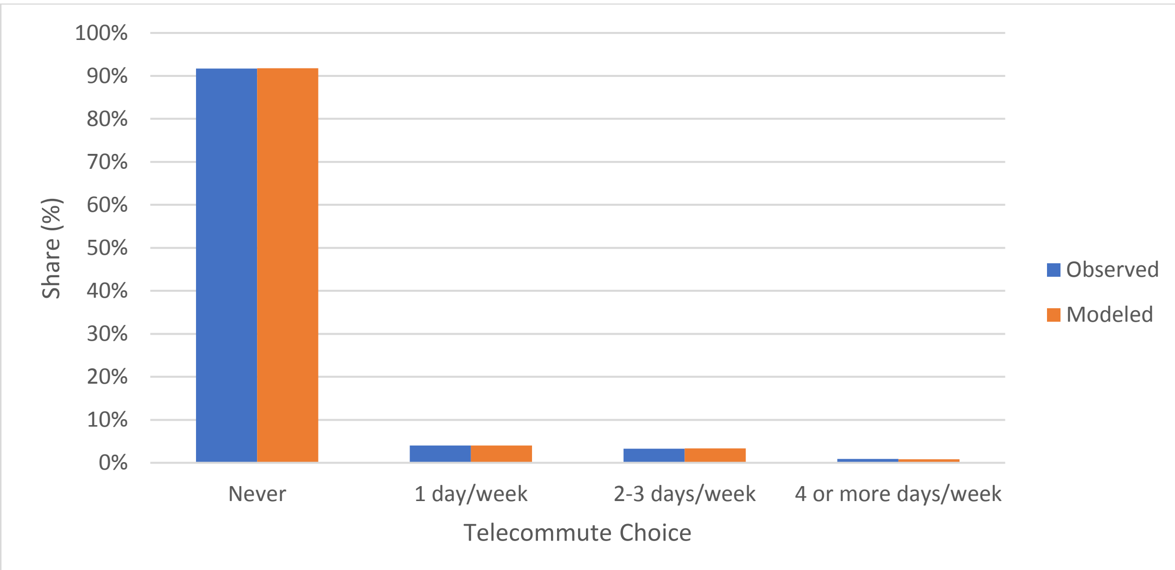

FIGURE 19: TELECOMMUTE CHOICE MODEL

COORDINATED DAILY ACTIVITY PATTERN MODEL

The coordinated daily activity pattern model (CDAP) determines each individual's daily activity pattern (DAP), as either Mandatory (M), Non-Mandatory (N), or stay at home (H). The activity pattern is Mandatory if the person undertakes at least one mandatory activity (work or school) during the day[9]. It is Non-Mandatory if the person did not go to work or school but participated in at least one non-mandatory activity (shopping, meal, social, recreation, etc.). If the person did not travel on the day and stayed home or was out of town, then the activity pattern is Home. Note that the activity pattern is M only if the mandatory activity resulted in person leaving the home. So, if the person is working/schooling at home then the activity pattern is N or H, depending on whether the person participated in non-mandatory activities or stayed at home.

The travel model was adjusted to match shares of M, N, and H patterns by person type by calibrating alternative-specific constants. Regionally, the ABM replicates the HTS daily activity patterns (Figure 20 and

[9] Currently CT-RAMP generate DAP as M for individuals working from home and schooling from home. The DAP for such individuals is recoded to N or H (depending on individuals' other travel) during creating summaries for comparisons.

Table 25) in total, with slightly more persons with at least one travel activity (M and N), thus fewer persons who stay at home.

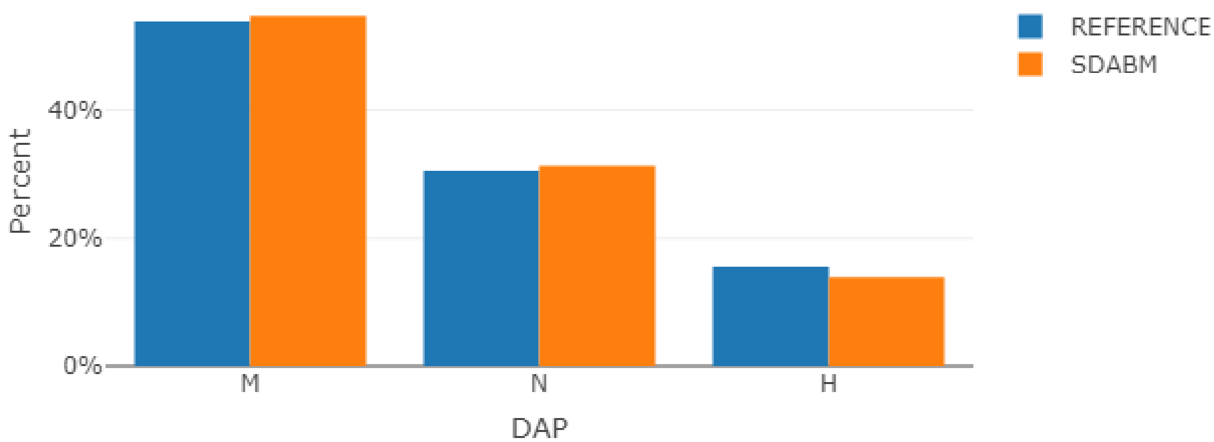

FIGURE 20: COORDINATED DAILY ACTIVITY PATTERN

TABLE 25: COORDINATED DAILY ACTIVITY PATTERN BY PERSON TYPE

	SURVEY			MODEL		
Person type	Mandatory	Non-Mandatory	Home	Mandatory	Non-Mandatory	Home
Full-time worker	82.0%	11.0%	7.0%	81.8%	11.2%	7.0%
Part-time worker	54.9%	32.0%	13.0%	54.8%	32.1%	13.1%
University student	64.3%	19.8%	16.0%	64.3%	19.8%	15.9%
Non-working adult	0.0%	74.0%	26.0%	0.0%	74.1%	25.9%
Non-working senior	0.0%	71.0%	29.0%	0.0%	71.0%	29.0%
Driving age student	66.1%	12.7%	21.2%	90.1%	4.2%	5.7%
Pre-driving student	67.1%	15.5%	17.4%	92.8%	5.9%	1.3%
Pre-school	26.4%	48.6%	25.0%	26.7%	48.3%	25.1%
Total	**54.2%**	**30.3%**	**15.5%**	**54.8%**	**31.4%**	**13.8%**

NON-MANDATORY TOUR DESTINATION CHOICE MODEL

The non-mandatory destination choice models choose a destination for the 'primary activity' on the tour. The primary activity for tours without a mandatory activity is chosen based on a set of fuzzy logic rules that assign a score to each activity on the tour based on activity purpose, activity duration, and distance from home (or work for work-based tours). A comparison of estimated versus observed distance between the tour origin and the primary destination is a useful comparison to ensure modeled travel distance is correct. This includes both average distance by purpose and the distribution of tours by tour length in one-mile increments. Based on this comparison, tour distance terms were adjusted in the model to improve goodness-of-fit between the estimated and observed tour length frequency distribution and the average tour length by purpose. Figure 21 below shows the TLFD for non-mandatory purposes.

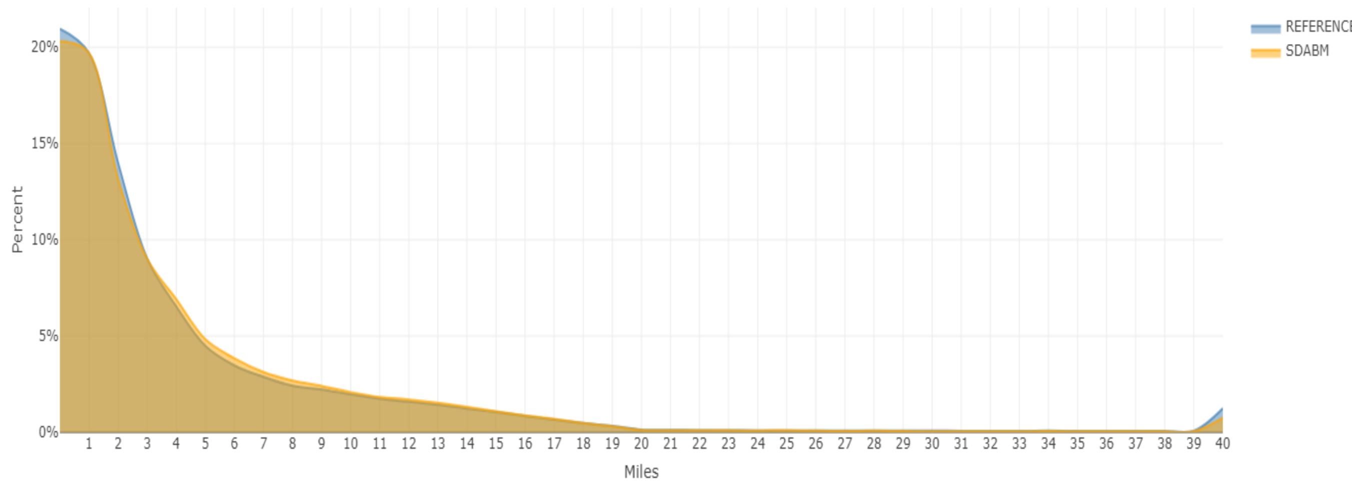

FIGURE 21: NON-MANDATORY TOUR DESTINATION CHOICE

TOUR MODE CHOICE MODEL

Tour mode is an abstract concept, defined as the main mode of travel used to get from the origin to the primary destination and back. The following 12 (13 for school purpose) tour modes are available in the ABM: SOV, HOV2, HOV3, walk, bike/moped, walk-transit, PNR-transit, KNR-transit, TNC-transit, TAXI, TNC-Single, TNC-Shared and school bus. The tour mode is coded in the survey based on a set of rules that are dependent on the combination of trip modes used on the tour.

Note that during the tour mode choice calibration, the ABM tour mode choice structure is adjusted to address some special travel reported in the HTS. The original model did not allow SOV tours for individuals from 0-vehicle households, however, such SOV tours are available in the HTS data. Further investigation revealed that most of such travel in the survey are made using other household vehicles (people may have borrowed vehicle from parents, neighbor or friends) and only a small portion of the SOV trips from 0-vehicle households used rental cars or car share. This travel is represented in the ABM by allowing SOV tours for members of the 0-vehicle households and calibrating the corresponding constant to match the share (6%) in the HTS data.

After scaling the original HTS targets to accommodate transit targets from the transit on-board survey and the TNC targets from the TNC survey, the HTS targets are scaled one more time for tour mode calibration. Generally, a tour mode choice calibration aims to adjust the mode choice model so that the distribution of tours by mode is similar to observed share. Therefore, tour mode choice adjustments are made to alternative-specific constants to match observed mode shares. As transit tour targets are calculated directly from a transit on-board survey and TNC targets from the TNC survey, the model needs to be calibrated to the same numbers. However, when calibrated using mode shares, the number of transit/TNC tours based on the share of transit mode in the HTS would result in a different number due to a different value of total tours in the ABM. For example, if a survey says that there are 100 transit tours among 10,000 total tours, then the transit share would be 1%. However, if the model is generating 12,000 total tours then calibrating the model to the survey transit share of 1% will result in 120 transit tours. Since we want to calibrate the model to match the absolute number of transit tours inferred from the on-board survey, we adjust observed tours by mode, keeping the transit tours constant but scaling other modes to match total tours in the model by purpose and auto sufficiency. The same rule is also applied for TNC tours.

The summaries presented below (Figure 22, Table 26) include the final scaled calibration targets.

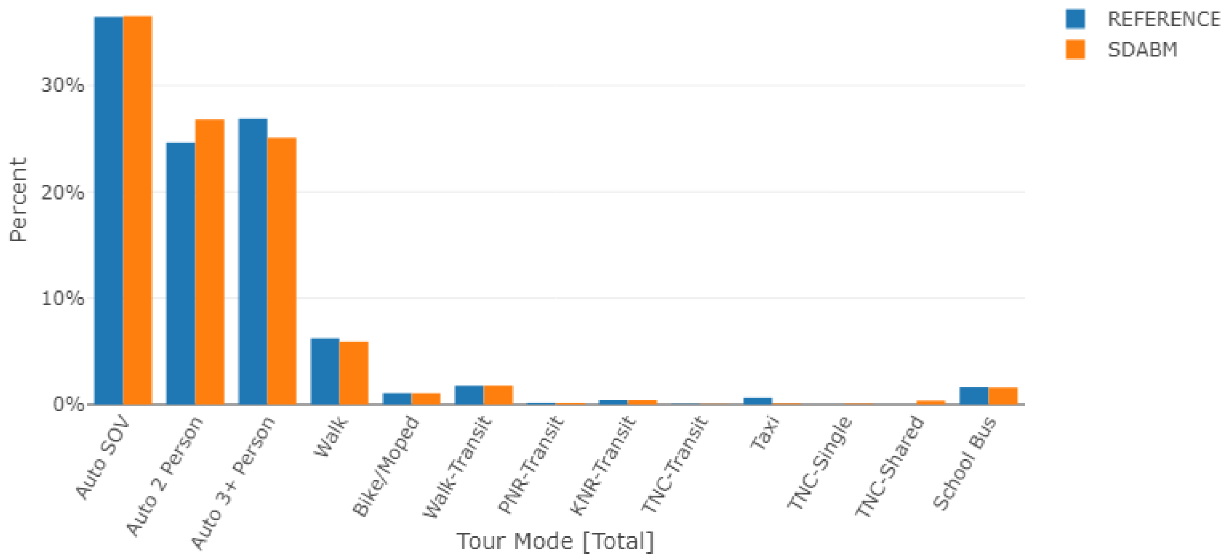

FIGURE 22: TOUR MODE CHOICE MODEL

TABLE 26: TOUR MODE CHOICE MODEL

MODE	SURVEY	%	MODEL	%
Auto SOV	1,615,637	36.5%	1,619,340	36.5%
Auto 2 Person	1,091,230	24.6%	1,188,400	26.8%
Auto 3+ Person	1,190,657	26.9%	1,111,600	25.1%
Walk	279,654	6.3%	261,760	5.9%
Bike/Moped	48,141	1.1%	47,820	1.1%
Walk Transit	79,143	1.8%	79,560	1.8%
PNR-Transit	7,258	0.2%	7,040	0.2%
KNR-Transit	19,962	0.5%	20,460	0.5%
TNC-Transit	1,633	0.0%	80	0.0%
MAAS (Taxi, TNC-Single, TNC-Shared)	25,600	0.6%	24,780	0.6%
School Bus	72,998	1.6%	71,380	1.6%

MODE	SURVEY	%	MODEL	%
Total	**4,431,913**	**100.0%**	**4,432,220**	**100.0%**

TRIP MODE CHOICE MODEL

Trip mode targets are prepared from the HTS data and updated with transit trip targets from the transit on-board survey. Also, the MAAS trip targets are updated with MAAS trips from the TNC survey. Other mode targets are appropriately scaled to keep the total trips by purpose the same, similar to the process described above for creation of tour mode choice targets. This ensures that the absolute number of expanded transit trips from the transit on-board survey is matched in calibration.

The calibration process involved adjustment of alternative-specific constants to match observed trips by trip mode and tour mode within each tour purpose. The trip mode choice model can be thought of as a 'mode switching' model, in which the tour mode constrains which modes are available for trips on tours. Overall, the ABM generates a trip mode distribution which is very similar to observed (Figure 23, Table 27). Both datasets indicate that on an average weekday, 47% trips in the region are drive alone and 42% are shared-ride (SR2 and SR3), approximately 1.6% of San Diego County resident trips are made by transit, and 8% are made by a non-motorized mode (walk or bike).

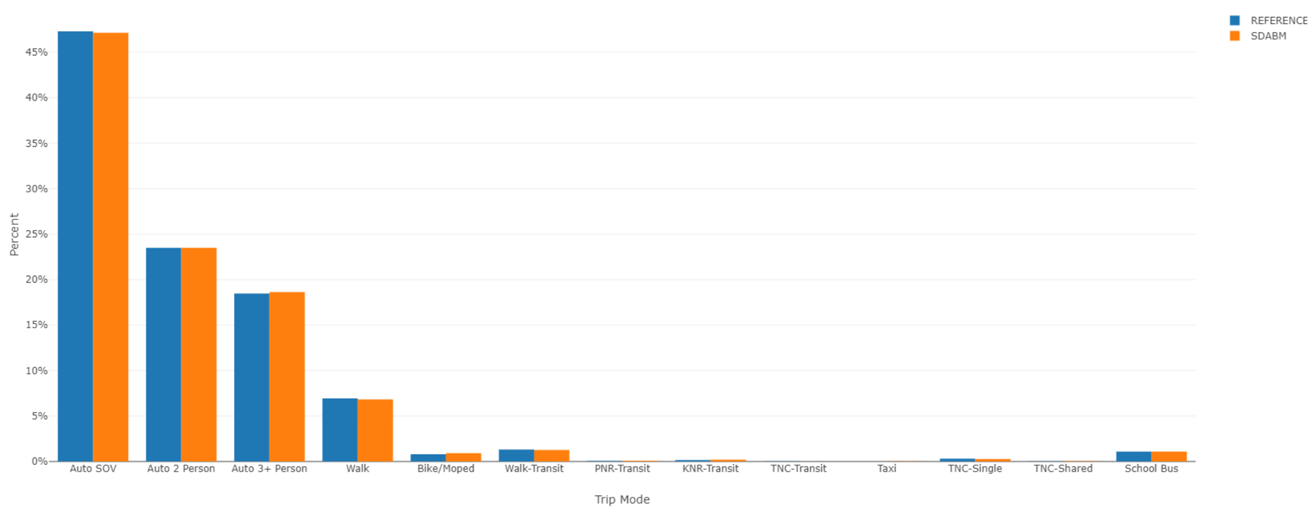

FIGURE 23: TRIP MODE CHOICE MODEL

TABLE 27: TRIP MODE CHOICE MODEL

TRIP MODE	SURVEY	%	MODEL	%
Auto SOV	6,163,867	47.3%	6,142,140	47.2%
Auto 2 Person	3,062,097	23.5%	3,059,740	23.5%
Auto 3+ Person	2,407,326	18.5%	2,424,480	18.6%

TRIP MODE	SURVEY	%	MODEL	%
Walk	904,235	6.9%	888,480	6.8%
Bike/Moped	103,724	0.8%	119,260	0.9%
Walk Transit	171,904	1.3%	165,260	1.3%
PNR-Transit	9,653	0.1%	10,920	0.1%
KNR-Transit	20,339	0.2%	23,760	0.2%
TNC-Transit	1,671	0.0%	620	0.0%
TAXI	349	0.0%	3,340	0.0%
TNC-Single	39,161	0.3%	34,580	0.3%
TNC-Shared	3,964	0.0%	6,340	0.0%
School Bus	142,760	1.1%	142,760	1.1%
Total	**13,031,049**	**100.0%**	**13,021,680**	**100.0%**

The Trip Mode Choice Model was calibrated using the latest land use (ID38). Please refer Appendix B for details.

7.2 | OTHER MODELS

MICRO-MOBILITY CHOICE MODEL

The newly added micro-mobility model produces e-scooter trips from the walk mode market. This includes solo micro-mobility trips and micro-mobility as access and/or egress to transit. The micro-mobility constant in the properties file was adjusted to produce 16,280 trips (both resident and visitor) against a target of 15,863. A constant of 60 minutes was used to reach calibration. The calibration targets were obtained from the San Diego Tribune report. (https://www.sandiegouniontribune.com/news/transportation/story/2019-10-24/e-scooter-ridership-plummets-in-san-diego)

VISITOR MODEL

Introduction of the TNC modes to mode choice structure required calibration of the visitor mode choice models. In absence of observed data related to the new TNC modes for visitors, the calibration prepared mode choice targets based on the previous calibrated model. The targets assumed that the TNC demand come from the previous TAXI demand. For both tours and trips, 80% of the TAXI trips were assigned to the TNC modes. The remaining 20% were considered to be made by the TAXI mode. The other mode shares were kept the same as the last calibrated mode shares. Note that all TNC trips are considered as TNC_Single. The TNC_Shared mode is turned off for visitors with assumption that as visitor trips are made together, they are less likely to be using TNC_Shared.

The calibration adjusted alternative specific constants in the visitor mode choice models.

Tour Mode

Table 28 and Figure 24 present comparison of the calibrated tour mode shares with the targets. The estimated tour mode distribution is very similar to the target shares.

TABLE 28: CALIBRATED VISITOR TOUR MODE SHARES

TOUR MODE	COUNT		SHARE	
	TARGET	*MODEL*	*TARGET*	*MODEL*
DRIVEALONE	1,644	1,692	2.5%	2.6%
SHARED2	4,564	4,586	6.9%	7.0%
SHARED3	32,426	32,347	49.3%	49.2%
WALK	14,292	14,308	21.7%	21.8%
BIKE	-	-	0.0%	0.0%
WALK_SET	214	213	0.3%	0.3%
PNR_SET	-	-	0.0%	0.0%
KNR_SET	-	-	0.0%	0.0%
TNC_SET	-	-	0.0%	0.0%
TAXI	2,516	2,530	3.8%	3.8%
TNC_SINGLE	10,063	10,043	15.3%	15.3%
TNC_SHARED	-	-	0.0%	0.0%
TOTAL	**65,719**	**65,719**	**100.0%**	**100.0%**

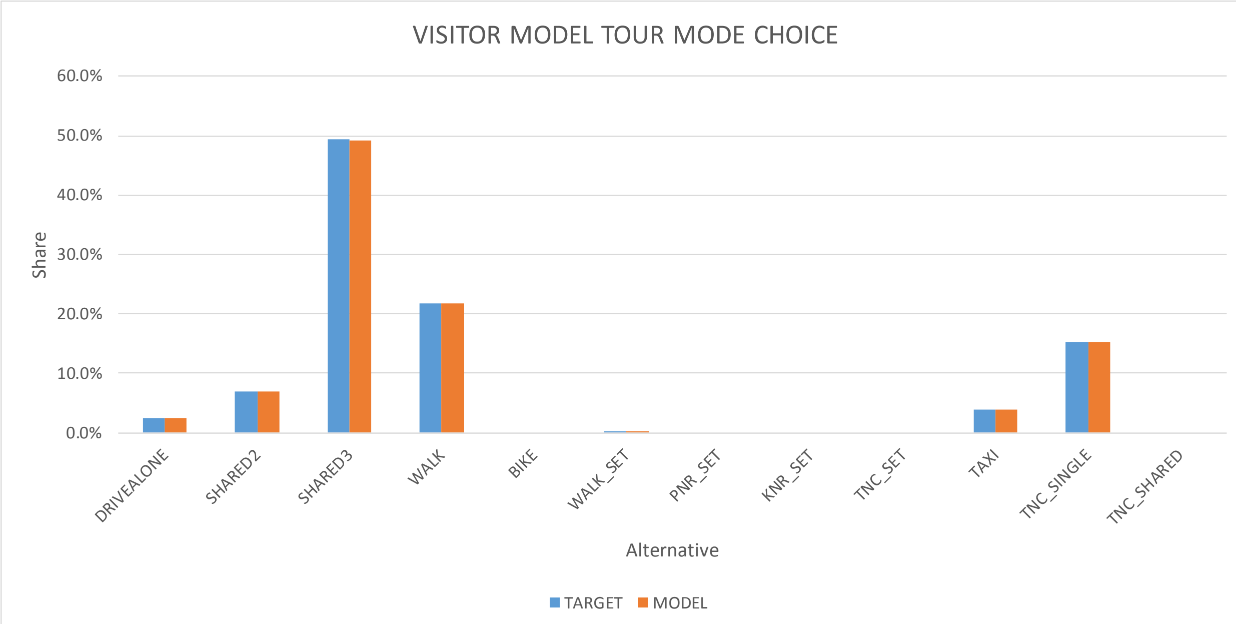

FIGURE 24: CALIBRATED VISITOR TOUR MODE SHARES

Trip Mode

Table 29 and Figure 25 present comparison of the calibrated trip mode shares with the targets. The estimated trip mode distribution is very similar to the target shares.

TABLE 29: CALIBRATED VISITOR TRIP MODE SHARES

TRIP MODE	COUNT		SHARE	
	TARGET	*MODEL*	*TARGET*	*MODEL*
DRIVEALONE	3,569	3,410	2.3%	2.3%
SHARED2	10,209	9,753	6.6%	6.5%
SHARED3	72,624	69,241	46.9%	46.4%
WALK	48,799	47,340	31.5%	31.7%
BIKE	-	-	0.0%	0.0%
WALK_SET	373	365	0.2%	0.2%
PNR_SET	-	-	0.0%	0.0%
KNR_SET	-	-	0.0%	0.0%
TNC_SET	-	-	0.0%	0.0%
TAXI	3,860	3,472	2.5%	2.3%
TNC_SINGLE	15,441	15,794	10.0%	10.6%

TRIP MODE	COUNT		SHARE	
	TARGET	*MODEL*	*TARGET*	*MODEL*
TNC_SHARED	-	-	0.0%	0.0%
TOTAL	**154,875**	**149,375**	**100.0%**	**100.0%**

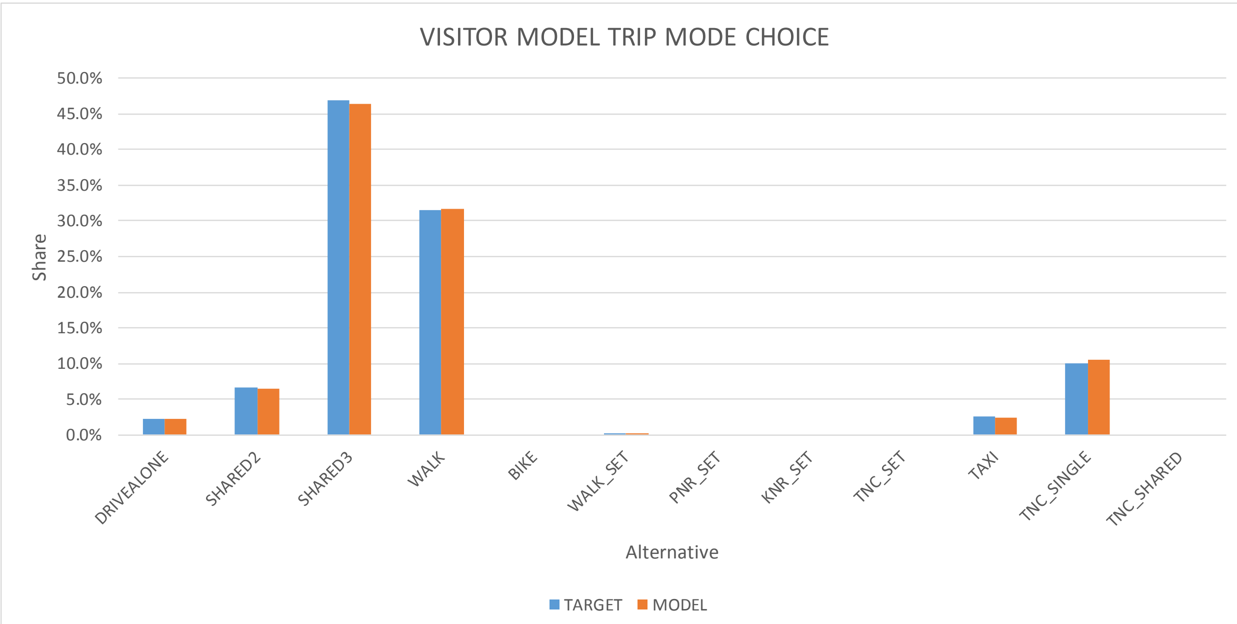

FIGURE 25: CALIBRATED VISITOR TRIP MODE SHARES

SAN DIEGO AIRPORT MODEL

The San Diego Airport ground access mode choice model was re-calibrated to recent data provided by the airport. The data summarizes taxi trips, TNC pickups and dropoffs, hotel/motel shuttle trips, vehicles for hire (VFH), airport short and long-term parking, off-airport parking, and rental car transactions by month between FY16 and most of FY19. Total enplanements were also provided. The data is shown in Figure 26. Note that TNC airport pickups were permitted and tracked since the start of the data period, while TNC dropoffs were allowed and tracked starting in FY19. For this reason, and to be consistent with the recent TNC survey conducted for SANDAG, FY19 data was used to generate calibration targets.

The calibration targets were calculated by scaling the FY19 transportation data to FY19 enplanements. Then, to calculate trips by mode, the enplanement factors by mode were multiplied by the average weekday enplanements estimated by the airport ground access model, after accounting for average number of travelers per vehicle and trips per vehicle for parking and rental car transactions. Note that some modes are not observed in the data, including transit and non-taxi\TNC pick-ups and drop-offs. Transit trips were held constant from the trips estimated in the most recent transit on-board survey. Pick-up/drop-off trips were estimated by subtracting the total estimated trips by mode from total trips and assuming equal proportion of pick-up/drop-off curbside versus escort (into terminal). Also, TNC trips do not separate TNC-single from

TNC-shared/pooled trips. We assert that 10% of TNC trips are TNC pooled at the airport. Obviously, it would be helpful to conduct another air passenger ground access survey to confirm these calculations and refine the calibration estimates.

The airport model has five distinct market segments, defined by a combination of resident\visitor status and business\recreational traveler status; the fifth segment covers all trips with an origin or destination outside San Diego County. Since the mode targets are not available by market segment, pre-calibration model outputs by market segment and mode were scaled to match the revised targets, using asserted alternative-specific constants for TNC modes. Table 30 shows the calibration results. All mode targets were calibrated within a few percent of observed shares.

TABLE 30: SAN DIEGO AIRPORT GROUND ACCESS MODEL MODE CHOICE CALIBRATION RESULTS

MODES	RESIDENT BUSINESS	RESIDENT PERSONAL	VISITOR BUSINESS	VISITOR PERSONAL	EXTERNAL	TOTAL	PERCENT
Short-term Parking	1,776	2,092	-	-	-	3,868	13%
Long-term parking	543	1,205	-	-	-	1,748	6%
Off-site Parking	282	544	-	-	-	826	3%
Pickup/Dropoff with Escort	43	128	-	30	27	228	1%
Pickup/Dropoff Curbside	547	2,007	204	1,099	103	3,960	13%
Car Rental	-	-	2,315	3,272	145	5,732	19%
Taxi	51	140	384	458	185	1,218	4%
TNC - Single	708	1,648	2,614	2,699	1,309	8,978	30%
TNC - Shared	458	638	377	426	88	1,987	7%
Shuttle\Van	45	190	339	402	20	996	3%
Transit	127	250	11	254	35	677	2%
Total	4,580	8,842	6,244	8,640	1,912	30,218	100%

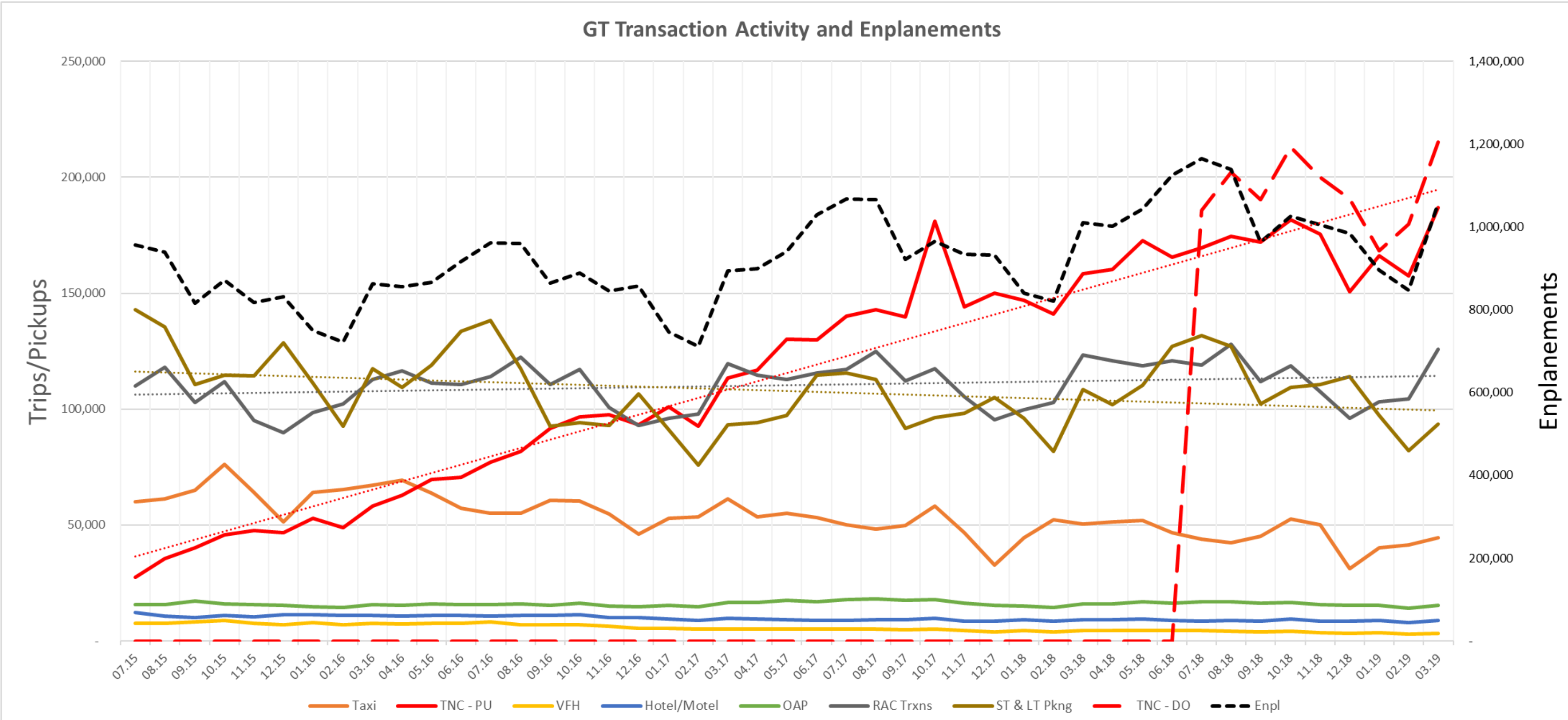

FIGURE 26: SAN DIEGO INTERNATIONAL AIRPORT GROUND TRANSPORT TRANSACTION ACTIVITY AND ENPLANEMENTS BY MONTH FY16 THROUGH FY19

7.3 | FUTURE AV SCENARIOS - AUTO OWNERSHIP

With new capabilities of modeling autonomous vehicles (AV), SANDAG is able to examine travel behavior in response to different level of autonomous vehicle ownership among the San Diego households. As the AVs have not arrived yet, the base year scenario does not include any AV ownership and all vehicles (autos) are human driven.

SANDAG examined the following two future scenarios with higher level of AV ownership:

1. 2035 Scenario with 20% AVs
2. 2050 Scenario with 50% AVs

This required calibrating the auto ownership model for the 20% and 50% AV ownership. As these are future scenarios, observed AO targets were not available. The team came up with some reasonable targets using the following assumptions:

- Total auto ownership
    - 20% AV ownership would result in 10% reduction in total auto ownership
    - 50% AV ownership would result in 25% reduction in total auto ownership
- 0-vehicle AO share would be the same as the base year (6%)
- A target distribution of number of AVs owned for AV-owning households – 75% AV owning households would own only 1 AV
- A target percentage of AV owning households who also own an HV
    - 50% in the 20% AVs
    - 25% in the 50% AVs

It was also made sure that the HV shares were reasonable in each scenario relative to each other and the base. For both AV scenarios, the initial auto ownership model calibration was performed using the base year model. After base year shares became closer to targets, the calibration used the respective future year scenarios to achieve the targeted AVs ownership.

The calibration modified alternative specific constants to match the targets.

2035 SCENARIO WITH 20% AVS

Table 31 and Figure 27 present comparison of the calibrated AO shares with the targets for the 2035 AV scenario. The estimated AO ownership distribution is very similar to the 20% AV target shares.

TABLE 31: CALIBRATED AO SHARES FOR 2035 SCENARIO WITH 20% AVS

CAR OWNERSHIP	TARGET SHARE	MODEL SHARE	DIFF
0_CARS	5.7%	6.8%	1.1%

CAR OWNERSHIP	TARGET SHARE	MODEL SHARE	DIFF
1_CAR_1HV	32.0%	31.7%	-0.3%
1_CAR_1AV	13.0%	13.0%	0.0%
2_CARS_2HV	23.2%	22.3%	-0.9%
2_CARS_2AV	0.5%	0.5%	0.0%
2_CARS_1HV1AV	7.5%	7.7%	0.2%
3_CARS_3HV	7.9%	7.0%	-1.0%
3_CARS_3AV	0.5%	0.6%	0.0%
3_CARS_2HV1AV	1.9%	1.8%	-0.1%
3_CARS_1HV2AV	4.6%	4.4%	-0.2%
4_CARS_4HV	4.2%	4.3%	0.1%
TOTAL	**100.0%**	**100.0%**	**0.0%**
AV Share	**20.0%**	**20.5%**	**0.5%**

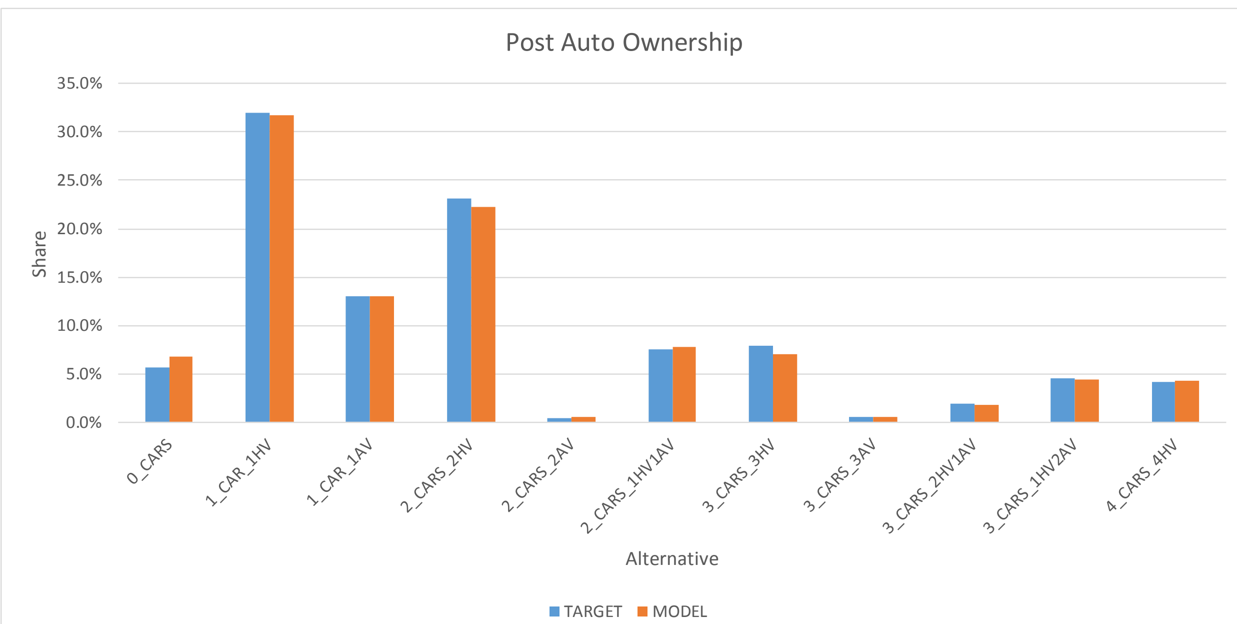

FIGURE 27: CALIBRATED AO SHARES FOR 2035 SCENARIO WITH 20% AVS

2050 SCENARIO WITH 50% AVS

Table 32 and Figure 28 present comparison of the calibrated AO shares with the target for the 2050 AV scenarios. The estimated AO ownership distribution is very similar to the 50% AV target shares.

TABLE 32: CALIBRATED AO SHARES FOR 2050 SCENARIO WITH 50% AVS

CAR OWNERSHIP	TARGET SHARE	MODEL SHARE	DIFF
0_CARS	5.7%	9.0%	3.3%
1_CAR_1HV	31.3%	30.8%	-0.5%
1_CAR_1AV	31.0%	31.7%	0.7%
2_CARS_2HV	3.0%	3.3%	0.4%
2_CARS_2AV	6.9%	6.4%	-0.5%
2_CARS_1HV1AV	11.2%	10.1%	-1.2%
3_CARS_3HV	3.7%	3.1%	-0.6%
3_CARS_3AV	2.8%	2.1%	-0.6%
3_CARS_2HV1AV	1.2%	0.9%	-0.3%
3_CARS_1HV2AV	1.4%	1.0%	-0.4%
4_CARS_4HV	2.2%	1.6%	-0.6%
TOTAL	**100.0%**	**100.0%**	**0.0%**
AV Share	**48.4%**	**48.9%**	**0.5%**

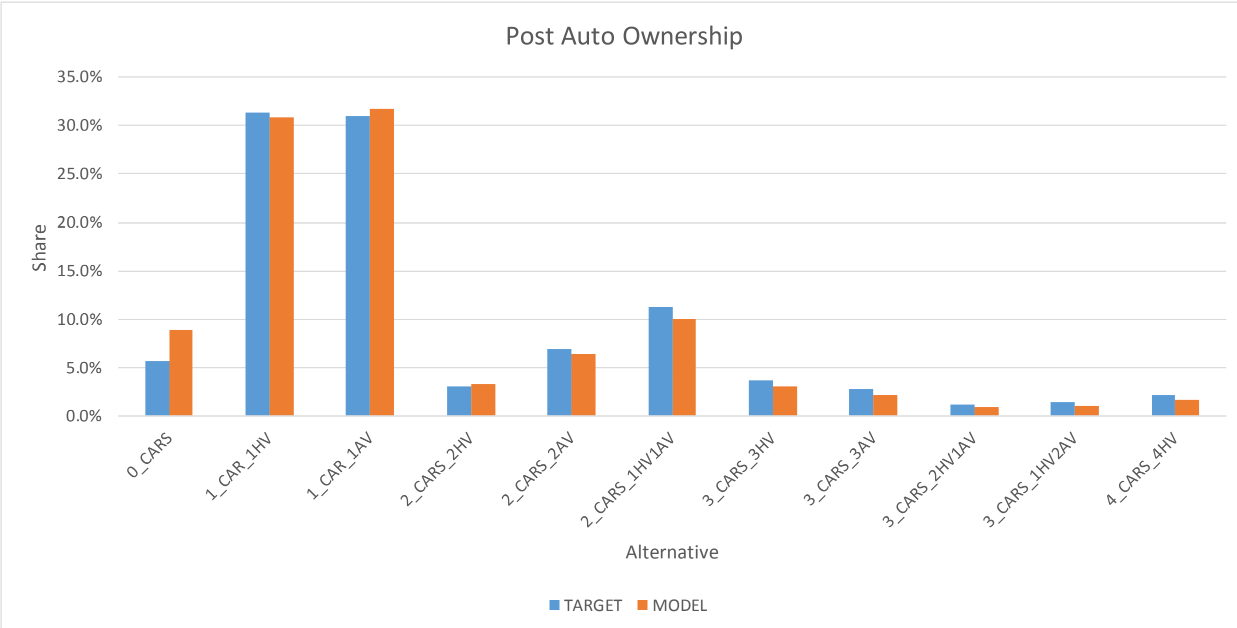

FIGURE 28: CALIBRATED AO SHARES FOR 2050 SCENARIO WITH 50% AVS

8.0 VALIDATION

A model validation tests the model's predictive capabilities before it is used to produce forecasts. There are two types of model validation; static validation, which compares model outputs against independent data that was not used to build the travel model, and dynamic validation, in which model inputs are systematically varied to assess the reasonableness of model responses. The static validation process compares outputs from model assignment with observed data. Model parameters are adjusted until the model outputs fall within an acceptable range of error.

In the assignment step, model demand (e.g. trips by time period, mode, and vehicle class\value-of-time) are loaded on to network. In highway assignment, the output includes vehicle flows on every link (road) in the highway network and for transit assignment, the output includes the number of boardings on each route. These are compared to observed traffic counts and observed transit ridership respectively.

The remaining of this chapter presents observed datasets and discusses validation summaries for the highway and the transit system in the San Diego region. The two transportation systems are discussed separately.

8.1 | OBSERVED VALIDATION DATA

Model validation describes the process used to compare model outputs to independent data, not used to estimate or calibrate model parameters, to ensure that it is ready to be used for forecasting. Estimated traffic volumes from the model are compared with traffic counts and estimated transit ridership is compared with observed transit boardings.

The next sections describe the observed data used in the model validation effort.

TRAFFIC COUNTS

SANDAG maintain a traffic count database that is assembled from various sources: PeMS (Performance Measurement System) counts, Caltrans District 11 State Highway Traffic Census Counts, arterial counts from local jurisdictions, and some special counts collected by SANDAG. Average weekday traffic (AWDT) was derived from PeMS daily counts collected over the year 2016 and are therefore the most reliable count data source for model validation. Local jurisdiction traffic counts typically do not cover the entire year and therefore are subject to larger error than the PeMS counts.

As shown in Table 33, a total of 2,246 counts are available to use for highway validation. Out of those, 45% are from PeMS or Caltrans District 11 and 51% are gathered from local jurisdictions. About 4% counts are collected by SANDAG on toll facilities in the region.

TABLE 33: 2016 TRAFFIC COUNTS BY SOURCE

DATA SOURCE	FACILITY	NUMBER OF COUNTS	% COUNTS
PeMS	Freeway and Ramp	766	34%
Caltrans District 11	Freeway, Arterial, and Collector	251	11%
Local Jurisdiction	Arterial and Collector	1,141	51%
Other (SANDAG)	Freeway including toll Facility (I-15 and SR-125)	88	4%
Total		**2,246**	**100%**

Performance Measurement System (PeMS)

PeMS is a traffic count database maintained by Caltrans. The traffic data is collected in real-time from nearly 40,000 individual detectors spanning the freeway system across all major metropolitan areas of the State of California. The data collection method uses vehicle detectors, which are physical loops embedded in road pavement. The count database is available to the public through a web-based interface. Annually, SANDAG downloads hourly PeMS traffic counts for freeways in the San Diego region (Caltrans District 11).

The 2016 PeMS database has about 1500 vehicle detector stations (VDS) on the same number of freeway (also ramp) segments in District 11. Ideally, each station would have 8,783 records (hours) of counts for the entire year. However, some stations report Null values (partial or full). SANDAG removed such stations if null counts exceed 15% of the total count records for the station. This resulted in about 10% of the total stations removed from the count database.

Further, for each count station, SANDAG excludes weekend and holiday counts and calculates annual average weekday count by five model time periods (EA, AM, MD, PM, and EV). All eligible count stations were joined to about 800 model network links using automatic ArcMap procedures coupled with manual reviews.

Caltrans District 11

Every year, Caltrans provides SANDAG traffic counts from the Traffic Census Program. The counts are Annual Average Weekly counts and are available by five model time periods. SANDAG received traffic counts for about 270 locations for 2016. Validation used 251 locations after removing some suspicious locations.

Local Jurisdictions

SANDAG staff assembled and compiled 2016 traffic counts from local jurisdictions in the San Diego County that collect weekday daily two-way counts on major arterials and collectors. SANDAG staff matched the counts to the model network links. In cases where a count matched multiple links, the staff picked the link with estimated traffic flow matching the count most closely.

For 2016, 586 arterial counts offering sampling coverage of 2% of the total arterial network links are processed. About 90 of these counts were removed due to various reasons: weekend day count, Christmas holiday week counts, duplicate counts, and metadata inconsistency.

These counts are one-time 24-hour or 72-hour counts, thus presenting a challenge to use them as an average daily weekday count. This is because some locations on the arterial network are subject to high ADT variance depending on the time of year. For example, roads near a shopping mall experience greater use during the holiday months and roads near local beaches are subject to variances that corresponds to construction delays, special events or inclement weather. Because of the low sample rate and high degree of seasonal variance, caution is encouraged when using these counts.

Other

SANDAG manages two toll facilities in the region: the I-15 express lanes and the South Bay Expressway (SR-125). SANDAG obtained transactional counts for each facility from the Intelligent Transportation Systems Group, Operation Department. The raw data is annual average weekday transponders by 15-minute intervals and by each pair of entry plaza and exit plaza. SANDAG converts the gate-to-gate toll transponders data into toll counts by five model time periods at model network link level. The 2016 toll transponders data are matched to about 12 links on SR-125 and 22 links on the I-15 express lane facility.

TRANSIT BOARDINGS

Estimated transit boardings from the model are validated against 2016 daily transit ridership from the SANDAG Passenger Count Program. The passenger Counting Program provided a true FY2016 count. The route 894 was removed as it is not coded in the model. The routes (such as 276, etc.) that are coded in the model but were missing observed data were estimated. The total FY2016 observed ridership is 355,143.

8.2 | HIGHWAY VALIDATION

As recommended by the FHWA and Caltrans, this report calculates the following four validation criteria to compare estimated traffic flows with the observed traffic counts:

1. **Gap** - difference between estimated flow and observed traffic count divided by the observed traffic count. It provides a general context for the relationship (i.e. high or low) between model flows and counts.
2. **Percent of links with volume-to-count (gap) within Caltrans deviation allowance**
3. **Correlation coefficient or R-squared** - estimates the correlation (strength and direction of the linear relationship) between the traffic count and the estimated traffic flow from the model. R-squared is square of the correlation coefficient. It is a statistical measure of how close the data are to the fitted regression line. R-squared is always between 0 and 1; a value of 0 indicates that the model explains none of the variability of the response data around its mean and a value of 1 indicates that the model explains all the variability of the response data around its mean.

4. **Percent root-mean squared error (PRMSE)** - square root of the estimated flow minus the observed traffic count squared divided by the number of traffic counts. It measures of accuracy of the entire model, representing the average error between observed and estimated traffic flow on a link.

The FHWA also specify thresholds for the above measures (except gap). The recommended thresholds are presented in Table 34.

TABLE 34: VALIDATION GUIDELINES

VALIDATION MEASURE	THRESHOLD
Percent of links with volume-to-count within Caltrans deviation allowance (Caltrans)	>=75%
Correlation coefficient (FHWA)	>=0.88
PRMSE (FHWA)	<40%

*Source: The Travel Model Validation and Reasonableness Checking Manual, II Second Edition, September 2010.

The subsequent sections discuss highway validation by:

- Region
- Road class
- Volume group
- PMSA
- Key freeway corridors
- RMSE comparison

The details of highway validation are documented at Appendix C.

REGION

The observed traffic count database used in this model validation effort encompass 2,246 links on the highway network. As presented in Table 35, the total real traffic across these links sum up to 67.4 million vehicles. On the same links, the ABM produce a comparable estimate of traffic volume (66.5 million vehicles) and is only 1.3% lower than the total observed vehicle count. According to the HPMS[10], on an average weekday in year 2016, the roadway travel in the San Diego region resulted in 83.76 million vehicle miles of travel (VMT). The estimated traffic flows from the ABM produce a daily regionwide VMT value of within 1% of the observed estimate from the HPMS.

[10] Highway Performance Monitoring System

Table 35: Highway Validation - Region

MEASURE	OBSERVED	SDABM16	DIFF	% DIFF
Traffic Volume	67,369,701	66,467,809	(901,892)	-1.3%
VMT*	83,763,007	83,389,958	(373,049)	-0.4%

Note: Observed VMT is from the HPMS estimate of the total VMT in the San Diego region for year 2016

A scatter plot in Figure 29 compares the estimated traffic flows with the observed traffic counts regionally. Points in the scatter plot are links where traffic counts are available. A point represents observed traffic count on the X-axis and the corresponding estimated flow on the Y-axis. The scatter plot includes several measures/guidelines assessing accuracy of the model flows with respect to the observed traffic counts.

First, the plot includes a 45-degree line representing a virtual scenario of perfect match between traffic counts and estimated flows. The 45-degree line is useful in quickly identifying overestimation (flow>count) or underestimation (flow<count) of a flow. A highway validation aims to make most points as close to this line as possible. An ideal validation would have all count locations on the 45-degree line. However, perfect match for all count locations is almost impossible to achieve due to various reasons such as error in traffic counts, simulation errors in the model etc. Acknowledging this fact, Caltrans rather provides recommendations on maximum (high and low) deviations of an estimation flow from the corresponding traffic count value. The scatter plot displays these Caltrans high and low deviations as dotted lines above and below the 45-degree line respectively. Lastly, a linear regressed line of all points is also added to the plot. Slope of the regressed line measures regional match between the estimated flows and the traffic counts - a slope of less than 1 means underestimation regionwide and more than 1 indicates overestimation. The plot also displays a R-squared value representing goodness of fit of all data points.

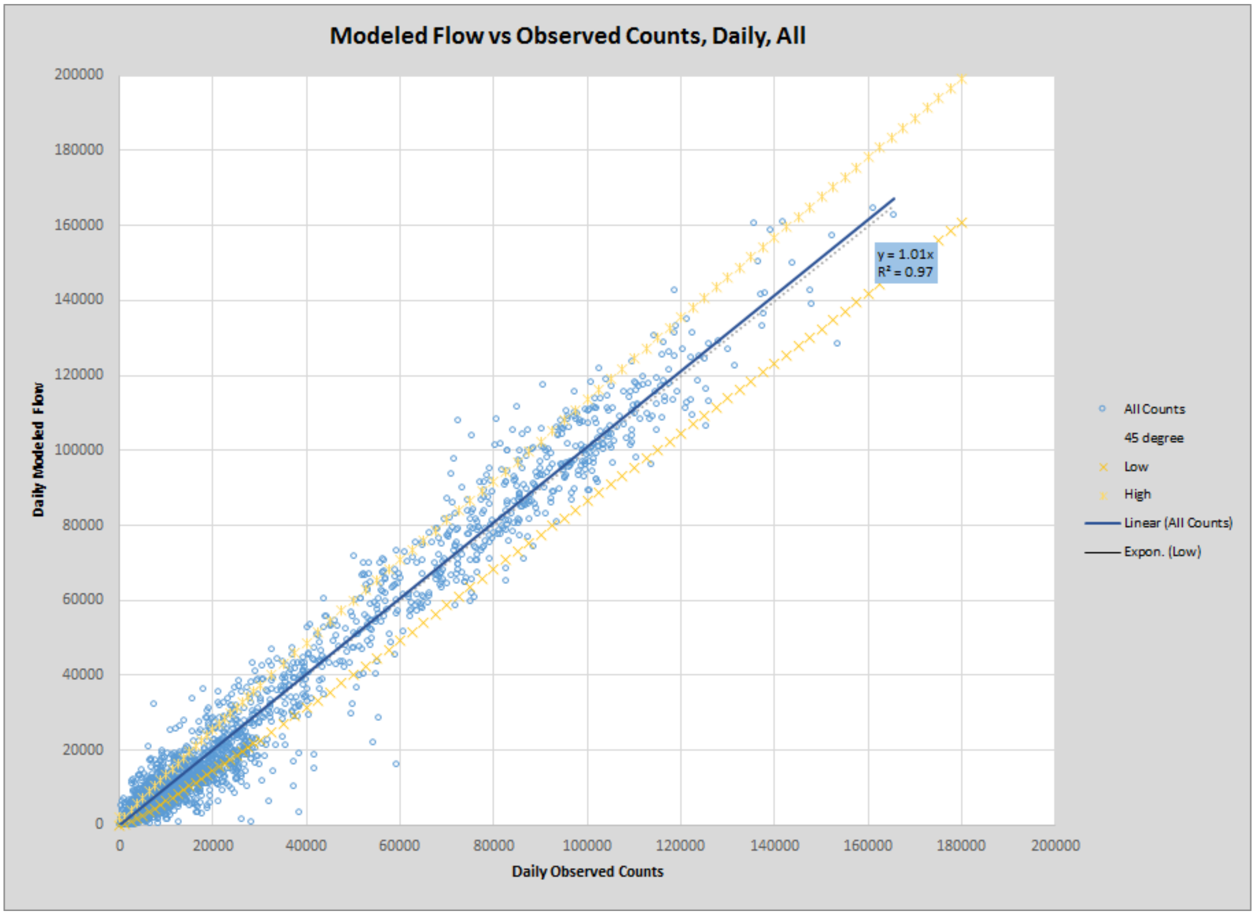

FIGURE 29: DAILY ESTIMATED FLOWS VS OBSERVED COUNTS – REGION

As displayed in the scatter plot, Figure 29, the linear regressed line has a slope of 1.01 and R-squared value of 0.97. The slope indicates a good balance of links with underestimation and overestimation. The r-squared value is close to 1.0 indicating that the fitted regressed line represents the data well.

Note that the model validation necessitated boosting of the commercial vehicle demand in the model system. The increase in the commercial vehicle demand was needed to achieve the same validation level as the previous version of the ABM. After exhausting the scope of increase in travel in the resident and other special market models, the lack of travel in the region was discovered to be caused by low CVM demand in the new ABM. The current version of the ABM has a new disaggregate commercial vehicle model (CVM) and the previous CVM validation effort[11] observed that the new disaggregated model generates significantly lower levels of commercial vehicle travel compared to the aggregated model used in earlier versions of the ABM and relatively low VMT for light commercial vehicle travel compared to other regions. This resulted in an under-estimate of overall VMT previously, and this relationship was also found in early model runs of ABM2, though not as significant as previous under-estimates due to the higher rate of travel in the resident models as a result of calibrating to the new HTS data. Further, the proliferation of TNCs, internet shopping, and for-hire services such as food delivery suggests that the CVM may need to be updated based on emerging trends that did not exist when the CVM survey data was collected. With this, the light truck commercial vehicle

[11] See *Activity-Based Model and Commercial Vehicle Model Validation Report*, dated October 31, 2016

demand in the mid-day (MD) period is increased by a factor of 3.0, the demand in other periods were kept untouched. In addition, the distribution of demand by vehicle class is adjusted by re-classifying 4% of the light vehicles and 64% of the medium vehicles as intermediate vehicles. These adjustments boosted the share of CVM VMT from 7% to 10% of the regional VMT. This percentage is still consistent with the FHWA analysis of VMT from commercial vehicles for other regions and was therefore felt to be a reasonable model adjustment. Note that only growth factors contributed in the VMT increase, the re-distribution of demand didn't result in any increase.

ROAD CLASS

As shown in the scatter plots, Figure 29 and Figure 30, barring some big outliers, most of the count locations appear close to the 45-degree line and within the Caltrans recommended deviation range. To quantify, Table 36 presents a summary of links in various gap ranges and by road class. Regionally the links with a positive gap value has an average gap value of 32% and the links with a negative gap value has an average gap value of -27%. However, due to higher number of links (57%) of negative gap values, the regional gap value is small (-1%). The small value suggests a good match of the estimated flows and the traffic counts regionally. The match is also good across the four road classes.

In general, an expectation is to have fewer links as the gap value increase. The regional pattern of links in different gap ranges follows the expected pattern and show most links in the smallest gap range and fewer links in higher ranges. However, the road classes aside freeway (ramps, arterials, collectors) have more underestimated links with bigger negative gap values. This results in more links with a negative gap value regionwide, thus suggesting that spatially the region is more underestimated then overestimated. Also, percent of links with volume-to-count (gap) within Caltrans deviations are calculated as 68%, thus falling a little short of the FHWA recommended threshold of at least 75%. By road class, again, freeway and ramp facilities are doing better by exceeding the recommended threshold with 83% and 77% links respectively within the Caltrans deviations, but other road classes, arterial and collector, fall short of the threshold. In summary, the estimated freeway flows from the model compare well with the traffic counts but the flows on arterial and collector do not match counts as well. This point to the difference in quality of the traffic counts on different road classes.

The traffic counts are obtained from various sources and the quality of the counts vary by the source. The freeway and ramp traffic counts come from Performance Measurement System (PeMS) and Caltrans Traffic Census, which are proven to be more reliable estimate of an average weekday travel, whereas, the traffic counts on arterials and collectors are obtained from local jurisdictions, which are more error prone as they are one-time 24-hour or 72-hours count, thus presenting a challenge to use them as an average daily weekday count. Because of the low sample rate and high degree of seasonal variance, the traffic counts on arterials and collectors are less reliable. Furthermore, the traffic assignment on lower volume facilities is more influenced by the aggregation bias caused by the size of TAZs and subject to higher variances due to uncertainty in the model. Because of these issues we would expect that the percent error in lower volume facilities to be higher than higher volume facilities.

The PRMSE value of 21% for all count locations is well within the recommended value (<40%). Moreover, PRMSE value for each road classes, except collector, also satisfies the recommendation. The Collectors are low volume facilities and are therefore hard to match with traffic counts. For smaller counts, even a small difference between estimated flow and traffic count could result in a big PRMSE value.

The correlation coefficient between the estimated flows and the traffic counts is 0.97 and is well above the recommended threshold (>0.88). Like the PRMSE values, the correlation coefficient for freeway locations is better than the recommended value but the other relatively lower speed facilities are not doing that well. Again, more likely due to suspect quality of traffic counts on those facilities.

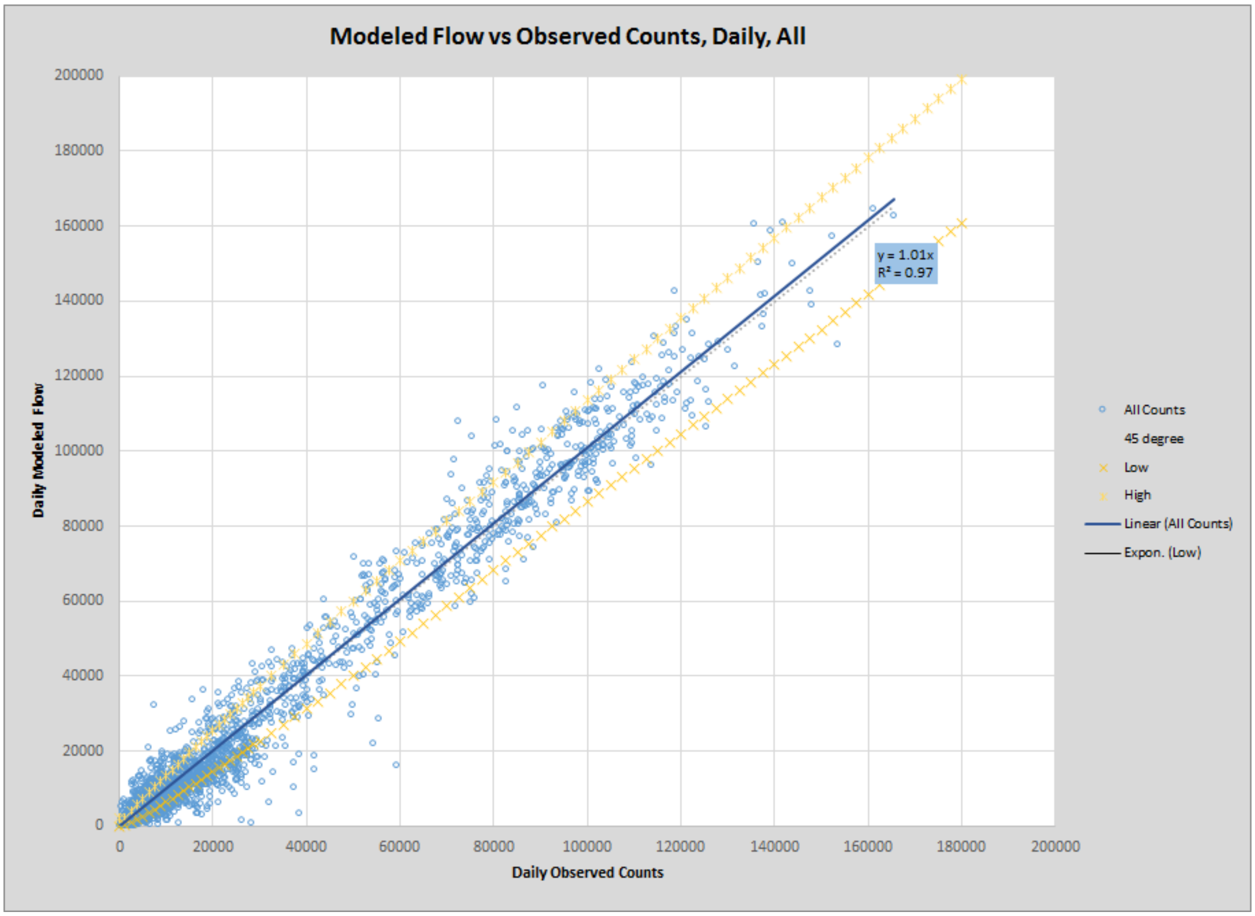

FIGURE 30: DAILY ESTIMATED FLOWS VS OBSERVED COUNTS – BY ROAD CLASS

TABLE 36: DAILY ESTIMATED FLOWS VS OBSERVED COUNTS – BY ROAD CLASS

	FREEWAY		RAMP		ARTERIAL		COLLECTOR		ALL	
	Count	%	Count	%	Count	%	Count	%	Count	%
Number of Links within Gaps										
>=100%	0	0%	12	3%	12	2%	35	6%	59	3%
50%~100%	5	1%	28	6%	22	4%	51	9%	106	5%
30%~50%	22	3%	35	8%	34	6%	37	6%	128	6%
20%~30%	23	4%	34	8%	24	4%	27	5%	108	5%
10%~20%	114	18%	29	7%	41	7%	39	7%	223	10%
0%~10%	192	30%	45	10%	55	9%	48	8%	340	15%
0%~-10%	198	31%	52	12%	85	15%	38	6%	373	17%
-10%~-20%	47	7%	65	15%	81	14%	51	9%	244	11%
-20%~-30%	16	3%	60	14%	75	13%	53	9%	204	9%
-30%~-50%	8	1%	56	13%	97	17%	100	17%	261	12%
<-50%	5	1%	21	5%	55	9%	119	20%	200	9%
total links	630	100%	437	100%	581	100%	598	100%	2246	100%
positive links	356	57%	183	42%	188	32%	237	40%	964	43%
negative links	274	43%	254	58%	393	68%	361	60%	1282	57%
-10% ~ +10%	390	62%	97	22%	140	24%	86	14%	713	32%
-20% ~ +20%	551	87%	191	44%	262	45%	176	29%	1180	53%
-30% ~ +30%	590	94%	285	65%	361	62%	256	43%	1492	66%
Average of Gaps										
Positive	12%		41%		33%		57%		32%	

	FREEWAY	RAMP	ARTERIAL	COLLECTOR	ALL
	Count %	Count %	Count %	Count %	Count %
Negative	-9%	-25%	-28%	-40%	-27%
All	3%	3%	-8%	-2%	-1%
Percent Root Mean Square Error (PRMSE), Trend Line Slope and R-Squared					
PRMSE	11%	36%	34%	58%	21% **(<40%)**
Correlation	0.97	0.85	0.84	0.65	0.98 **(>=0.88)**
Slope	1.02	0.95	0.89	0.79	1.01
R-squared	0.94	0.72	0.71	0.42	0.97
Links Within/Outside Caltrans Acceptable Deviation					
Within	524	335	338	334	1531
Outside	106	102	243	264	715
Acceptable %	83%	77%	58%	56%	68% **(>75%)**

*Note: numbers in parenthesis are the FHWA's recommended thresholds.

PMSA

The summaries, Table 37, compare the estimated traffic flow and the observed traffic count by 8 pseudo MSAs in the San Diego region (see Appendix A for description and spatial location of the districts). The comparison generally shows reasonable gaps and PRMSE values across all links within a PMSA. The average gaps are generally within 10%. However, the model flows in the East County exhibit larger overestimation overall (average gap=13%); 42% of the links are overestimated or underestimated by a gap of more than 50%, resulting in a relatively large RMSE value (52%) for the links in the district. However, due to the relatively low number of count locations (41) in the district, it is difficult to make any conclusions from these results. The slope of the regression line is close to 1.0 for all districts.

TABLE 37: DAILY ESTIMATED FLOWS VS OBSERVED COUNTS – BY MSA

	CENTER CITY		CENTRAL		NORTH CITY		SOUTH SUBURBAN		EAST SUBURBAN		NORTH COUNTY WEST		NORTH COUNTY EAST		EAST COUNTY		ALL	
	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Number of Links within Gaps																		
>=100%	3	4%	12	2%	28	4%	7	4%	4	1%	2	1%	2	1%	4	10%	62	3%
50%~100%	5	6%	37	7%	34	5%	5	3%	9	3%	2	1%	9	4%	6	15%	107	5%
30%~50%	5	6%	27	5%	47	7%	15	9%	13	4%	6	3%	11	5%	4	10%	128	6%
20%~30%	4	5%	25	5%	35	5%	3	2%	18	5%	11	6%	11	5%	1	2%	108	5%
10%~20%	5	6%	67	12%	82	12%	11	7%	29	8%	8	4%	19	9%	2	5%	223	10%
0%~10%	7	9%	100	18%	112	17%	22	13%	43	13%	26	13%	28	13%	2	5%	340	15%
0%~-10%	5	6%	81	15%	121	18%	20	12%	58	17%	58	29%	27	13%	3	7%	373	17%
-10%~-20%	9	12%	57	10%	61	9%	21	13%	41	12%	28	14%	21	10%	6	15%	244	11%
-20%~-30%	7	9%	33	6%	52	8%	15	9%	42	12%	26	13%	26	12%	3	7%	204	9%
-30%~-50%	13	17%	62	11%	53	8%	22	13%	52	15%	18	9%	38	18%	3	7%	261	12%
<-50%	14	18%	52	9%	40	6%	22	13%	33	10%	12	6%	21	10%	7	17%	201	9%
total links	77	100%	553	100%	665	100%	163	100%	342	100%	197	100%	213	100%	41	100%	2251	100%

	CENTER CITY		CENTRAL		NORTH CITY		SOUTH SUBURBAN		EAST SUBURBAN		NORTH COUNTY WEST		NORTH COUNTY EAST		EAST COUNTY		ALL	
	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
-10% ~ +10%	12	16%	181	33%	233	35%	42	26%	101	30%	84	43%	55	26%	5	12%	713	32%
-20% ~ +20%	26	34%	305	55%	376	57%	74	45%	171	50%	120	61%	95	45%	13	32%	1180	52%
-30% ~ +30%	37	48%	363	66%	463	70%	92	56%	231	68%	157	80%	132	62%	17	41%	1492	66%
positive links	29	38%	268	48%	338	51%	63	39%	116	34%	55	28%	80	38%	19	46%	968	43%
negative links	48	62%	285	52%	327	49%	100	61%	226	66%	142	72%	133	62%	22	54%	1283	57%
Average of Gaps																		
Positive	42%		28%		37%		39%		25%		21%		33%		73%		33%	
Negative	-35%		-28%		-23%		-32%		-28%		-20%		-29%		-39%		-27%	
All	-6%		-1%		7%		-5%		-10%		-8%		-6%		13%		-1%	
Percent Root Mean Square Error (PRMSE) and Trend Line Slope																		
RMSE	36%		21%		19%		28%		24%		13%		27%		52%		22%	
Slope	1.05		1.04		1.01		0.96		0.98		0.98		1.00		0.96		1.01	

VOLUME GROUP

The summaries in Table 38 compare the estimated traffic flows and the traffic count in 11 volume groups that are formed based on the range of the observed traffic counts. Each volume group consists a traffic range of 10k with the first group as less than 10k and the last group as more than 100k. Generally, links with lower volumes show larger gaps and PRMSE values. This is not surprising given that lower volume links are more likely to be collectors or arterials and as previously discussed have more error. Further, the slope of the regressed line for the lower volume links (<40k) indicate underestimation on those links. This concurs with the observations from the comparisons by road class where arterials and collectors showed underestimation overall.

TABLE 38: DAILY ESTIMATED FLOWS VS OBSERVED COUNTS – BY VOLUME GROUP

	<10K		10K-20K		20K-30K		30K-40K		40K-50K		50K-60K		60K-70K		70K-80K		80K-90K		90K-100K		>100K		ALL	
GAP	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Number of Links within Gaps																								
>=100%	55	6%	6	1%	0	0%	1	1%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	62	3%
50%~100%	90	11%	13	3%	3	1%	0	0%	1	2%	0	0%	0	0%	0	0%	0	0%	0	0%	0	0%	107	5%
30%~50%	66	8%	31	6%	16	7%	4	4%	2	4%	3	4%	0	0%	4	5%	2	3%	0	0%	0	0%	128	6%
20%~30%	51	6%	13	3%	15	6%	6	6%	3	5%	10	13%	0	0%	3	4%	6	8%	1	1%	0	0%	108	5%
10%~20%	56	7%	28	6%	14	6%	15	16%	14	25%	15	19%	13	24%	18	21%	13	16%	20	26%	17	13%	223	10%
0%~10%	73	9%	46	9%	24	10%	22	23%	14	25%	23	29%	11	20%	26	31%	23	29%	27	35%	51	38%	340	15%
0%~-10%	79	9%	55	11%	40	16%	14	15%	9	16%	15	19%	24	44%	23	27%	30	38%	27	35%	57	43%	373	17%
-10%~-20%	85	10%	77	15%	24	10%	17	18%	8	14%	3	4%	6	11%	8	9%	5	6%	2	3%	9	7%	244	11%
-20%~-30%	71	8%	75	15%	43	18%	4	4%	2	4%	6	8%	0	0%	2	2%	1	1%	0	0%	0	0%	204	9%
-30%~-50%	101	12%	100	20%	51	21%	6	6%	1	2%	2	3%	0	0%	0	0%	0	0%	0	0%	0	0%	261	12%
<-50%	120	14%	54	11%	15	6%	7	7%	2	4%	2	3%	0	0%	1	1%	0	0%	0	0%	0	0%	201	9%
total links	847	100%	498	100%	245	100%	96	100%	56	100%	79	100%	54	100%	85	100%	80	100%	77	100%	134	100%	2,251	100%
-10% ~ +10%	152	18%	101	20%	64	26%	36	38%	23	41%	38	48%	35	65%	49	58%	53	66%	54	70%	108	81%	713	32%

	<10K		10K-20K		20K-30K		30K-40K		40K-50K		50K-60K		60K-70K		70K-80K		80K-90K		90K-100K		>100K		ALL	
GAP	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
-20% ~ +20%	293	35%	206	41%	102	42%	68	71%	45	80%	56	71%	54	100%	75	88%	71	89%	76	99%	134	100%	1,180	52%
-30% ~ +30%	415	49%	294	59%	160	65%	78	81%	50	89%	72	91%	54	100%	80	94%	78	98%	77	100%	134	100%	1,492	66%
positive	391	46%	137	28%	72	29%	48	50%	34	61%	51	65%	24	44%	51	60%	44	55%	48	62%	68	51%	968	43%
negative	456	54%	361	72%	173	71%	48	50%	22	39%	28	35%	30	56%	34	40%	36	45%	29	38%	66	49%	1,283	57%
Average of Gaps																								
Positive	57%		27%		20%		15%		15%		14%		10%		12%		11%		8%		7%		33%	
Negative	-35%		-30%		-26%		-24%		-17%		-17%		-7%		-10%		-6%		-4%		-5%		-27%	
All	8%		-14%		-13%		-5%		2%		3%		1%		3%		3%		3%		1%		-1%	
Percent Root Mean Square Error (PRMSE) and Trend Line Slope																								
RMSE	53%		37%		30%		28%		22%		20%		10%		15%		11%		9%		8%		22%	
Slope	1.00		0.86		0.87		0.95		1.02		1.03		1.01		1.03		1.03		1.03		1.01		1.01	

KEY FREEWAY CORRIDORS

Highway corridor performance is an important metric for regional stakeholders. The examination of model results by highway corridor helps establish a travel model's precision in regional planning applications. The list of examined corridors is presented in Table 39.

TABLE 39: KEY FREEWAY CORRIDORS

CORRIDOR	FREEWAY
North-South	I-5, I-5HOV, I-15, I-15HOV I-805, SR-67, SR-125, and SR-163
East-West	I-8, SR-52, SR-54, SR-56, SR-78, SR-94, and SR-905

The model flows on freeway corridors are compared by four corridor directions (NB, SB, EB, and WB) for daily as well as two peak time periods (AM and PM).

Table 40 compares daily flows on all key freeway corridors by direction. Overall, the flows match well with the observed counts - slope is 1.02 and the average gap is 3%. The flows by direction also compare well.

Table 41 compares all key freeway corridors by direction and in the AM peak period. Overall, the slope of 1.15 and the average gap of 26% indicate overestimation of traffic flows in the AM period. The overestimation is consistent across the four corridor directions. The SB and the EB directions of the corridors are overestimated the most with the slopes of 1.18 and 1.27 respectively and the average gaps of 28% for both. The NB and the WB directions are doing better with the slopes (1.10 and 1.13 respectively) relatively closer to 1 and the average gaps (23% and 17% respectively) smaller in magnitude. Comparisons of key freeway corridors (results are too long to include) by direction provide more insight into SB and EB overestimations. Generally, all corridors in the south bound direction show significant overestimation, except I-15 HOV which is underestimated. The east bound direction is similarly overestimated as well, except SR-54 and SR905 which are doing well.

Table 42 compares all key freeway corridors by direction and in the PM peak period. Overall, the slope of 1.11 and the average gap of 12% indicate overestimation of traffic volume in the PM period. The overestimation is consistent across the four corridor directions. The NB direction of the corridors is overestimated the most with the slope of 1.20 and the average gap of 29%. Other directions are doing well with slopes relatively closer to 1.0 and average gaps smaller in magnitude. Comparisons at corridor level (results are too long to include) by direction show that overestimation in the north bound direction is generally on all corridors, except I-15 HOV which is slightly underestimated.

Detailed validation plots showing validation of daily flows by count locations on the I-5, I-15, I-805, and SR-125 corridors are shown in Figure 31, Figure 32, Figure 33, Figure 34, Figure 35, Figure 36, Figure 37, Figure 38, Figure 39, and Figure 40.

TABLE 40: KEY FREEWAY CORRIDORS BY DIRECTION – DAILY

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Number of Links within Gaps										
>=40%	6	3%	7	4%	0	0%	2	2%	15	2%
30%~40%	3	2%	2	1%	6	5%	0	0%	11	2%
20%~30%	8	4%	5	3%	6	5%	4	4%	23	4%
10%~20%	30	15%	38	19%	21	17%	24	24%	113	18%
0%~10%	53	27%	69	35%	34	27%	33	32%	189	30%
0%~-10%	66	33%	49	25%	51	41%	32	31%	198	32%
-10%~-20%	19	10%	14	7%	6	5%	7	7%	46	7%
-20%~-30%	12	6%	2	1%	1	1%	0	0%	15	2%
-30%~-40%	1	1%	4	2%	0	0%	0	0%	5	1%
<=-40%	1	1%	7	4%	0	0%	0	0%	8	1%
total	199	100%	197	100%	125	100%	102	100%	623	100%
-10%~10%	119	60%	118	60%	85	68%	65	64%	387	62%

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
-20%~20%	168	84%	170	86%	112	90%	96	94%	546	88%
-30%~30%	188	94%	177	90%	119	95%	100	98%	584	94%
Positive	100	50%	121	61%	67	54%	63	62%	351	56%
Negative	99	50%	76	39%	58	46%	39	38%	272	44%
Average of Gaps										
Positive	12%		11%		12%		11%		12%	
Negative	-9%		-13%		-6%		-7%		-9%	
All	2%		2%		3%		4%		3%	
Percent Root Mean Square Error (PRMSE) and Trend Line Slope										
RMSE%	11%		12%		10%		11%		11%	
Slope	1.02		1.03		1.00		1.03		1.02	

TABLE 41: KEY FREEWAY CORRIDORS BY DIRECTION - AM

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Number of Links within Gaps										
>=40%	30	15%	61	31%	9	7%	26	25%	126	20%
30%~40%	12	6%	23	12%	7	6%	17	17%	59	9%
20%~30%	20	10%	33	17%	22	18%	22	22%	97	16%
10%~20%	34	17%	34	17%	48	38%	17	17%	133	21%
0%~10%	34	17%	28	14%	35	28%	13	13%	110	18%
0%~-10%	41	21%	3	2%	4	3%	4	4%	52	8%
-10%~-20%	17	9%	2	1%	0	0%	2	2%	21	3%
-20%~-30%	4	2%	6	3%	0	0%	1	1%	11	2%
-30%~-40%	2	1%	1	1%	0	0%	0	0%	3	0%
<=-40%	5	3%	6	3%	0	0%	0	0%	11	2%
total	199	100%	197	100%	125	100%	102	100%	623	100%

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
-10%~10%	75	38%	31	16%	39	31%	17	17%	162	26%
-20%~20%	126	63%	67	34%	87	70%	36	35%	316	51%
-30%~30%	150	75%	106	54%	109	87%	59	58%	424	68%
Positive	130	65%	179	91%	121	97%	95	93%	525	84%
Negative	69	35%	18	9%	4	3%	7	7%	98	16%
Average of Gaps										
Positive	24%		33%		20%		30%		27%	
Negative	-14%		-28%		-6%		-11%		-16%	
All	11%		28%		19%		27%		20%	
Percent Root Mean Square Error (PRMSE) and Trend Line Slope										
RMSE%	23%		30%		17%		34%		26%	
Slope	1.10		1.18		1.13		1.27		1.15	

TABLE 42: KEY FREEWAY CORRIDORS BY DIRECTION – PM

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
Number of Links within Gaps										
>=40%	29	15%	16	8%	11	9%	5	5%	61	10%
30%~40%	29	15%	16	8%	5	4%	3	3%	53	9%
20%~30%	42	21%	17	9%	13	10%	18	18%	90	14%
10%~20%	42	21%	31	16%	12	10%	35	34%	120	19%
0%~10%	20	10%	30	15%	27	22%	30	29%	107	17%
0%~-10%	19	10%	35	18%	35	28%	11	11%	100	16%
-10%~-20%	7	4%	30	15%	17	14%	0	0%	54	9%
-20%~-30%	9	5%	6	3%	0	0%	0	0%	15	2%
-30%~-40%	1	1%	3	2%	1	1%	0	0%	5	1%
<=-40%	1	1%	13	7%	4	3%	0	0%	18	3%

	NB		SB		WB		EB		ALL	
GAP RANGE	COUNT	%	COUNT	%	COUNT	%	COUNT	%	COUNT	%
total	199	100%	197	100%	125	100%	102	100%	623	100%
-10%~10%	39	20%	65	33%	62	50%	41	40%	207	33%
-20%~20%	88	44%	126	64%	91	73%	76	75%	381	61%
-30%~30%	139	70%	149	76%	104	83%	94	92%	486	78%
Positive	162	81%	110	56%	68	54%	91	89%	431	69%
Negative	37	19%	87	44%	57	46%	11	11%	192	31%
Average of Gaps										
Positive	28%		22%		21%		16%		23%	
Negative	-12%		-18%		-11%		-4%		-14%	
All	21%		4%		6%		14%		12%	
Percent Root Mean Square Error (PRMSE) and Trend Line Slope										
RMSE%	29%		22%		17%		16%		23%	
Slope	1.20		1.05		1.02		1.11		1.11	

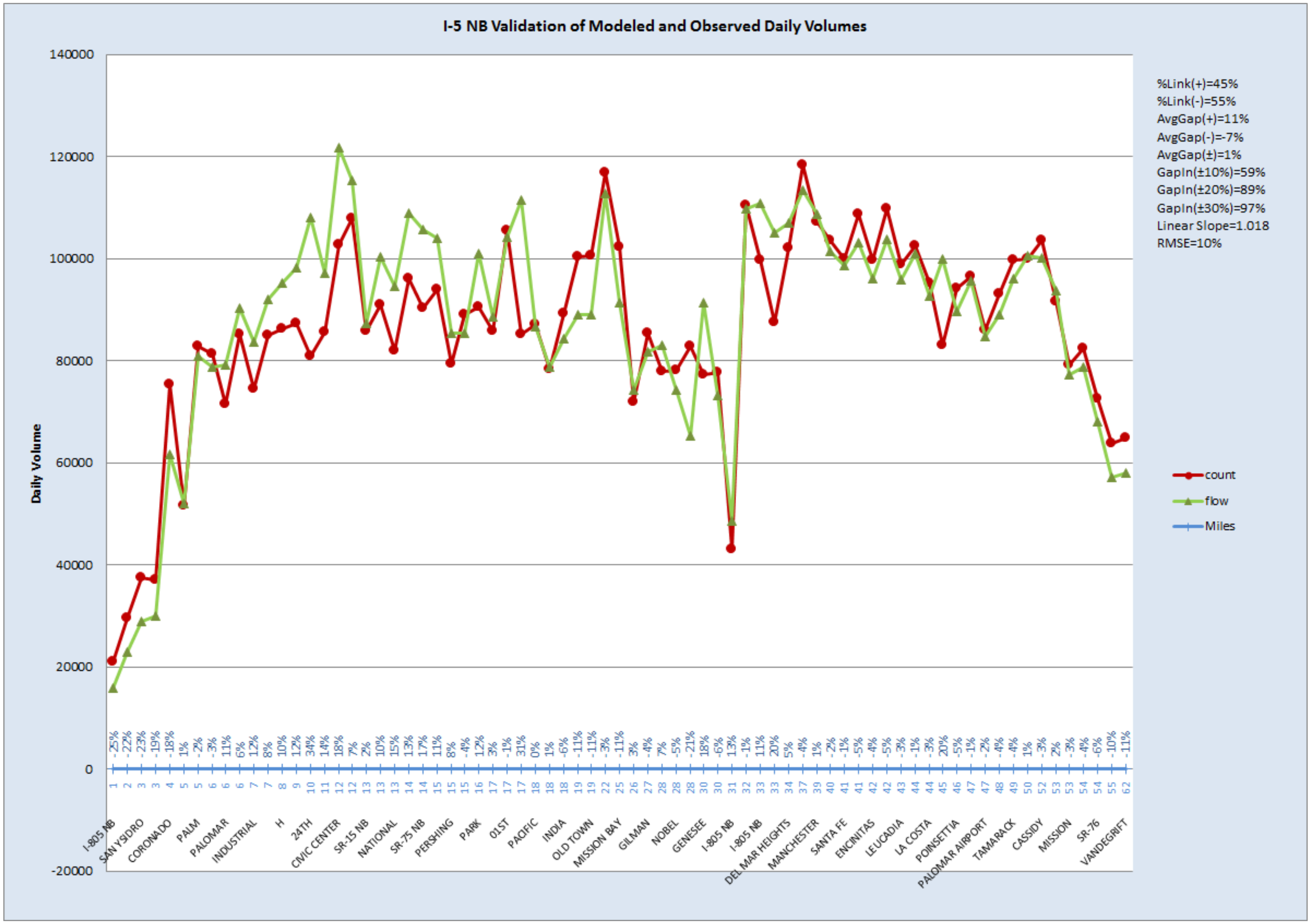
I-5 NB Validation of Modeled and Observed Daily Volumes
Daily Volume
%Link(+)=45%
%Link(-)=55%
AvgGap(+)=11%
AvgGap(-)=-7%
AvgGap(±)=1%
GapIn(±10%)=59%
GapIn(±20%)=89%
GapIn(±30%)=97%
Linear Slope=1.018
RMSE=10%
count
flow
Miles

FIGURE 31: KEY CORRIDOR VALIDATION - I-5 NB

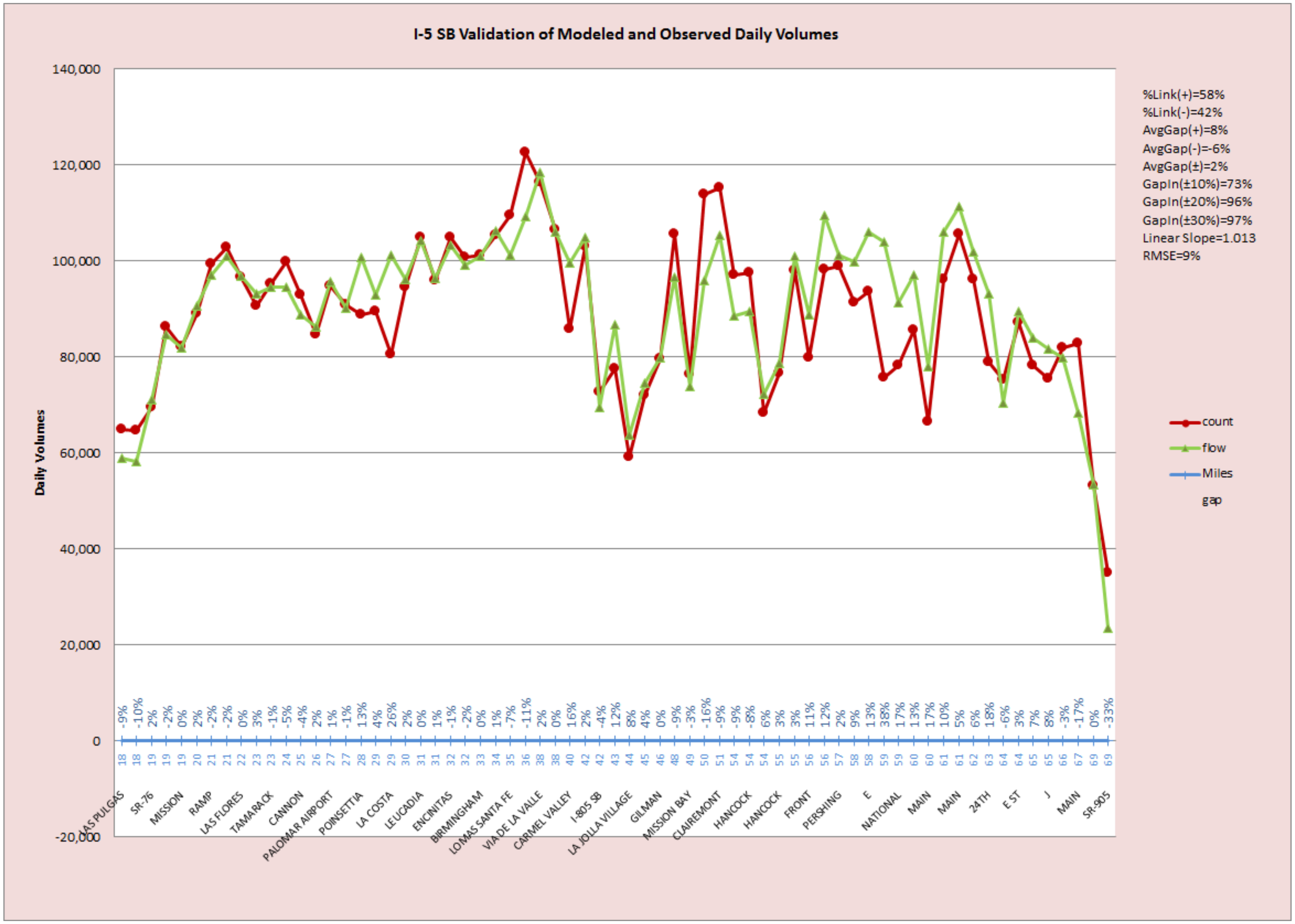

FIGURE 32: KEY CORRIDOR VALIDATION - I-5 SB

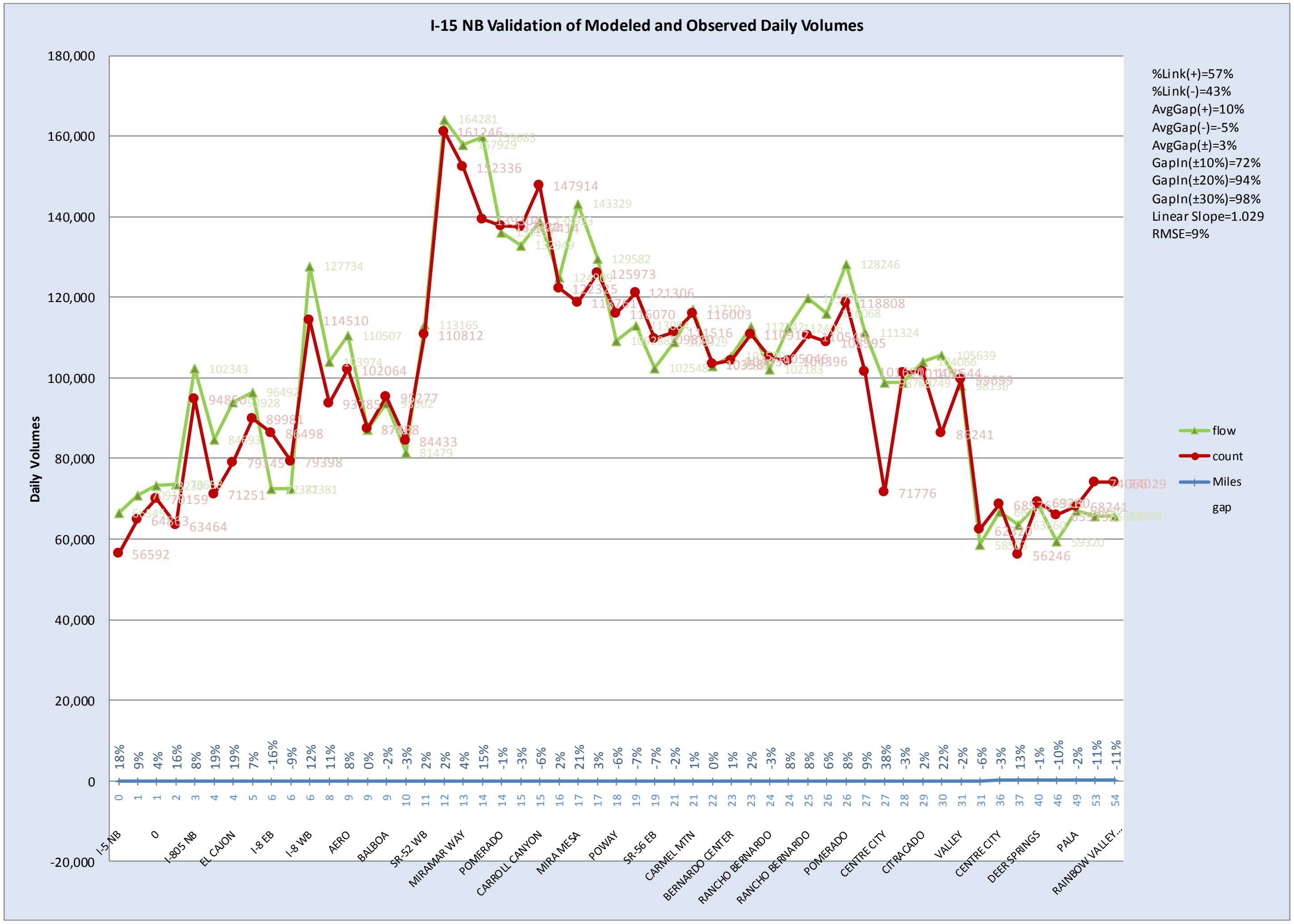

FIGURE 33: KEY CORRIDOR VALIDATION - I-15 NB

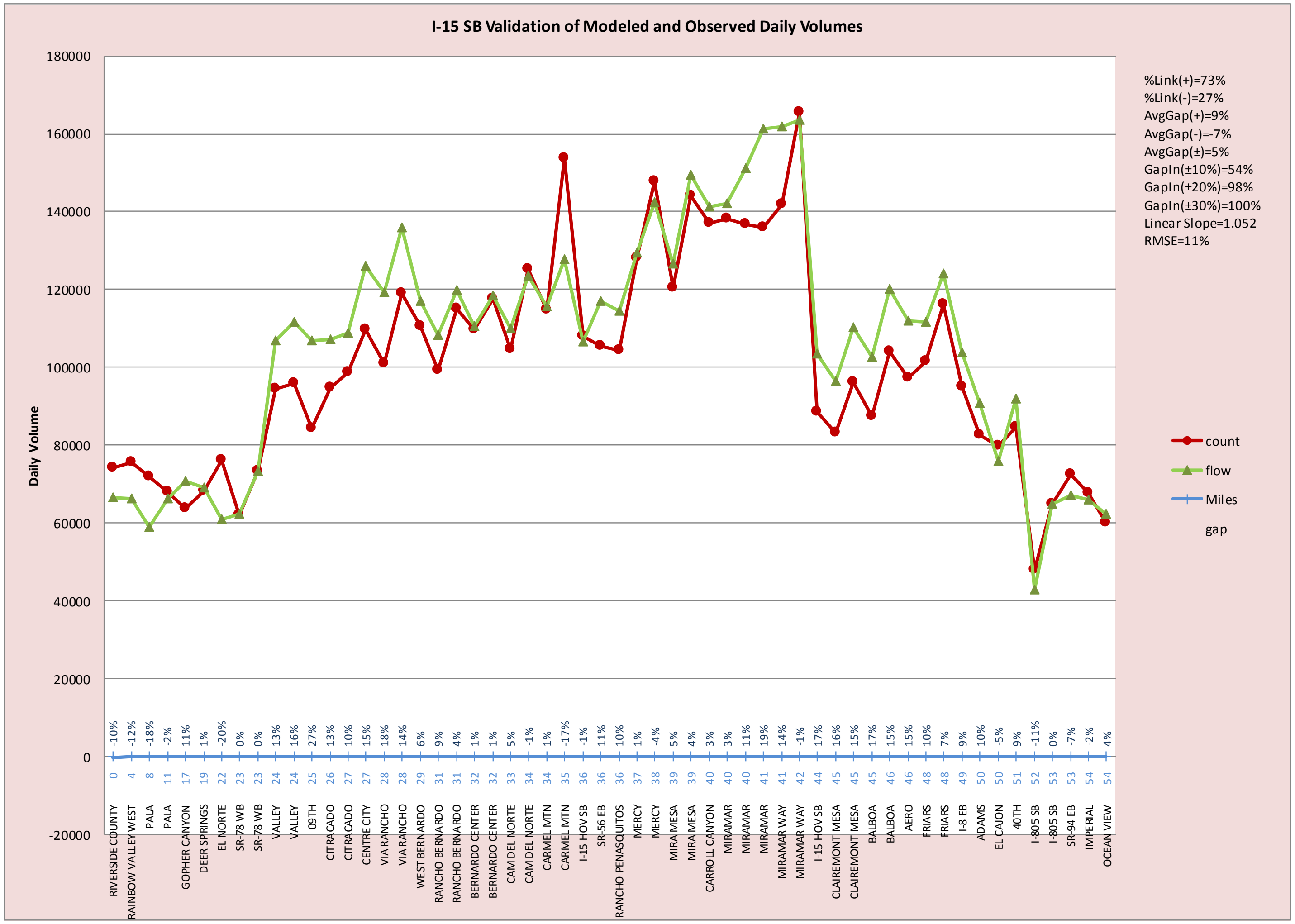

FIGURE 34: KEY CORRIDOR VALIDATION - I-15 SB

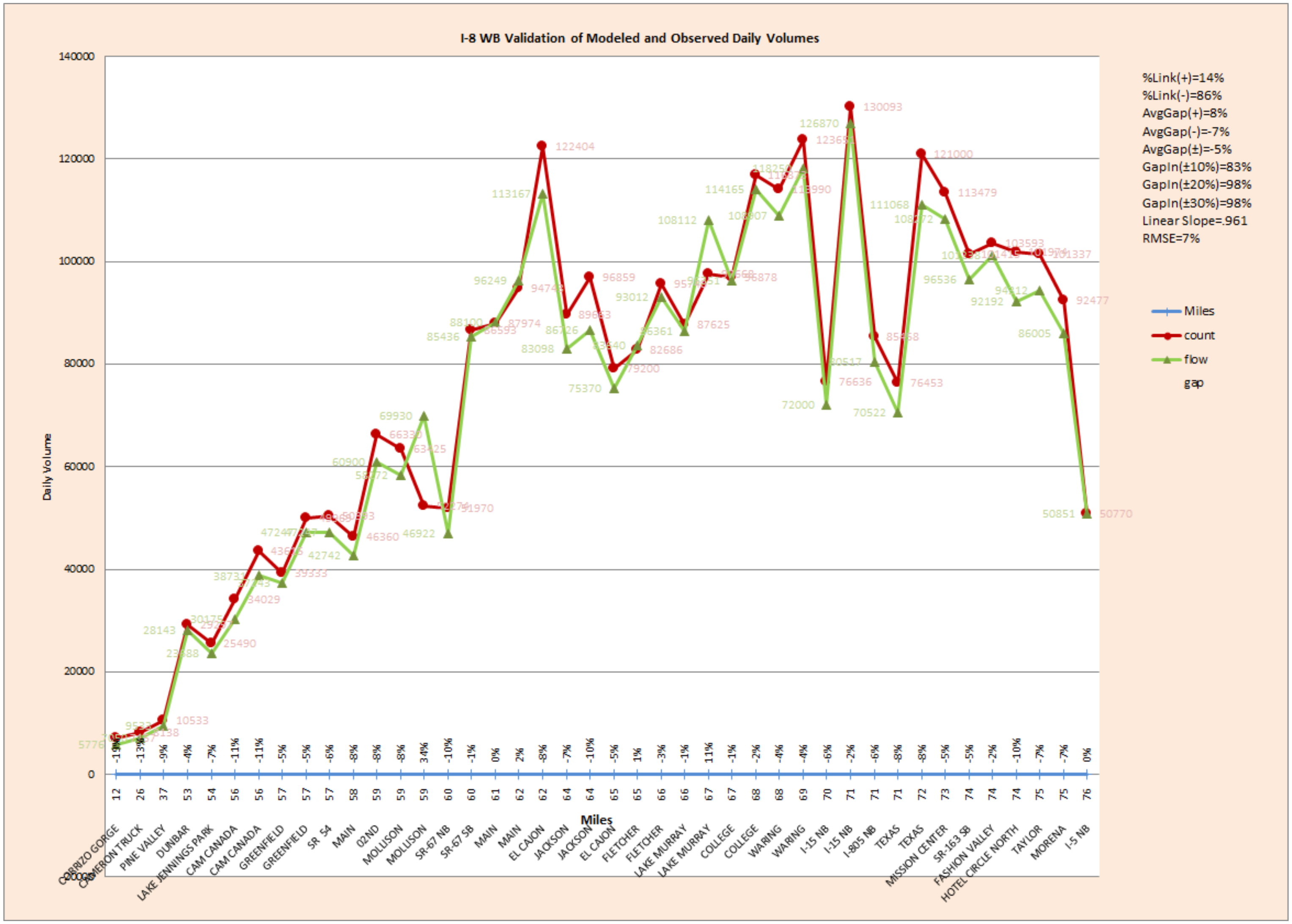

FIGURE 35: KEY CORRIDOR VALIDATION - I-8 WB

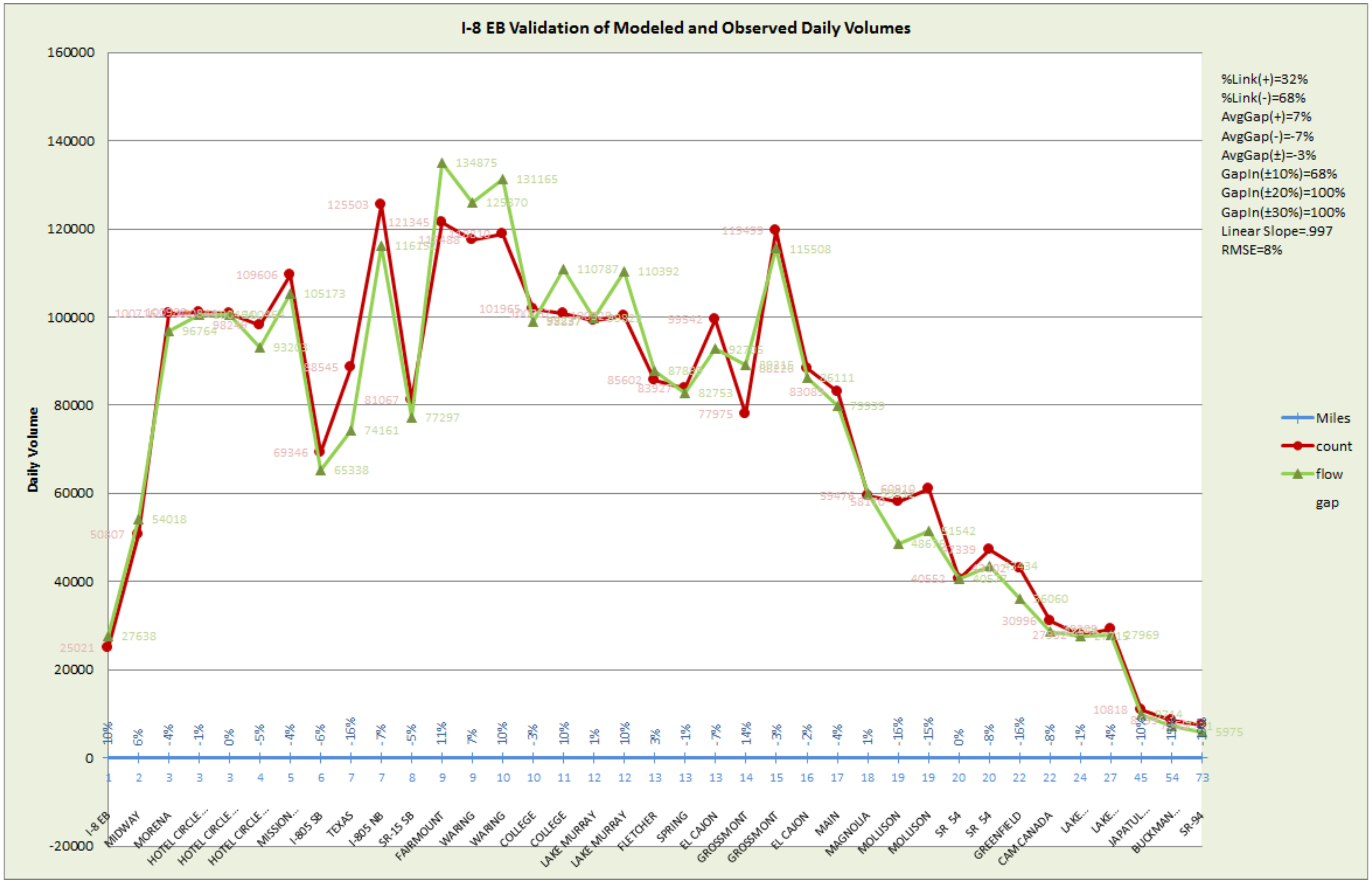

FIGURE 36: KEY CORRIDOR VALIDATION - I-8 EB

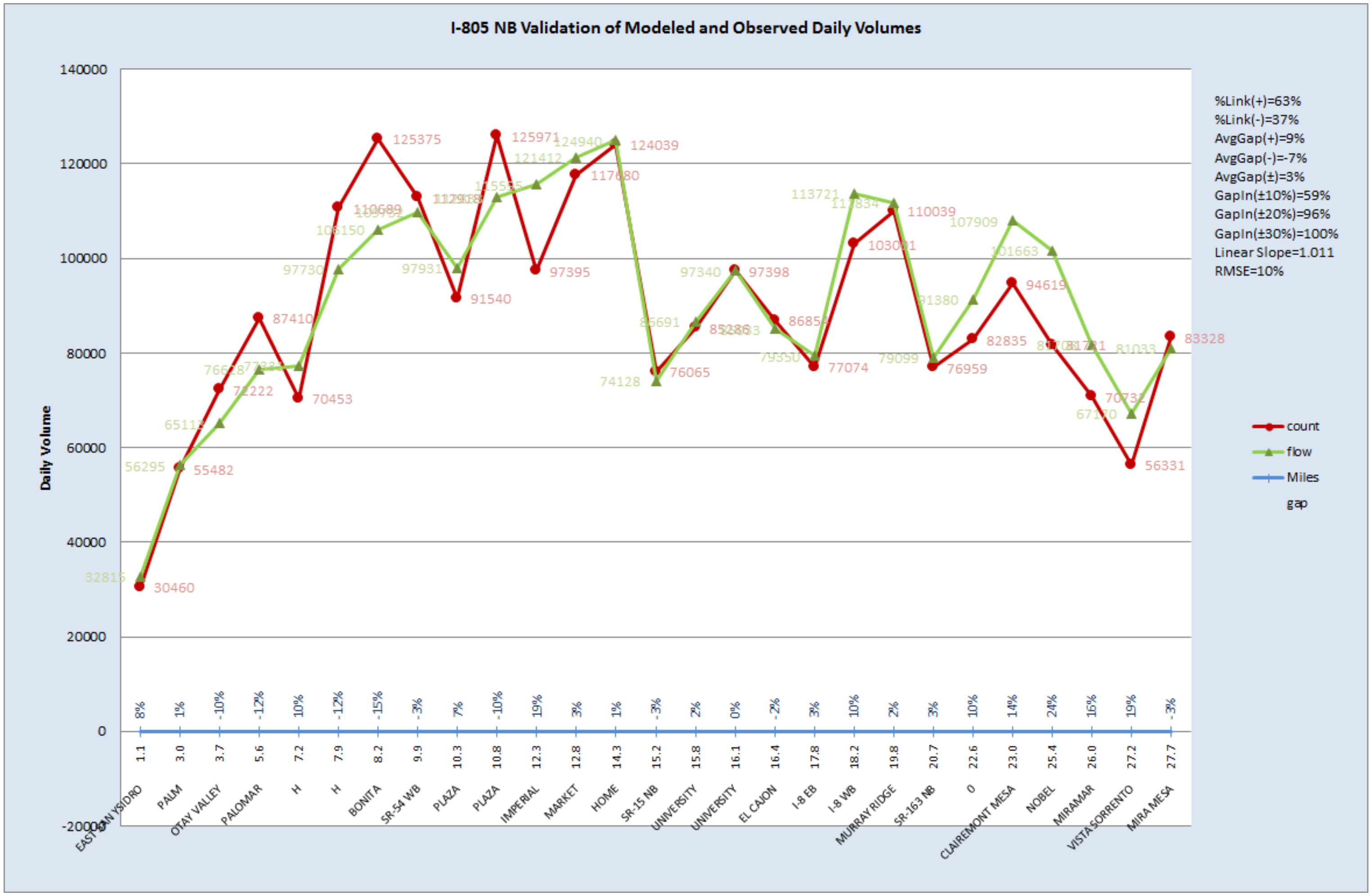

FIGURE 37: KEY CORRIDOR VALIDATION - I-805 NB

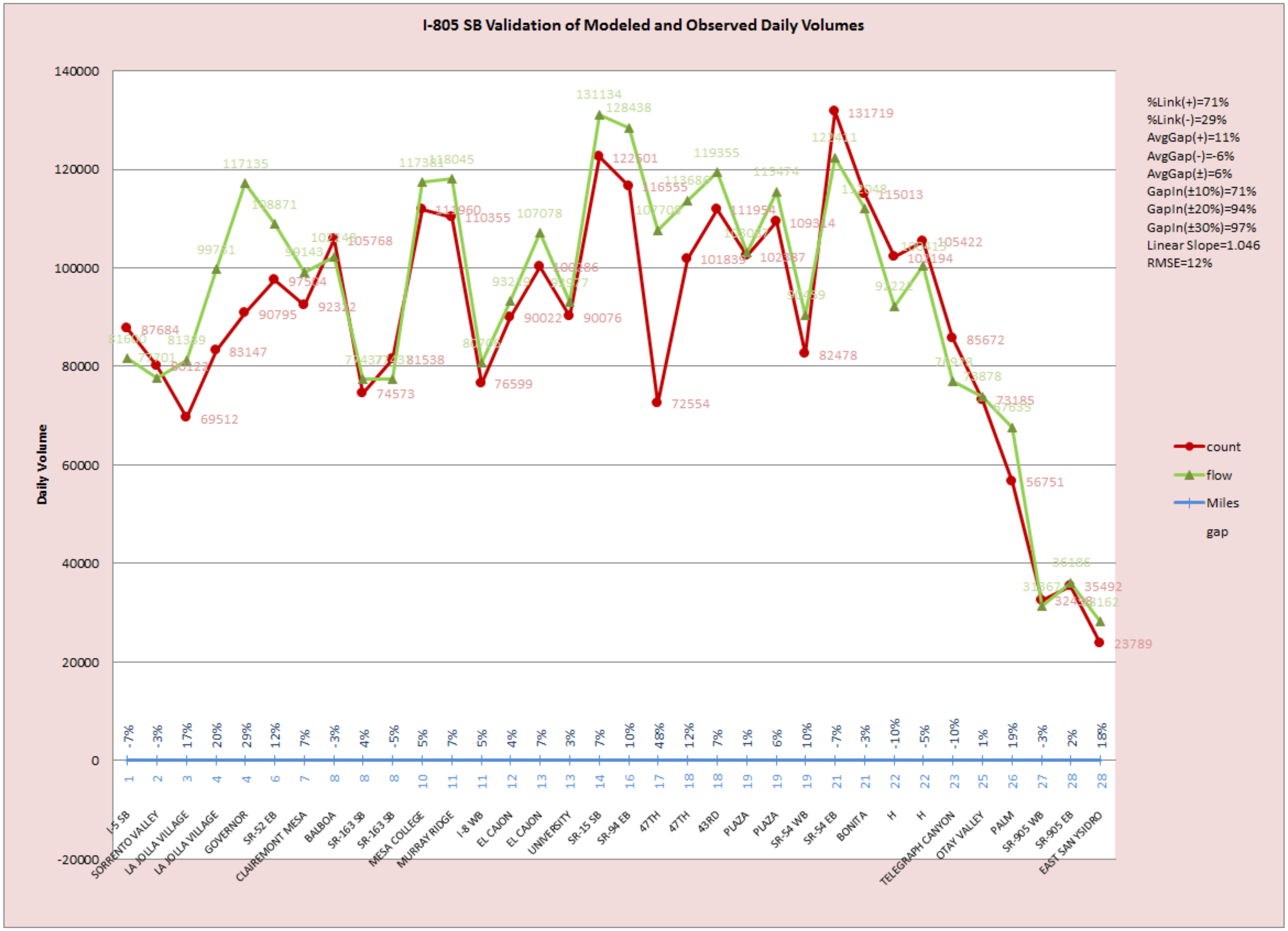

FIGURE 38: KEY CORRIDOR VALIDATION - I-805 SB

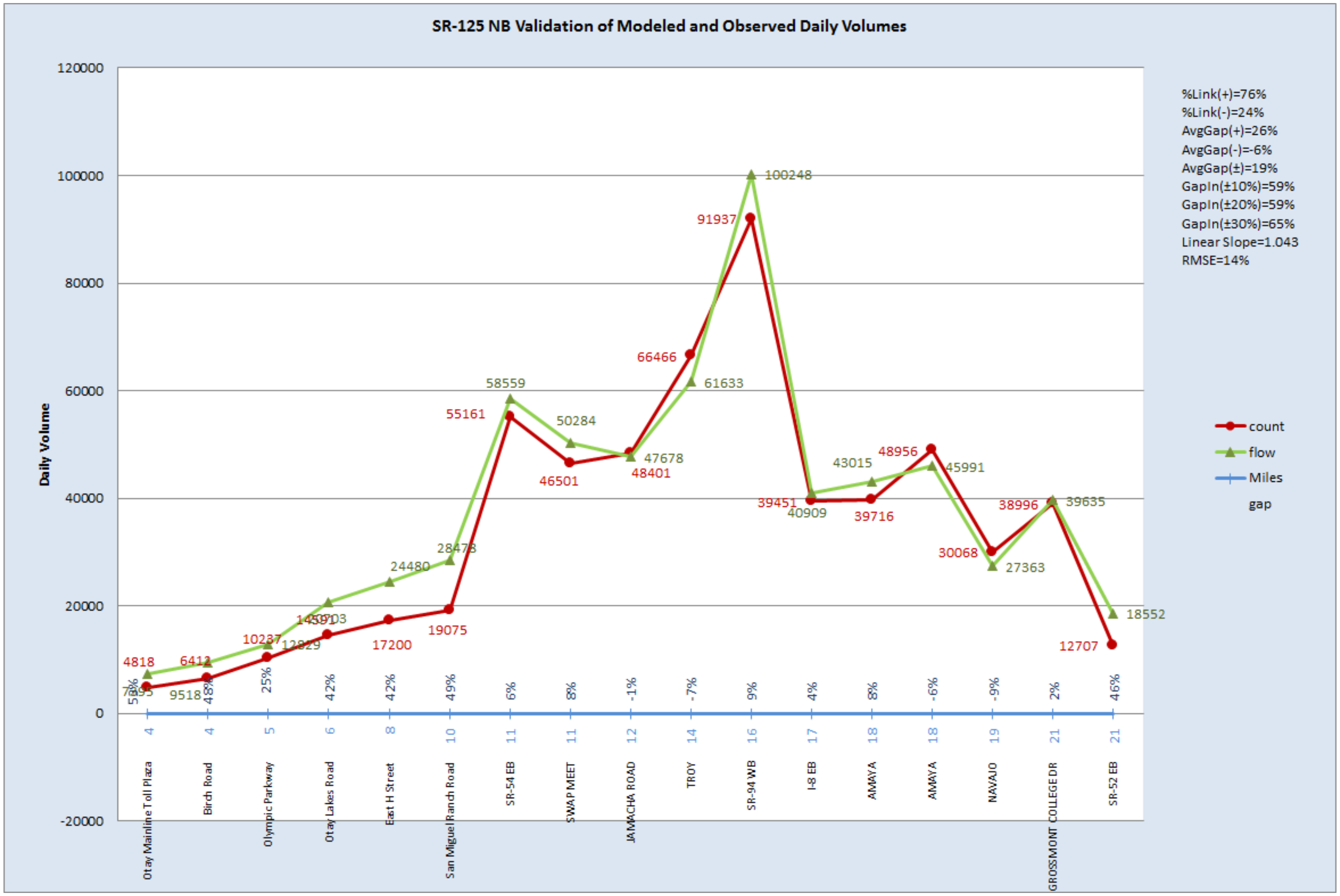

FIGURE 39: KEY CORRIDOR VALIDATION – SR-125 NB

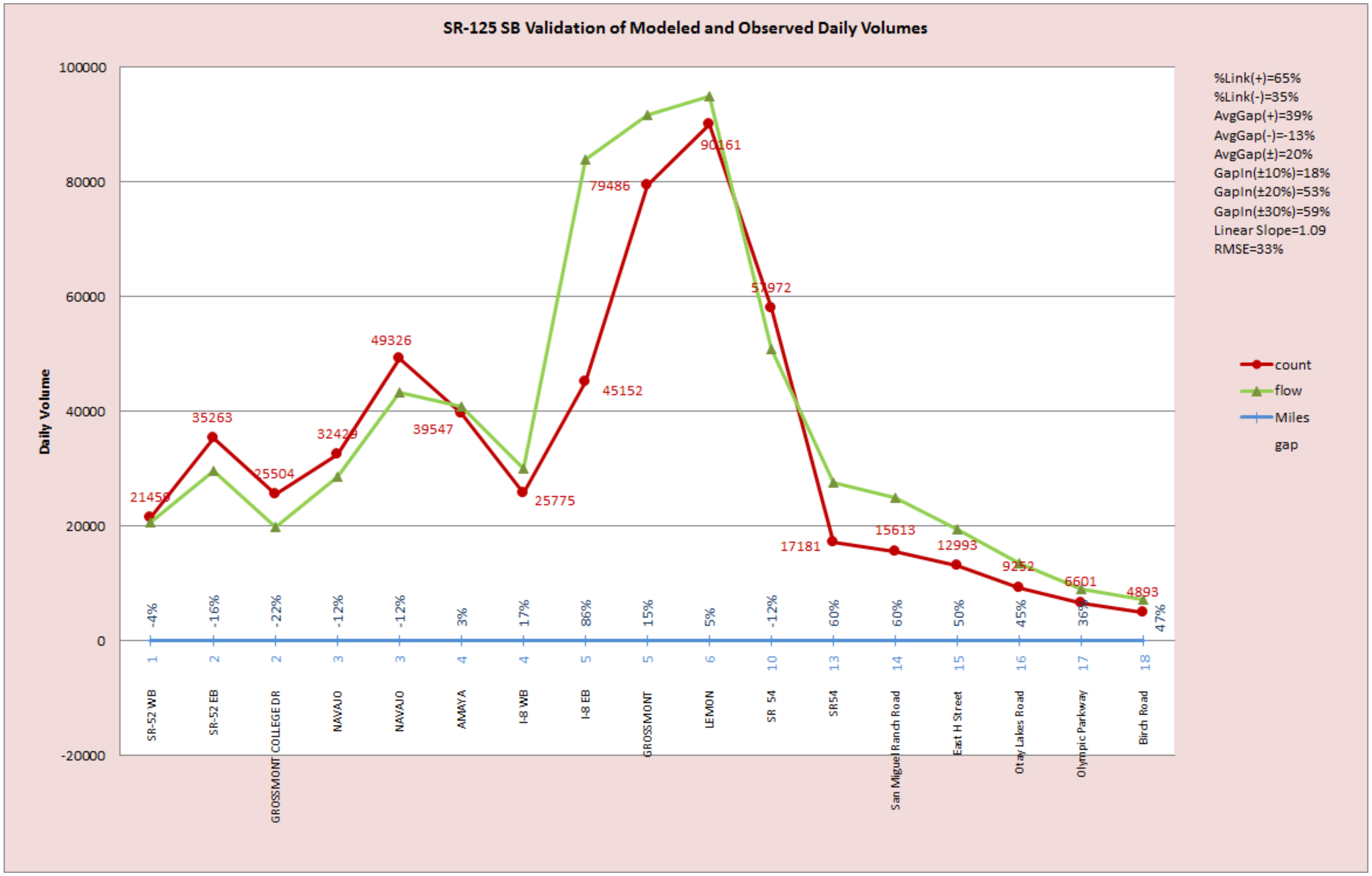

FIGURE 40: KEY CORRIDOR VALIDATION – SR-125 SB

PRMSE COMPARISON

The FHWA report provides example guidelines on PRMSE by volume range using data sources[12] from various States Ohio, Florida, and Oregon. Figure 41 compares the RMSE from the SANDAG ABM with these guidelines. The comparison is by link volume.

For higher volume (>50K) roads, the SANDAG ABM outperforms most guidelines. For lower volume roads (<50K), the ABM generally show higher RMSE values, though very close to the guidelines. As discussed in validations by volume group, this points to the quality of traffic counts on arterials and collectors.

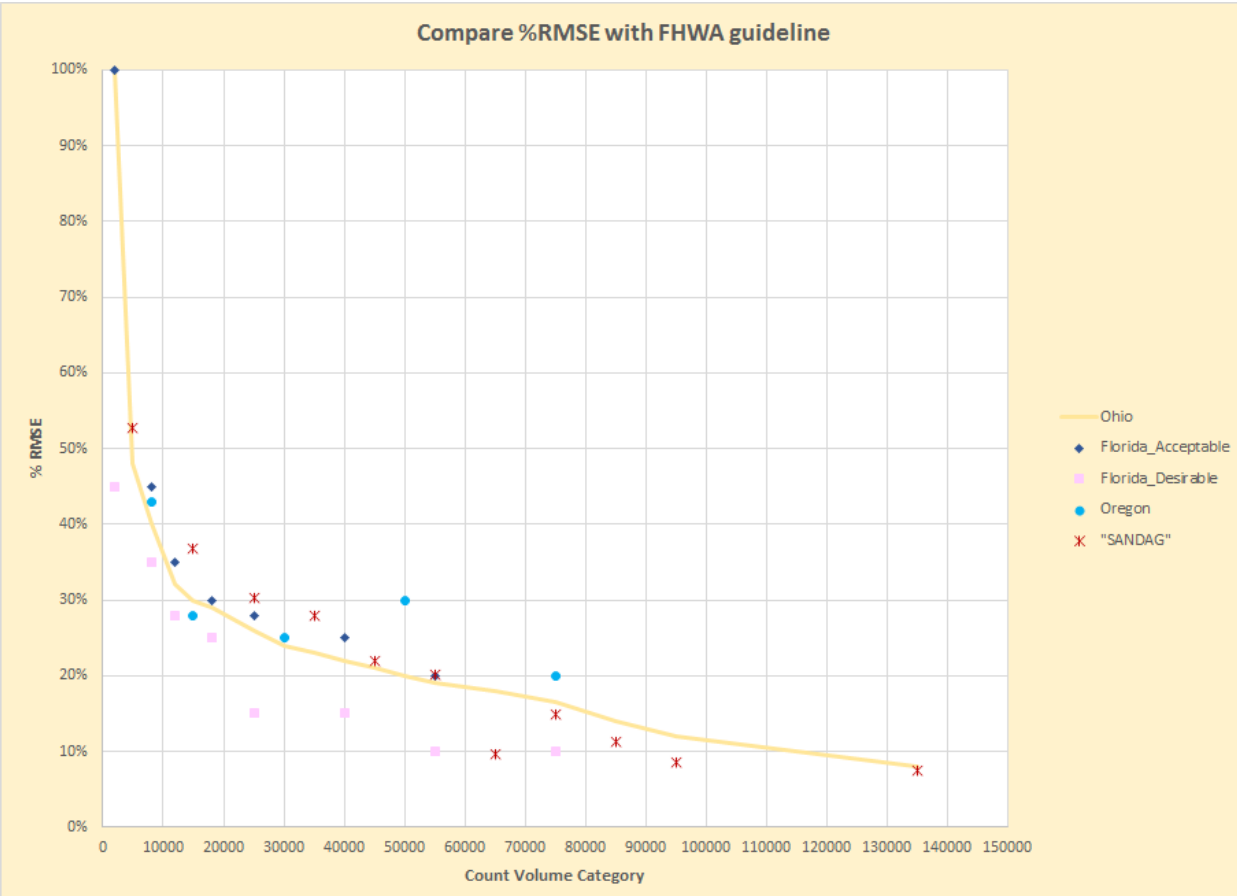

FIGURE 41: MODEL RMSE WITH FHWA GUIDELINES

[12] Figure 9.8 Example %RMSE Guidelines on page 9-20, Travel Model Validation and Reasonableness Checking Manual, 2nd Edition, TIMP

8.3 | TRANSIT VALIDATION

Transit ridership produced by the model is compared against the observed ridership obtained from the Passenger Count Program. The ridership (boarding) is compared by transit line-haul mode as well by transit line.

The FHWA provides guidelines to check reasonableness of the transit assignment results from a model. The recommended guidelines are presented in Table 43.

TABLE 43: THE FHWA'S TRANSIT VALIDATION GUIDELINES

METRIC	THRESHOLD
Difference between actual counts and model results for a given year by route group (e.g. local bus, express bus, etc.)	+/- 20%
Difference between actual counts and model results for a given year by Transit Mode (e.g. light rail, bus, etc.)	+/- 10%

*Source: The Travel Model Validation and Reasonableness Checking Manual, II Second Edition, September 2010.

The subsequent sections discuss the transit validation by:

- Region
- Transit Line-Haul Mode
- Transit line

REGION

Regionally, Table 44, the ABM generates 7% more transit boardings than the observed data and well within the Caltrans threshold of 10% (Table 43). However, the corresponding transit trips in the ABM are underestimated (-4%), thus indicating a higher regional boarding rate[13] in the model (1.48) compared to the survey (1.23). Note that the transit boardings and the transit trips in the observed data are from two different sources; the transit boardings are from the transit on-board survey, whereas the transit trips are from the transit on-board survey. Also, in general, the observed boarding rate appear low compared to other regions in the nation. The boarding rate in the current version of the model (ABM2+) is very similar to the previous calibration and validation effort (ABM2).

TABLE 44: TRANSIT SUMMARIES - REGIONAL

MEASURE	OBSERVED	SDABM16	DIFF	% DIFF
Boarding	355,143	380,623	25,480	7%
Trips	266,337	256,966	(9,371)	-4%

[13] Boarding rate is a measure of number of times transit service is boarded for every transit trip. The regional boarding rate is calculated as the total number of transit boardings divided by the total number of transit trips

MEASURE	OBSERVED	SDABM16	DIFF	% DIFF
boarding rate	1.33	1.48	0.15	11%

TRANSIT LINE-HAUL MODE

Based on their speed and operation (rail or bus), the transit services in the region are categorized into five line-haul modes: local bus, rapid bus, express bus, light rail (LRT), and commuter rail (CR). In 2016, a total of 114 local bus routes serve the region. The rapid and the express bus transit services operate 9 and 10 bus routes respectively. The light rail mode includes four rail services: blue line, orange line, green line, and sprinter. The commuter rail is a single route rail service that runs along the coast north to south through the San Diego county, serving eights stations between Oceanside and downtown San Diego.

The distribution of the observed ridership in the five line-haul modes, Table 45, indicate that the local bus and the light rail carry most of the burden of transit travel in the region. This is expected as the two transit services serve the most population in the region. The commuter line is a single transit line and serve limited population, thus transport the least riders within the region.

Transit line-haul mode preference of rides in the ABM show good match with the observed data. The rapid and the express bus which are overestimated by 18% and 26% respectively. The commuter rail is underestimated by 25%. Other line-haul modes are well within the 10% of the observed data, satisfying the FHWA's recommendation of within 10% (see Table 43). Note that the rapid and the express bus carry only a 12% of the total transit riders in the region. The two heavily used transit line-haul modes in the region, local bus and light-rail, are doing well.

It is noteworthy to mention here that even though the commuter rail is a single line service, its unique nature[14] of the service made it difficult for the model to produce ridership that reasonably match the observed data. The last calibration effort involved substantial effort and time in updating the model to replicate the observed commuter rail travel in the region, however, various changes made in the recent model updates made the commuter rail ridership worse. Schedule constraints did not allow the team to look into the underestimation. Future efforts would be allocated to investigate ridership of the line-haul mode.

TABLE 45: TRANSIT BOARDINGS – LINE HAUL MODE

TRANSIT MODE	OBSERVED	SDABM16	DIFF	DIFF (%)
Local	175,628	193,490	17,862	10%
Rapid	25,842	30,526	4,684	18%
Express	17,566	22,123	4,557	26%

[14] Several shuttle buses connect the population far from the service directly to coaster stations. The schedule of the buses is generally organized around the arrival and departure of the coaster rail. It competes with a parallel high-speed roadway facility, I-5. Its primary purpose is serving commuters, however, the observed data indicated only 50% of the commuter rail trips as work-related.

LRT	130,911	130,581	(330)	0%
Commuter Rail	5,196	3,903	(1,293)	-25%
TOTAL	**355,143**	**380,623**	**25,480**	**7%**

TRANSIT LINE

A comparison of ridership by transit line examines the model's ability of producing transit ridership by transit line. A scatter plot in Figure 43 shows the relationship between the transit boardings from the ABM and the observed boarding by transit line. The X-axis in the plot represent the observed boardings and the estimated boardings from the model are presented on the Y-axis.

A high R-squared value of 0.95 indicates that the linear regression line is a very good fit for all data points or in other words the model matches route level boardings very well. Further, the regression line has a slope of 1.01, suggesting a good balance of underestimated and overestimated transit lines in the region.

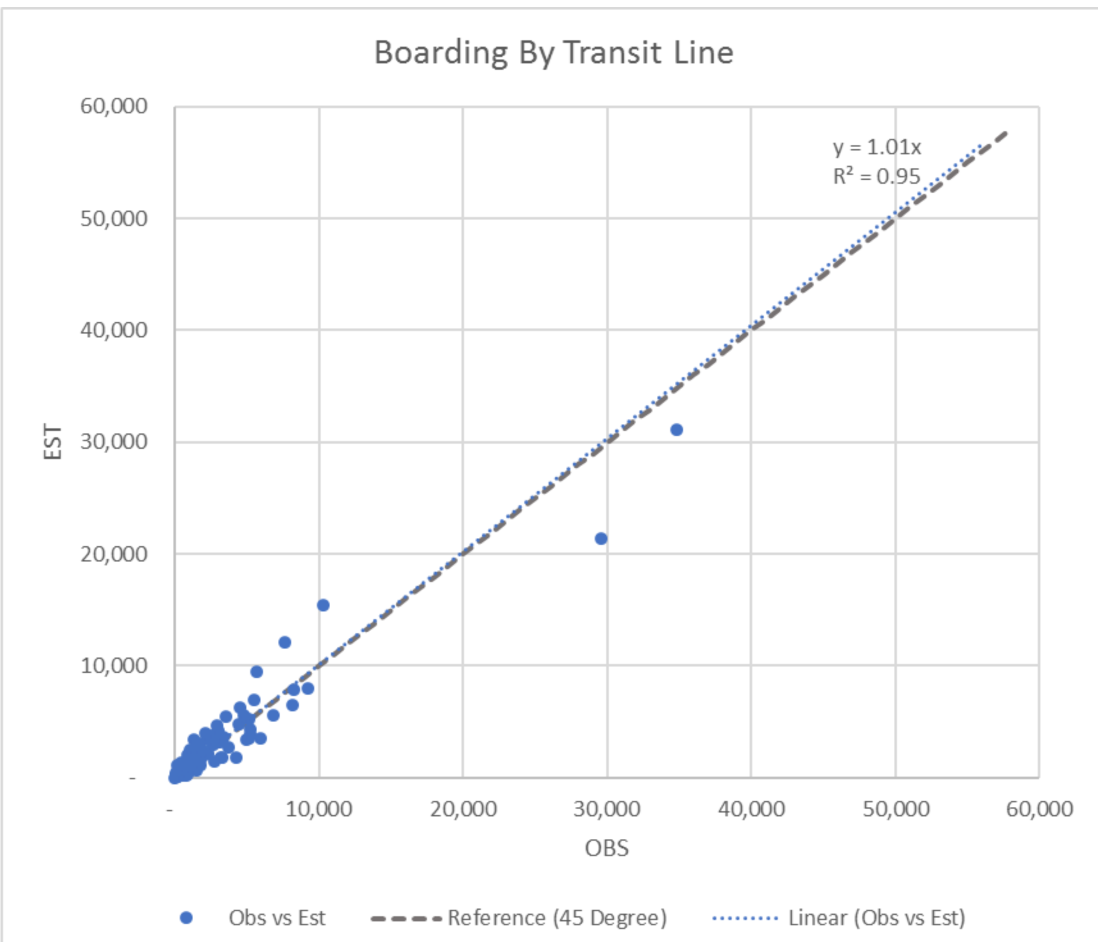

FIGURE 42: OBSERVED AND ESTIMATED TRANSIT BOARDINGS

A comparison of number of boardings by individual transit lines is presented in Figure 43. The X-axis is transit line id and the Y-axis is number of boardings. The transit lines are sorted from high observed boarding to low observed boarding. Note that the higher boarding lines in the map are LRT lines. The plot shows a reasonable match across all transit lines.

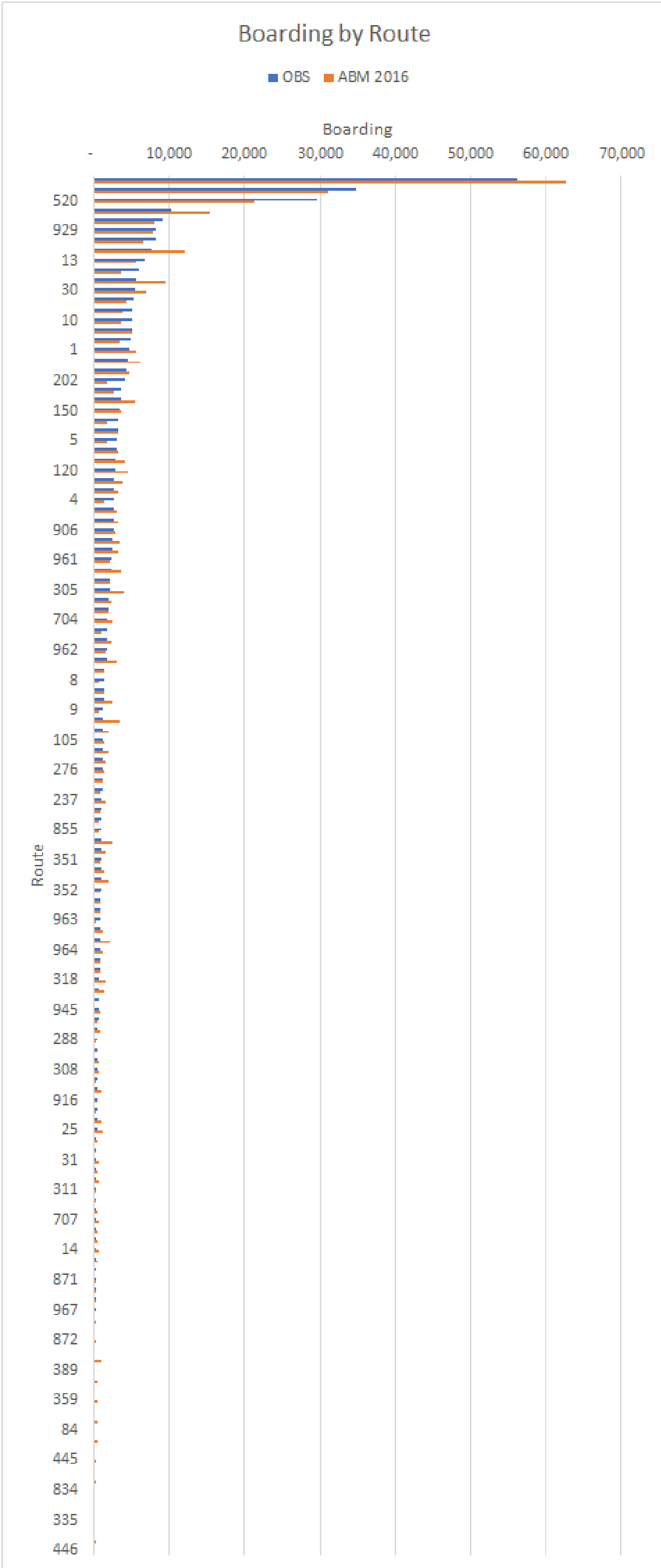

FIGURE 43: ESTIMATED AND OBSERVED BOARDINGS BY TRANSIT LINE

8.4 | SUMMARY

The present model validation uses a traffic count database from various sources that vary in terms of their accuracy for representing real traffic on the count location. Specifically, the traffic counts on freeways and ramps are from Caltrans and are more reliable, whereas the other traffic counts (arterials and collectors) are obtained from local jurisdictions and are more error prone due to their sample size and high degree of seasonal variance on those road facilities. The model is also expected to exhibit greater error for lower-volume facilities, due to the size of TAZs and uncertainty in forecasts for smaller groups of decision-makers. The model results show an excellent match for count locations on freeways.

The highway validation uses the FHWA's various measures of reasonableness checks including, volume-to-count (gap), R-squared, RMSE, and percent links with volume-to-count within Caltrans deviation allowance. The following are a few key takeaways:

- Regionwide, the total traffic flow and the VMT produced by the ABM are close to the observed values for the same. Both the estimated traffic flow and the estimated VMT are within 2% of the observed values.
- The estimated traffic flows from the model compare well with the observed traffic counts. The linear regression line for the relationship between the estimated traffic flow and the real traffic counts has a slope of 1.01 and a R-squared value of 0.97.
- Across all measures, the freeway facilities outperform the FHWA's recommendations.
- The arterials and the collectors slightly underperform, raising questions about accuracy of the traffic counts from local jurisdictions. The two road classes are generally underestimated.
- The AM and PM peak periods are overestimated.

The transit validation compares transit ridership by line-haul mode as well as by transit line. The two set of comparisons show a good representation of the observed transit behavior in the ABM. The following are a few takeaways:

- Regionwide, the ABM overestimate transit boardings by 7%
- The boarding rate in the latest model (ABM2+) is similar to the previous version of the model (ABM2), although, the boarding rate in the ABM (1.48) is still higher than the observed boarding rate (1.23).
- The estimated boardings by transit line-haul modes generally meet the FHWA's recommended guideline (+/- 10%). Exceptions being the rapid, the express bus, and the commuter rail services which carry only 14% of the transit travel in the region.
- The estimated boardings compare well by transit line as well. The linear regression line for the relationship between the observed and estimated boardings has a slope of 1.01 and a R-squared value of 0.95.

APPENDIX A. SANDAG PMSA

TABLE 46: SANDAG PMSA

ID	DISTRICT (PMSA)
1	Downtown
2	Central
3	North City
4	South Suburban
5	East Suburban
6	North County West
7	North County East
8	East County

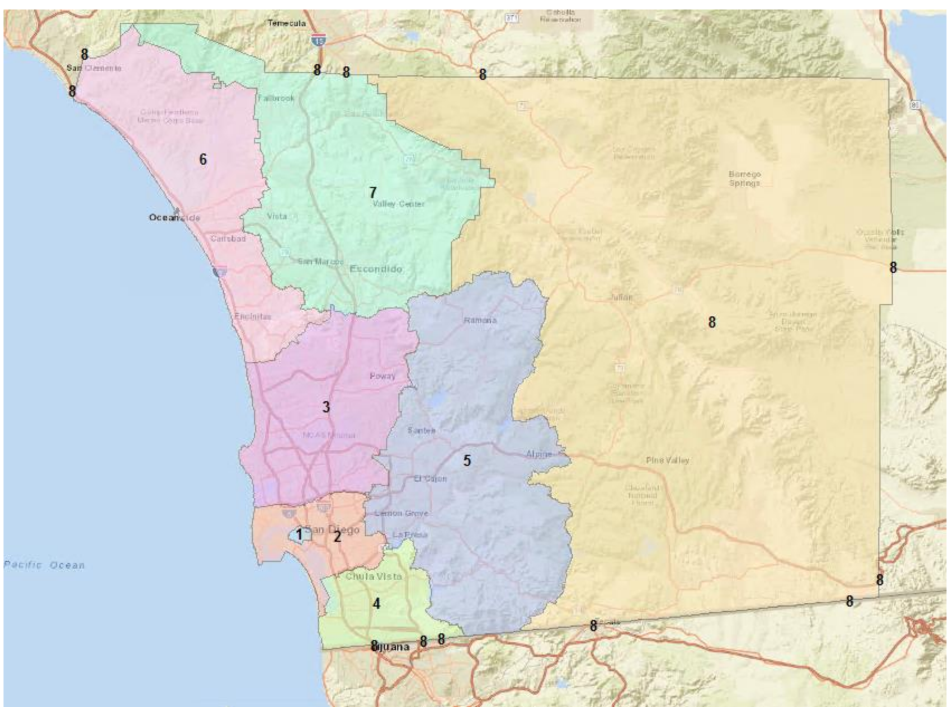

FIGURE 44: A MAP OF SANDAG PMSA

APPENDIX B. TRIP MODE CHOICE RECALIBRATION

After the ABM 2+ was calibrated and presented at the TAC 2020 meeting, the land use data was updated to the latest version (LU ID 38). Auto trip share was slightly underestimated and transit, on the contrary, was slightly over estimated based on LU ID 38, when compared to the trip mode share target displayed above. As a result, the AMB 2+ has been calibrated once more to accommodate the land use distribution. Similarly, the calibration process involved adjusting both the tour mode choice model and the trip mode choice model with the same alternative-specific constants match observed trips by trip mode and tour mode within each travel purpose. The summaries presented below (Table 47-48) include the final calibration results.

TABLE 47: TOUR MODE CHOICE MODEL

MODE	SURVEY	%	MODEL	%
Auto SOV	1,615,637	36.5%	1,608,515	36.5%
Auto 2 Person	1,091,230	24.6%	1,182,625	26.9%
Auto 3+ Person	1,190,657	26.9%	1,094,360	24.9%
Walk	279,654	6.3%	273,135	6.2%
Bike/Moped	48,141	1.1%	41,595	0.9%
Walk Transit	79,143	1.8%	79,330	1.8%
PNR-Transit	7,258	0.2%	6,680	0.2%
KNR-Transit	19,962	0.5%	18,785	0.4%
TNC-Transit	1,633	0.0%	1,335	0.0%
MAAS (Taxi, TNC-Single, TNC-Shared)	25,600	0.6%	25,355	0.6%
School Bus	72,998	1.6%	70,225	1.6%
Total	4,431,913	100.0%	4,401,940	100.0%

TABLE 48: TOUR MODE CHOICE MODEL

TRIP MODE	SURVEY	%	MODEL	%
Auto SOV	6,163,867	47.3%	6,196,600	47.4%
Auto 2 Person	3,062,097	23.5%	3,073,455	23.5%
Auto 3+ Person	2,407,326	18.5%	2,419,575	18.5%
Walk	904,235	6.9%	896,380	6.9%
Bike/Moped	103,724	0.8%	103,885	0.8%
Walk Transit	171,904	1.3%	165,880	1.3%
PNR-Transit	9,653	0.1%	12,580	0.1%
KNR-Transit	20,339	0.2%	24,170	0.2%
TNC-Transit	1,671	0.0%	440	0.0%
TAXI	349	0.0%	3,735	0.0%
TNC-Single	39,161	0.3%	34,010	0.3%
TNC-Shared	3,964	0.0%	7,415	0.1%
School Bus	142,760	1.1%	140,450	1.1%
Total	13,031,049	100.0%	13,078,575	100.0%

APPENDIX C. ABM2+ HIGHWAY VALIDATION USING CALTRANS PEMS COUNT INVENTORY

Introduction

San Diego Association of Governments (SANDAG) modeling staff aims to validate the latest Activity Based Model (ABM2+) output using available traffic counts. The traffic counts were collected through the vehicle detector stations (VDS) of Caltrans Performance Measurement System (PeMS). Each station represents a point location with geospatial information (e.g., latitude/longitude) and a traffic count for a specific time period. The objectives of this work are to (1) develop a series of sophisticated scripting solutions to minimize the existing workflow for acquiring the count inventory in good quality and to (2) update existing validation EXCEL templates with more available count inventory.

The work resulted in a new PeMS inventory with 498 counts which is 172 more than the existing 326-count PeMS inventory. Also, the new count inventory was built based on observed 5-minute data rather than the one-hour data used to create the existing count inventory. This improvement provides more accurate observed count inventory for validating traffic flow of each ABM TOD. Combined with other count inventories, the final count inventory has 797 counts available for validating traffic flow of mainlane freeway. Traffic flow on other facility types (i.e., ramp, arterials, and collectors) will be developed using the same procedure as described in the following sections.

Loading PeMS Count Inventory into Database

PeMS data was downloaded through Data Clearinghouse at http://pems.dot.ca.gov/.The raw data comes from Metadata at District11, Station 5-Minute/Hour/Day/AADT, and Census V Class Hour. Staff downloaded and loaded the raw data into a SQL database (i.e., [sql2014a8].[travel_data].[pems]). Due to the large size of the raw dataset, the Station 5-minute data is only available for 2016, 2018 and 2019 through manual downloading. Please refer to the SANDAG Github repository for gaining access and processing PeMS datasets: https://github.com/SANDAG/PeMS-Datasets/wiki.

Geospatially Cross-Reference PeMS Count Locations to SANDAG Highway Network Coverage

The location of the Caltrans PeMS product is a point dataset (station), while the geometry of the SANDAG highway network coverage is a polyline dataset (link). For validation of the ABM model, the idea is to compare the ABM traffic flow of each link with the PeMS traffic count of the nearest station. Staff developed a scripting solution to automatically cross-reference the nearest station to each link based on proximity analysis. A lookup table containing each unique station ID and the corresponding link ID is generated.

Produce Annual Average Weekday PeMS Count by ABM Time of Day (TOD)

The simulated traffic flow from the SANDAG ABM output is constrained to ABM TOD. The raw PeMS counts need to be appropriately aggregated to ABM TOD. Staff developed a Python procedure to produce the annual weekday PeMS counts aggregated by Day and ABM TOD. If any missing data in any ABM TOD, the count will not be used in the average process. The averaged counts are aggregated by station 5-minute data and weighted by sample size which was received by each station every 5 minutes. This provides more accurate observed count inventory to validate traffic flow of ABM TOD, compared to existing count inventory aggregated by station one-hour data. Note that only AM and PM of the aggregated ABM TOD are used in the validation process.

Quality Assurance of New PeMS Count Inventory

The QA processes include (1) checking new and old PeMS count inventory for the same (intersected) station IDs, (2) comparing the difference in the percentage (gap) of the two versions of counts and the base year (2016) model flow, and (3) manually updating the current cross-referenced results if the old results (an old lookup table associating with old PeMS count inventory) are more reasonable. For intersected counts, the station-link locations and gaps have been manually checked. For those mutually exclusive counts (i.e., only exist in either new or old count inventory), manual adjustment was applied to determine the reasonable count. However, due to the timeframe, more manual investigation is needed for those cross-referenced results only existing in either the new or old lookup table. The station-link location and gap need to be manually checked.

Update Existing Validation Templates

The existing validation templates use different sources for count inventory, including PeMS, SANDAG, Caltrans District 11, City of San Diego and other jurisdictions. The current work replaces all the existing PeMS count inventory with the new one produced through the above procedures. In addition, the new update improves the reusability of existing validation templates by automating a worksheet (embedded in three freeway validation templates) in a required table structure and establishing a dynamic connection to the PeMS source file (source_Count.csv). For near-term work, the summary of major statistical area (MSA) and jurisdiction (JUR) inside the validation template for all classes need to be updated.