SAN DIEGO ASSOCIATION OF GOVERNMENTS

ABM3 MODEL DEVELOPMENT PLAN

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PREPARED FOR

San Diego Association of Governments

PREPARED BY

RSG

Data Perspectives Consulting, LLC

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

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1.0 INTRODUCTION

The San Diego Association of Governments serves as the forum for regional decision-making for the San Diego region. SANDAG is governed by a Board of Directors composed of mayors, councilmembers, and county supervisors from each of the region's 19 local governments. SANDAG also serves as the Metropolitan Planning Organization (MPO) for San Diego County, whose role it is to prioritize spending on transportation projects to improve efficiency, promote safety, increase equity, and address other transportation planning objectives. The regional travel demand model is a key tool in SANDAG's toolbox used to analyze transportation and land-use projects and investments, quantify their impacts, and assess their performance relative to these objectives.

In 2009, SANDAG began development of an activity-based travel demand model, in the family of travel models referred to as CT-RAMP (Coordinated Travel Regional Activity-Based Travel Modeling Platform). The model was completed in 2013 and used for the 2015 RTP. The model was updated several times since the initial development - calibrated to new survey data, enhanced for additional sensitivities, expanded to consider emerging transportation technologies, etc. The latest version of the SANDAG ABM is referred to as ABM2+. The objective of this project is to develop Activity-Based Model 3 (ABM3) for the 2025 Regional Plan (2025 RP). The ABM3 development for the 2025 RP includes model estimation using recent surveys, ABM software update to ActivitySim, model calibration and validation, sensitivity tests, policy analysis enhancements, streamlining processes, risk evaluation, and general ABM support. The ABM3 development plan addresses the structure of the model system, the use of big data and innovative modeling approaches, outline the software architecture, the plan for model estimation, calibration, validation, and sensitivity testing, the integration of the activity-based model with SANDAG's other analytical tools and processes, and the use of the tool for policy analysis. These topics are described in further detail below.

2.0 ACTIVITYSIM MODEL

The ABM3 model system will be based on the ActivitySim platform. The current version of ActivitySim follows the SANDAG resident model structure closely since they are both based on the Coordinated Travel Regional Activity-based Modeling Platform (CT-RAMP). Recently, RSG implemented the cross-border travel model in ActivitySim under a separate task order. Other special market models (for overnight visitors and airport ground access) will be converted to ActivitySim format under this project. A special event simulation model was also developed as part of the initial activity-based model development project. However, this model has not been applied since its initial development nearly 10 years ago; therefore we do not plan to convert it to ActivitySim under this work plan. Other model components, including the aggregate heavy truck model, the disaggregate commercial vehicle model, and the aggregate external-internal and external-external models are also outside the purview of this task order.

Figure 1 shows the current ActivitySim model design. In order to understand the flow chart, some definitions are required. These are described in more detail below and in the appendix.

- *Tour*: A sequence of trips that start and end at an anchor location. In ActivitySim, anchors are home or work.
- *Primary destination*: The “main” activity of the tour; this activity determines the tour purpose. It also divides the tour into two "legs"; the sequence of trips from the anchor location to the primary destination is the outbound leg, and the sequence of trips from the primary destination back to the anchor location is the inbound or return leg.
- Mandatory activity: Work or school
- *Non-mandatory activity*: Any out of home activity that is not work or school, including maintenance activities such as shopping as well as discretionary activities such as out-of-home recreation and eating out.
- *Fully joint tour*: A tour in which two or more household members travel together to all out-of-home activity locations and return home together. In other words, no household member is picked-up or dropped-off en route.
- *Intermediate stop*: An out-of-home activity location on the tour other than the anchor location or the primary destination. Intermediate stops are made on the way from the anchor location to the primary destination (outbound) or on the way from the primary destination back to the anchor location (inbound).

- *Tour mode*: The "main mode" or "preferred mode" of the tour. This is an abstract concept used categorize the tour with respect to accessibility and constrain the availability of modes for trips on the tour to ensure some consistency of modes used for each trip.

The first model in the sequence is mandatory location choice; this model is run for all workers and students regardless of whether they attend work or school on the simulated day. Next, one or more mobility models are run. This currently includes a model that predicts whether workers and students have subsidized transit fares and if so, the percent of transit fare that is subsidized, and whether each person in the household owns a transit pass. Next, household auto ownership is predicted, and worker free parking eligibility. A vehicle type model (not shown) is currently under development.

Next, the daily activity pattern model is run, which predicts the general activity pattern type for every household member. Then Mandatory tours are generated for workers and students, the tours are scheduled (their location is already predicted by the work/school location choice model), and the tour mode is chosen. Fully joint tours are generated at a household level, their composition is predicted (adults, children or both), the participants are determined, and a tour mode is chosen. The primary destination of fully joint tours is predicted, the tours are scheduled, and a tour mode is chosen. Next, non-mandatory tours are generated, their primary destination is chosen, they are scheduled, and a tour mode is chosen for each. At-work subtours are tours that start and end at the workplace. These are generated, scheduled (with constraints that the start and end times must nest within the start and end time of the parent work tour), a primary destination is selected, and a tour mode is chosen.

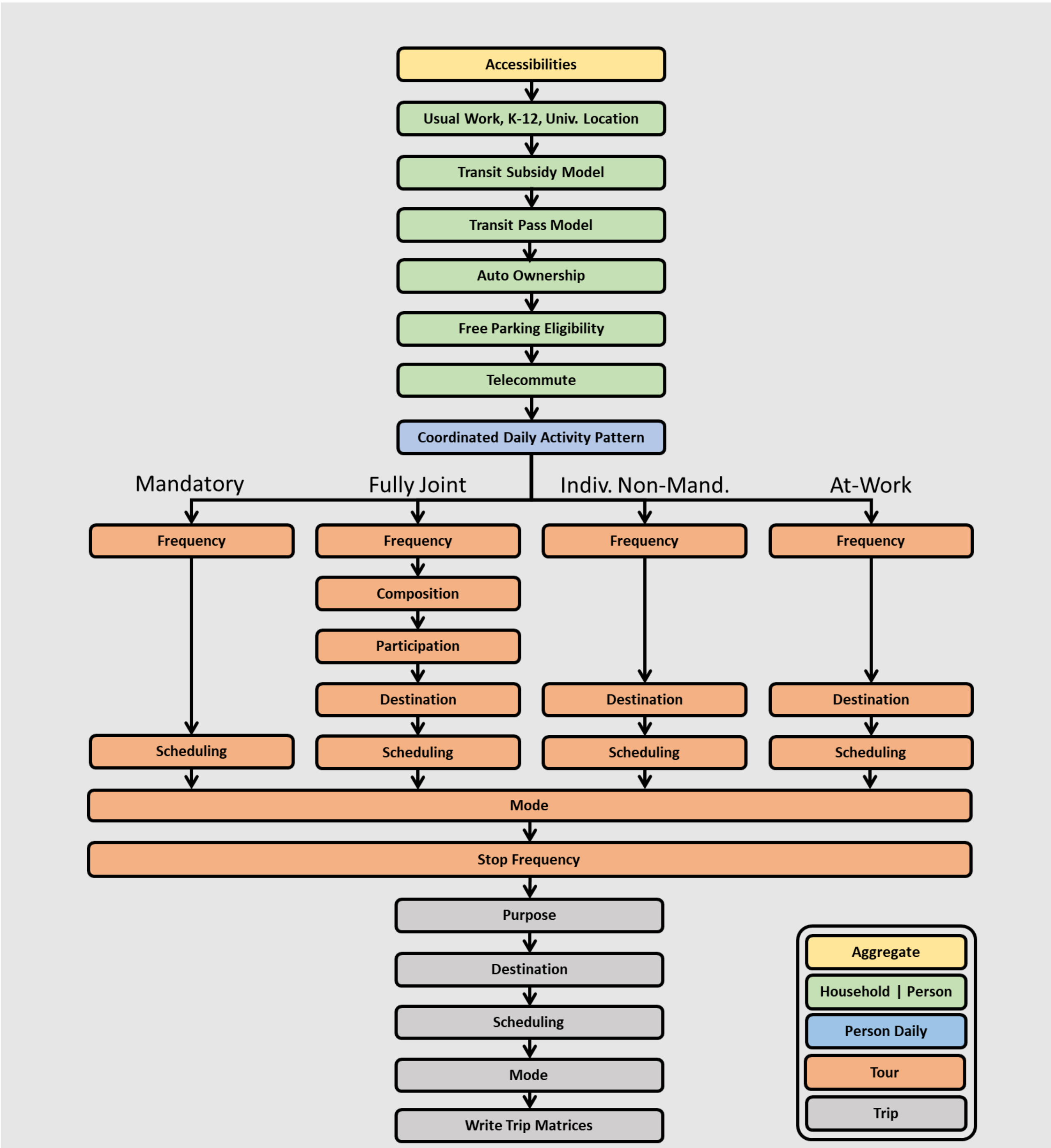
At this point, all tours are generated, scheduled, have a primary destination, and a selected tour mode. The next set of models fills in details about the tours - number of intermediate stops, location of each stop, the departure time of each stop, and the mode of each trip on the tour. Finally, the parking location of each auto trip to the central business district (CBD) is determined.

After the model is run, the output files listed above are created. The trip lists are then summarized into origin-destination matrices by time period and vehicle class or transit mode and assigned to the transport network. Skims are created based on congested times, and the model system is iterated multiple times until either some convergence threshold is attained, or a predetermined number of iterations is reached.

ActivitySim will be used to represent all internal travel made by residents of the SANDAG region (modeled area). The decision-makers in the model system include both persons and households. These decision-makers are created (synthesized) for each simulation year and land-use scenario, based on Census data and forecasted distributions of households and persons by key socio-economic categories. The decision-makers are used in the subsequent discrete-choice models in a microsimulation framework where a single alternative is selected from a list of available alternatives according to a probability distribution. The probability distribution is generated from a logit model which considers the attributes of the decision-maker and the attributes of the various alternatives. The application paradigm is referred to as Monte Carlo simulation, since a random number draw is used to select an alternative from the probability distribution. The decision-making unit is an important element of model estimation and implementation and is explicitly identified for each model specified in the following sections.

A key advantage of using the micro-simulation approach is that there are essentially no computational constraints on the number of explanatory variables that can be included in a model specification. However, even with this flexibility, the model system will include some segmentation of decision-makers. Segmentation is a useful tool to both structure models (for example, each person type segment could have their own model for certain choices) and to characterize person roles within a household. Segments can be created for persons as well as households.

FIGURE 1: ACTIVITYSIM MODEL COMPONENTS



ABM3 Model Design

The ABM3 model will be based upon the current SANDAG ABM2+ model. This model has several features that differentiate it from other models currently implemented in ActivitySim, such as:

- Utilization of spatial system consisting of microzones and transit access points
- Extensive accessibility calculations (nearly 50) at microzone level of geography
- Non-motorized time calculations based on an all-streets network and bike logsums calculated using a stochastic bike path model.
- School pickup/drop-off model that explicitly links drivers to students needing a ride to/from school.
- Autonomous vehicles are modeled explicitly at the household and tour level
- Value of time segmentation in mode choice (with upstream impacts on destination and time-of-day choice via logsums)
- E-scooters, first/last mile transit modeled via a mode choice post-processor
- Vehicle routing models for taxis, TNCs. and privately-held autonomous vehicles

There are several other enhancements as well. Each model feature of ABM2+. as well as a comparison of that feature (if relevant) to ActivitySim, and a recommendation for implementation in ABM3, is provided in Table 1. In addition to these features, ABM2+ also includes the following model components which need to be converted to ABM3 in Python:

Mexico resident travel model: This model addresses all travel made by Mexico residents in San Diego County as well as their choice of U.S./Mexico boarding crossing station and mode. It has been implemented in ActivitySim and is currently being estimated/calibrated to new travel survey data.

Overnight visitor travel model: This model represents all travel made by overnight visitors in San Diego County. It will be converted to ActivitySim.

Airport travel models: There is one airport travel model for each of two airports in San Diego: San Diego International Airport, and the Cross-Border Express terminal access to Tijuana International Airport. The model will be converted to ActivitySim and implemented for each airport.

Special event model: A model addresses travel to and from special events. This model has not been used by SANDAG and therefore will not be converted to ActivitySim.

TABLE 1: SANDAG ABM2+ FEATURES AND RECOMMENDATIONS

No.	Model Component	SANDAG ABM2+ Implementation	ActivitySim Implementation	Recommendation	Explanation
1	Synthetic Population Treatment in ActivitySim	Household-level expansion factors are used in CT-RAMP to reduce Monte Carlo variance for county-level applications	Expansion factors specified globally instead of by household	Implement household-level expansion factors in ActivitySim (affects shadow pricing)	Household-based expansion factors are needed for traffic impact studies and other types of local model applications.
2	Walk and bike time and logsum calculator	Java code calculates walk and bike generalized time and logsums on an all-street network prior to model run.	There is no equivalent code in ActivitySim.	Implement walk and bike time and logsum calculations using EMME.	The java code is slow and difficult to maintain. Moving these calculations to either EMME or Python will reduce runtime and model complexity.
3	Accessibilities	Aggregate accessibilities calculated using simplified mode and destination choice models for ~50 combinations of mode, auto sufficiency, period, and purpose.	Much simpler aggregate accessibilities consistent with MTC Travel Model One.	Implement disaggregate accessibilities for sample population, as per disaggregate mode choice utility calculator, and merge with synthetic population for use in model system.	Aggregate accessibilities are difficult to maintain as they require a completely separate aggregate mode and destination choice model. Disaggregate accessibilities that rely on the ActivitySim code are easier to maintain and reflect

					all of the features of the current model system.
4	Parking Costs	Weighted average parking costs calculated for each MGRA based on nearby MGRAs, weighted by distance and number of spaces	Zonal input parking costs	Calculate zonal input parking costs using pre-model Python script. Simplify parking cost calculations.	Parking costs are currently calculated in the MGRA data manager which is inefficient, and parking zone types are confusing.
5	Auto ownership	Run twice, once before work location choice (with origin-based simplified accessibilities) and once after (with origin and origin-destination simplified accessibilities). Also, considers autonomous vehicle ownership, more explicit accessibility terms.	Run once, after work location choice. Does not consider autonomous vehicles	Implement ABM2+ structure. Also see Vehicle type model below.	Revisions need to implement AV model functionality. Using origin-based accessibilities for auto ownership prior to work location choice improves model sensitivities to transit investments.
6	Transponder ownership	A transponder ownership model runs at household level and constrains use of managed lane facilities	Not implemented	Implement ABM2+ structure, and re-estimate the model, simplifying explanatory variables.	Without a transponder ownership model, demand on I-15 is over-estimated.
7	Vehicle type model	The current auto ownership model includes an AV choice.	Design: Vehicle type model predicts age, body type, and	Implement ActivitySim model once complete; update to	Vehicle type will be useful to reflect different assumptions

		In the new ActivitySim design, the AV choice will be handled along with other vehicle attributes in the vehicle type model.	fuel type after auto ownership model.	include AVs. Do not model AVs as part of auto ownership	about fuel type on auto operating cost and greenhouse gas emissions.
8	Parking reimbursement	Considers full reimbursement and partial reimbursement.	Only considers full reimbursement or no reimbursement	Implement ABM2+ structure	Many workers are only partially reimbursed; explore SANDAG parking survey data when available.
9	Work location choice	Size terms are segmented by occupation.	Size terms are segmented by household income.	Implement size terms by occupation (ABM2+).	Occupation segments are more correlated with employment types than income segments.
10	School location choice	School districts constrain school location choice	School location choice is unconstrained.	Do not implement school districts as constraints.	Reduce complexity of ABM3 travel model and inputs.
11	Work and school location choice shadow pricing	Shadow prices are calculated by size term segment and model is iterated for all workers/students until specified iterations reached.	Shadow prices are calculated by size term segment and model is iterated for all workers/students until either specified iterations or minimum error reached.	Replace shadow price segmentation by size term segment with global shadow prices and change iteration procedure to re-simulated subset of workers or students.	The shadow pricing mechanism is inefficient and not guaranteed to converge to input employment or enrollment. The proposed changes are described in greater detail below.
12	Internal-external tour generation	A mode predicts whether internal-external trips are	Does not model internal-external travel	Implement ABM2+ model	Internal-external travel is an important component of travel demand and there is

		generated, and if so, their destination			no alternative to implementing the current model.
13	Coordinated Daily Activity Pattern Model	Considers fully joint travel episodes	Does not consider joint travel episodes	Implement ABM2+ structure	The joint travel episode feature was added to prevent cases where joint tours cannot be scheduled to match person participation for two worker households.
14	School pickup/dropoff Model	A school pickup/drop-off model links students to drivers and models tours with stops for school pickups and dropoffs explicitly.	No such model exists	Suggest that ActivitySim consortium implement ABM2+ model.	The school pickup/drop-off model is a key step in explicitly linking household members together in shared vehicles and in the eventual explicit allocation of vehicles to tours.
15	Joint tour frequency	Simultaneous model (Frequency and composition)	Sequential model (frequency, composition, participation)	Suggest that ActivitySim consortium implement ABM2+ model.	The simultaneous treatment of joint tour frequency and composition is a convenient modeling mechanism but probably does not have a significant effect on model sensitivities.

16	AV availability/ allocation model	Between tour frequency and mode choice	A similar model will be implemented in the vehicle type model under development	Implement ActivitySim vehicle type model under development.	The vehicle allocation model allows tour and trip mode choice to use vehicle-specific auto operating costs and autonomous vehicle factors without overly complicating the model structure.
17	Tour and Trip Mode choice	Considers autonomous vehicles, value of time segmentation in skims	Does not consider autonomous vehicles, value of time segmentation in skims	Implement ABM2+ structure. Also implement TNC access and egress modes, e-scooter mode, and e-bike mode. Implement mobility hubs (below) to control availability of modes.	Autonomous vehicle parameters are useful for scenarios exploring AV fleet penetration. Value of time segmentation in travel skims has been demonstrated to improve model goodness-of-fit to toll road volumes. Emerging modes (e-bikes, e-scooters) are better handled as an integrated component of mode choice than a post-processor.
18	Time-of-day choice	Half-hourly periods, where the first and last periods of the day are aggregations of multiple periods	Hourly or half-hourly periods. The half-hourly period model does not aggregate time periods	Implement half-hourly periods with no aggregation for first and last period.	Aggregation of first and last periods is confusing to model users.

19	Stop frequency	Allows intermediate stops on drive-transit tours, with rules about stop location to ensure that PNR lot can be accessed.	Stops not allowed on drive-transit tours to ensure symmetry	Implement ABM2+ structure	Prohibiting stops on drive-transit tours reduces the ability of the model to match observed VMT and station area impacts of park-and-riders.
20	Disaggregate mode choice utility calculator	A sample synthetic population is built covering key market segments and run through CT-RAMP to create mode choice utility diagnostics	Not implemented	Implement ABM2+ mode choice utility diagnostics in ABM3	The tool is useful to understand mode choice and provides insights into the model's representation of transit accessibility.
21	Micromobility choice model	After mode choice, walk trips are split out into walk, e-scooter, and micro-transit.	E-scooters and microtransit (TNC egress) modes are not implemented yet (though TNC is available as both access and egress modes.	Implement e-bikes, e-scooters, and TNC egress modes directly in mode choice models.	See tour mode choice, above.
22	Taxi/TNC Routing Model	A Taxi/TNC routing model generates vehicles and assigns them to trips	There is no Taxi/TNC routing model in ActivitySim	Explore options; EMME, MatSIM, or conversion of Java code to Python	Shared vehicles has the potential to increase or reduce VMT given a number of assumptions; accounting for these assumptions in the model is useful.
23	Private Autonomous	A private AV routing model allocates vehicles to vehicle trips within a household.	There is no private AV routing model.	Explore options; EMME, MatSIM, or conversion of Java code to Python	Privately held AVs could increase VMT by serving multiple trips made by

	Vehicle Routing Model				household members. The AV routing model accounts for this potential VMT increase.

2.2 ABM3 SIMPLIFICATIONS AND ENHANCEMENTS

This section lists specific simplifications and potential enhancements to the current ABM2+ model including and in addition to the topics listed in Table 1. The issues listed below are of specific interest to SANDAG and therefore warrant additional detail and consideration.

Workplace shadow pricing

The current implementation of shadow pricing computes either multiplicative factors on size terms or alternative-specific constants that are added to utility equations to better match input employment. These adjustments occur by worker size term market segment, which are currently defined as groups of household income. In ABM2+, size term segmentation is by worker occupation. The calibration of shadow prices is inefficient for two reasons. First, the calibration of shadow prices by size term segment infers an expectation that the distribution of size terms for each segment is exactly proportional to the expected spatial distribution of workers by segment. In other words, that the size terms are error-free. However, since size term coefficients are typically calculated using sample data (either a household survey or Census distributions of workers by employment type and size term segment), and through a statistical process subject to measurement error, this places undue burden on the accuracy of size term coefficients. In short, it cannot be mathematically proven that calibrating size term parameters by size term market segment will result in a spatial distribution of total workers across all segments that matches the spatial distribution of total employment. Second, the calibration process is computationally inefficient because workers from all zones are affected by size term adjustments in any one zone. in other words, even zones whose total workers matches exactly total input employment could potentially switch workplace locations in the calibration process, leading to oscillations in goodness-of-fit.

We propose to address these inefficiencies as follows. First, we will replace the size term adjustment factors with one set of alternative-specific constants (by zone) that will be calibrated based on a comparison of total scaled workers compared to total employment. This will ensure that the workplace location choice model matches total employment rather than scaled workers by size term segment. Second, we will implement a method where in each iteration after the first iteration, the workplace location choice model will re-simulate a random sample drawn from workers who chose to work in "over-subscribed" zones. The model will re-choose a workplace for these workers after eliminating all zones where the number of scaled workers in the last iteration is equal to or over total employment in the zone. These changes will significantly reduce the computational burden required to match input employment and ensure a closer match to input employment data. A similar method will be implemented for school location choice, where constants will be calibrated by grade level (K-12 and College/University).

Parking Cost Model Simplifications

The current implementation of parking costs requires the user to specify detailed parking-related inputs for each microzone (MGRA). These inputs include:

- Hourly, daily, and monthly (amortized to daily) parking costs in dollars
- The number of hourly, daily, and monthly parking spaces in the MGRA, segmented by whether the space is available for a destination in the MGRA or a destination outside the MGRA
- The number of hours of free parking allowed before parking charges begin in hourly stalls
- A parking area field, with the following values:
  - 1: Trips with destinations in this MGRA may choose to park in a different MGRA, parking charges apply (downtown)
  - 2: Trips with destinations in parking area 1 may choose to park in this MGRA, parking charges might apply (quarter mile buffer around downtown)
  - 3: Only trips with destinations in this MGRA may park here, parking charges apply (outside downtown paid parking, only show cost no capacity issue)
  - 4: Only trips with destinations in this MGRA may park here, parking charges do not apply (outside downtown, free parking)

In areas with parking area equal to 1 or 2, a floating parking price calculation is used where the parking cost is a weighted average of all zones with a parking cost in parking area 1, weighted by number of spaces and distance. Outside of these MGRAs, only the parking cost for the destination is considered in mode choice.

These inputs are difficult to maintain and challenging to modify to test different parking policies. We recommend simplifying the parking inputs as follows. First, only daily parking cost will be required as an input. Hourly and monthly parking costs will be estimated by a model that includes daily cost as an independent variable. Second, exact number of spaces by type will not be required as an input. Instead, only total spaces will be tracked explicitly as an input, and if not provided, number of spaces will be estimated from a model. Third, number of hours of free parking before parking charges begin will not be tracked or used. Finally, parking area will not be required. Instead, the floating parking cost calculation will be applied to all zones.

Additionally, the user will be able to specify a maximum walk distance for parking cost calculations. This setting will allow the user to test policies where extremely high parking costs in a downtown area make driving prohibitively expensive.

Internal-External Model

The current internal-external model is inconsistent with the rest of the travel models. We propose some changes that will make the model more internally consistent and reduce the number of utility expression files that must be maintained. First we describe the current implementation and its shortcomings, then describe the proposed revised implementation.

Currently, internal-external tours are generated at a person level in the household mobility choice models, after transponder ownership, and right before the Coordinated Daily Activity Pattern model. The tour generation model is a binary choice model indicated whether any internal-external tours are made. The results of this model do not affect any downstream household choice models. After the household choice models are run and results are written to disk, the InternalExternalModel is run. This model reads the output household and person files, and generates exactly one external tour for each person with an external tour choice in the internal-external trip generation model. The departure and arrival time for the external tour is chosen by simulating from a probability distribution. The destination of each internal-external tour is modeled, where the choice set is limited to an external station. Two trips are generated for the tour. A model is run to determine trip mode for each external trip.

There are a number of shortcomings associated with this implementation. First, work and school location choice assume all workers and students work or go to school in the region; the shadow pricing mechanism is unaffected by workers or students who commute outside the region. Second, all downstream models (tour generation, tour scheduling, tour destination, tour mode, etc.) assume all travel is internal. This can lead to problematic estimates of traffic impacts at cordon stations. Third, the model can double-count travel for travelers who leave the region, since their internal travel is unaffected by whether they leave the region. Fourth, the model requires maintenance of a code base (InternalExternalModel) and Utility Expression Calculator Files (InternalExternalTripModeChoice.xls) extraneous to the internal travel demand models.

We propose simplifying the process as follows: We will implement an "external worker/student identification model" that will identify, for each worker and student, whether they work and/or go to school outside the model region. This model will be run before work and school location choice. If they work outside the region, a special external station destination choice model will be run instead of the usual work/school location choice models, and they will not be considered in shadow pricing. For non-mandatory tours, an "external non-mandatory tour identification model" will be run after tours are generated. If a non-mandatory tour is identified as external, the tour will use the special external station destination choice model instead of the internal destination choice model. All other models (tour frequency, time-of-day, mode, stop frequency, etc.) will run exactly the same for these tours as for other tours, though we may want to add indicator variables to identify these tours as external in case we need to add special calibration parameters for them.

These changes will solve the issues identified above with the current approach; shadow pricing will consider only workers and students who work or go to school in the region; travel patterns will be internally consistent; travel forecasts at external stations will very likely be more accurate; and the code will be simplified as the separate InternalExternalModel component will no longer be necessary.

Modeling Pricing

SANDAG has identified priced infrastructure as a key area of focus in future transportation planning efforts. Pricing may take a number of forms; toll roads, managed lanes, a flat Vehicle Miles of Travel tax, and area/cordon pricing, in addition to changes in auto operating cost, transit fare, and parking pricing. Table 2 lists pricing policies and how they will be represented in the ABM3 model. Most policies are represented adequately in ABM2+. Certain policies, especially cordon/area pricing, may require enhancements. However, modeling these policies is very dependent on the exact type of scheme modeled.

For example, the London-based pricing scheme charges every vehicle that crosses a cordon line encircling the core pricing zone on a weekday between 7AM and 6PM a daily fee. Residents receive a 90% discount and registered disabled people can travel for free. Emergency services, motorcycles, taxis and minicabs are exempt. In order to model this policy in ABM3, network links would be coded with the fee for crossing into the zone. Currently this cost would affect all vehicles; in order to represent the discounts, additional segmentation would need to be added to trip tables assigned to the network. In order to represent the daily cap, the demand model would need to be modified to track the daily cost for any trips into the priced area, and cap the cost at the daily total. Finally, mode choice utility expressions would need to be modified to calculate discounts for certain markets such as residents of the priced area. Such code changes are significant and should not be made until the pricing policy is well-defined, including the following information:

- The exact priced zone or zones
- The fee for entering the zone, the hours that the fee is applied, and the daily cap for the fee, if any

- The vehicles and/or markets to be discounted or free, and the exact amounts or percentage discounts

Based on this information, and the desired fidelity for which the policy should be modeled, the development team can refine the model to represent the policy.

TABLE 2: PRICING POLICIES AND MODEL REPRESENTATION

Policy	Application methodology	Enhancement(s) required
Parking price	Modify MAZ-based parking prices	See parking costs section, above. Reduced/discounted/free parking for shared-ride trips can be represented via parking cost modifiers in tour and trip mode choice utility equations.
Fuel cost	Vehicle type-specific fuel costs will be modeled in ABM3	Vehicle type table described above
Toll roads and managed lanes	Network coding	None required to represent current tolled/managed lane facilities; enhancements may be required to model discounts for certain market segments
Transit Fare	Skimmed transit fares should be cash fares; transit subsidy and transit pass ownership model can be applied to represent discounted fares	Implement ActivitySim transit subsidy and transit pass ownership model as described above. This model allows testing fare subsidies and pass ownership for various person types, income groups, etc. Free transit for all can be modeled by setting input fare to 0.Single fare for all trips including

		transfers can be modeled by modifying EMME scripts.
VMT tax	Modify auto operating costs. Can be segmented by vehicle type if desired	Implement ActivitySim vehicle type table described above. Discounted VMT fees for certain households or persons, or different VMT costs by time of day, can be set by modifying mode choice utility equations and/or trip assignment settings. Increased VMT fee for 'deadheading' vehicles can be represented by adding cost to TNCs (assuming these costs would be passed on to riders) and by increasing costs of private AV allocation in AV allocation model.
Area\cordon pricing	Most area pricing is implemented as a cordon price where vehicles are charged for crossing the cordon. This can be implemented as a one-way toll cost for every link into the pricing zone.	None required for a cordon price; enhancements may be required to model discounts for residents, low-income households, etc. or to reflect one-time tolls.

Mobility Hubs

Mobility Hubs are whole communities that feature a convenient mix of (publicly subsidized and privately offered) travel choices, safer streets, and supporting amenities. Mobility Hubs help people get to and from Transit Leap services while making it easier to make shorter trips without relying on a car. A fully connected network of regional Mobility Hubs ensures seamless connections to major work, school, shopping, health care, and leisure destinations using public transit and Flexible Fleets. These fleets can include shared or personally owned e-scooters, e-bikes, ridehail options, and/or microtransit. The goals of Mobility Hubs include providing a range of transport modes with seamless transfers between them, and integrated, real-time information technology to optimize travel planning.

The current ABM2+ model represents mobility hubs in the following ways:

- Transit services to and from mobility hubs are explicitly represented in the transit network including frequency of service, specific stop locations (Transit Access Points), fare, and transit vehicle/technology type. Timed transfers can be coded explicitly using a similar method to what is currently used for commuter rail stations.
- TNC vehicles used for door-to-door single-payer trips or shared payer trips with designated stops are represented explicitly in the mode choice model as two separate options with fare specified for each type of trip (e.g. shared TNC trips can be specified with a cheaper fare) and wait time varying according to a function which considers density
- There is a transit-access mode in mode choice which allows the model to consider taking a TNC to transit at the home end of the trip, or returning home from transit via TNC. The model assumes in such cases that the TNC used is a privately-operated TNC in which the price is independent of transit, rather than a publicly-sponsored TNC in which there is a seamless fare system involving free transfers.
- Micro-mobility (specifically, e-scooters) and micro-transit (specifically, publicly sponsored door-to-door transit via shared mobility provider) are handled in a post-processing procedure in which walk trips (both walk-all-the-way and walk as an access mode to/from transit) are split into are split into walk, micro-mobility, and micro-transit based on a logit choice model. The model considers the following attributes:
    - Walk: The origin-destination travel time at a user-specified walk speed (default 3 mph)
    - Micro-mobility: The origin-destination travel time at a user-specified speed (default 15 mph), the time it takes to access a scooter at the origin end of the trip (varying depending on the origin microzone,, with prohibitively long access times outside urban areas), the time it takes to rent the vehicle (default 1 minute), fixed/variable rental costs ($0.81 plus $0.16/mile), and an alternative specific constant calibrated to observed micro-mobility usage data from the City of San Diego in 2018.
    - Microtransit:: The origin-destination travel time at a user-specified speed (default 17 mph), the average wait time (default 4 minutes), the average walk access/egress time (default 0 minutes, assuming door-to-door service) fixed/variable micro-transit costs (default $2.03 + $0/mile), an availability indicator specified at the origin microzone (e.g. constrained to be available for only trips with an origin and destination in a mobility hub) and an alternative-specific

constant set to roughly the value of the kiss-and-ride transit constant compared to the walk constant for work tours.

For ABM3, transit and TNC modes will be handled in the same way as in ABM2+. However, the TNC as an access mode will be expanded to handle TNC as both access and egress (e.g. at both the home and *non-home* end of transit trips). Furthermore, we will build unique paths for TNC as access and egress modes, rather than the current approach in which kiss-and-ride paths are essentially replicated for TNC. This will allow us to represent unique availability attributes of TNC as first/last mile transit, such as making the mode only available to/from specific transit stations rather than all bus stops, or offering free transfers for certain movements. Such a change is expected to have significant run-time implications that will need to be assessed.

We expect to add a specific mode for e-scooters to mode choice as well. This would represent door-to-door e-scooter travel. For e-scooter as an access mode to/from transit, or to transfer between transit stops, we may want to consider the new 'mixed-mode' journey option in EMME. However, this is also likely to significantly increase runtime, since it explodes the number of paths for which a transfer is available. And it is not clear whether the mixed-mode journeys work with SANDAG's system of TAPs. More research is required before making a decision here. A fallback position would be to implement the current post-processing approach in ABM3.

Airport Access and Choice

The current ABM2+ model has a separate airport ground access choice model for San Diego International Airport (SDIA) and for the Cross-Border Express (CBX) terminal that provides access to Tijuana International Airport from the United States. Each model uses the same software code, which will be converted to ActivitySim format. The model considers the non-airport trip origin (for departing passengers) or destination (for arriving passengers), their mode of access/egress, and the parking type (curbside pickup/drop-off, on-site, off-site airport or off-site private). Each model predicts number of trips based on a projection of enplanements that is unique to each facility. There is no formal airport choice model in which demand is generated by residents (or visitors) and an airport is chosen for travel. Such models can be helpful to predict enplanements for new airports, and to test competition between airports based on changes in attributes of a specific facility, in cases where airports compete for passengers.

For example, in the San Francisco Bay Area, there are three key airports - San Francisco International Airport (SFIA), Oakland International Airport, and San Jose International Airport.

Each airport serves similar destinations in the United States and Canada, while SFIA serves many international destinations that neither airport serves. For domestic travel, some level of competition exists between the airports, depending on the origin/destination of the traveler in the SF Bay Area.

It is clear that the same level of competition does not exist between SDIA and CBX. 99% of travelers at Tijuana International Airport travel in Mexico, while SDIA primarily serves domestic locations. The only international flight at the airport was cancelled due to COVID. The CBX facility is used to save time crossing at the border for travelers who want to use the airport to travel to Mexico destinations. Therefore since there is very little competition between the airports, there is no obvious reason to model airport choice.

However, there may be other issues that the airport models do not adequately address. It would be helpful if SANDAG could provide examples of policies of interest that involve either airport, as enhancements may be warranted.

Corridor level/operational modeling

ABM2+ has several features that make the model suited to representing corridor level and operational modeling, such as a volume-delay function that considers both mid-block and intersection level capacity, and a system of transit stop coding (Transit Access Points) that are capable of representing the exact location of transit stops. These features will also be implemented in ABM3.

RSG is also working on implementing variable household sampling methods in ABM2+ for the SANDAG Service Bureau. Variable household sampling allows one to vary the sample rate based on the geographic location of a household in order to reduce Monte Carlo variance for a specific area. A typical application would be to over-sample households within a study area and gradually reduce the sample rate based on distance from the study area. This method has been shown to reduce Monte Carlo simulation variance while maintaining or reducing runtime. A potential (unfunded) extension to this work would be to use discrete integerization to convert probability distributions to choices rather than Monte Carlo simulation. This method would result in choice outcomes that are closer to expected values than the random number draws currently used.

In addition to the tools implemented in ABM3, SANDAG has developed a Dynamic Traffic Assignment (DTA) model in Aimsun. This model assigns temporally-disaggregated activity-based model, commercial vehicle model, external model, and heavy truck model output auto trips to a time-dependent path that considers much more detailed road characteristics (intersection geometry, signal timing) and queuing that the static equilibrium model used for ABM2+ and ABM3 does not. Conversion of the code required to convert trips into Aimsun format is shown in Table 3.

Are there other corridor study requirements/needs that are not currently being met with either the AB model or Aimsun?

E-Commerce

E-commerce was a steadily growing phenomenon pre-COVID that increased significantly due to COVID. Research has shown demonstrable substitution effects between internet shopping and in-person shopping. The increasing availability of food delivery is likely to also demonstrate substitution for eating out travel. Calibration to base-year data ensures that the travel model represents base-year rates of e-commerce and substitution effects. RSG conducted a national panel survey[1] to ascertain the impacts of COVID on travel patterns and likely post-COVID travel patterns. We have used information from this survey to model "what if" scenarios under certain assumptions such as return to work rates, attitudes towards transit, and so on. We recommend that SANDAG closely monitor changes in travel patterns over the next several years. By the time the ABM3 model is complete, travel patterns may have stabilized into a new post-COVID 'normal'. We can also assist SANDAG with specifying modifications to travel rates under different assumptions of post-COVID e-commerce (and remote working) travel substitution effects. Such modifications would be implemented using the 'scenario planning' toolkit initially developed for ABM2 and re-implemented in ABM3.

[1] https://rsginc.com/covid-19-transportation-insights-panel/

3.0 DATA FOR MODEL DEVELOPMENT

3.1 CURRENT AND PLANNED TRAVEL SURVEYS

Household Travel Survey. The last regional household travel survey was conducted by SANDAG in 2016/2017. The survey collected travel data for nearly 6k households; approximately 70% of households used RSG's smartphone application, rMove, and data was collected for an average of 3.5 days per household. This data was used to create calibration targets for ABM2+ and will be the basis for ABM3 model development. The data has already been coded into ActivitySim format using RSG's Survey Processing Application code.

SANDAG is moving towards implementation of a continuous cross-sectional household travel survey, to be conducted once every two years. It is likely that any given year would yield a smaller household sample than the last survey, but the data would provide more current data on travel behavior than a once-every-ten-year survey (about 2000 households every other year) and allow SANDAG to ask questions tailored to timely transportation issues. Given the timing of this effort, it is unlikely that data will be available to use for development of ABM3.

Transit On-board Survey: The last systemwide transit on-board survey was conducted in 2015, and collected approximately 34k origin-destination trips on the Metropolitan Transit System (MTS) Bus, MTS Rail (Trolley), NCTD BREEZE, NCTD COASTER, and NCTD SPRINTER lines. SANDAG will likely conduct another systemwide on-board survey in 2023, after the mid-coast transit extension is open and ridership has stabilized. It is unlikely that the new on-board survey data will be available for ABM3 calibration, currently anticipated to occur between October 2022 and June 2023.

Transportation Network Company (TNC) User Survey: In 2019, SANDAG was awarded a Caltrans grant along with other large Metropolitan Planning Organizations in California to collect data on TNC users. A person-based travel diary survey was conducted in 2019 using rMove, and resulted in 17,340 person-days of travel across 2,382 total respondents. The data is currently being re-expanded to account for sampling bias associated with over-sampling geographies with relatively higher rates of TNC travel. This data has been processed with RSG's Survey Processing Application and will be used for development of ABM3. The TNC data will be used to understand wait times and fares paid for TNC modes - both single-payer and pooled, how TNC use relates to land-use intensity, and who is using TNC modes. It will also be interesting to compare the non-TNC aspects of the survey, such as trip rates and lengths, against the 2016/17 household travel survey data.

Parking Survey: SANDAG is currently contracting for collection of parking survey data. It is possible that this data would be available in time to use for development of ABM3. Given the recommended changes to the parking data and parking model, the RSG team looks forward to participating in the design of the survey instrument and sample frame.

Commercial Vehicle Survey: The last commercial vehicle survey was conducted in 2013 and was used to develop the current disaggregate commercial vehicle model. SANDAG is developing a scope of work to procure services related to the design and implementation of a commercial vehicle survey, to be used in an update of the commercial vehicle model. It is unlikely that this data will be available for use in ABM3 calibration.

3.2 PASSIVE DATA

SANDAG currently has a contract with StreetLight Data for passive data. StreetLight purchases Location-Based Services (LBS) data and in-vehicle navigation device data and processes that data to create origin-destination flows, vehicle volumes, and select link analyses. RSG used an earlier version of StreetLight data, along with targeted traffic counts, to understand travel patterns associated with special generators (beaches, parks, major shopping centers, hospitals, and casinos) and calibrate AB model parameters to better match those patterns.

SANDAG is acquiring Replica data. Replica uses similar passive data as StreetLight to build a synthetic representation of travel for a region. This dataset is similar to a travel model, but is built using machine learning (ML) algorithms on passive data, coupled with data on the built environment, and linked to a synthetic population, to generate synthetic activity patterns and travel tours.

Both StreetLight and Replica are potential data sources for model development. Clearly COVID-19 has affected travel patterns in San Diego and will continue to affect travel for some time. The key promise of passive data is a near real-time way to monitor how those travel patterns are changing. Such data can provide a dataset upon which to compare ABM3 outputs, both for the current 2018 base-year (if historical data is available) as well as a more recent, post-COVID base-year.

However, both StreetLight data and Replica data are synthetic (Replica more than StreetLight). These data, along with RSG's rMerge data product and other travel data built from passive sources, require heuristics and algorithms to re-construct travel patterns from the LBS data stream. The quality of the data is highly dependent on the extent to which these algorithms correct for known and unknown biases. Because the data is anonymous, attribution of socio-economic characteristics is also synthetic and requires assumptions about the correlation of the synthetic population or OD travel patterns to Census and other sources of socio-economic variables.

In short, in order to assess the quality of passive data, and in our opinion in order to adequately identify and correct for biases in the data, a well-designed and implemented household travel survey is essential. We believe that the current advantage of these datasets for AB model development is as a source of comparison for models estimated with household survey data rather than as a replacement for a household survey. Though it may be possible to use this data to estimate an AB model at some point in the future, the data is still a very long way from providing all of the attributes and contextual information that is available in a household travel survey. We suggest that the model development team works closely with SANDAG to analyze this data as it becomes available and further explore strengths and weaknesses of the data vis-a-vis ABM3 development.

3.3 TRAVEL TIME AND TRAFFIC COUNTS

SANDAG has access to INRIX travel time data, and uses PeMS, INRIX, and local jurisdiction traffic counts for model validation. SANDAG conducts a transit passenger count program and uses the data for transit validation. All of these datasets will be used in ABM3 validation.

3.4 INNOVATIVE MODELING

Discrete choice models have traditionally been used as a mechanism to understand how travelers make decisions and forecast those decisions into the future. In addition to being derived from decision-making theory and relatively tractable in terms of their derivation, discrete choice models are interpretable. That is, estimated parameters directly measure how an explanatory variable affects the probability of an outcome and how a change in that parameter will change the probability of an outcome (e.g. elasticity). In contrast, machine learning (ML) models such as neural network models, a subfield of Artificial Intelligence (AI), are becoming increasingly used to predict travel behavior. In contrast to discrete choice and other econometric models, ML models are derived to explicitly maximize predictive accuracy. They are often non-linear and not interpretable to the same extent that discrete choice models are. In other words, the analyst cannot state with certainty how the model will react to a change in a given independent variable without resorting to simulation. However, ML models have been demonstrated to outperform discrete choice models on predictive capabilities.

ML models have been applied to a number of aspects of travel demand including car ownership, trip distribution, mode choice, and other components of travel. ML models are also used to complement the smartphone-based survey and impute survey data. For example, RSG uses ML algorithms to guess at trip purpose and other aspects of travel to reduce response burden in the rMove smartphone survey application. RSG recently developed an ML model to impute part-time/full-time status for workers in the Southeast Michigan Council of Governments household travel survey.

In addition to the use of ML methods to impute data for SANDAG, the RSG team will explore the use of ML models to address parking quantity data for MGRAs where parking spaces are not specified, and hourly and monthly parking costs. There may be other uses of ML algorithms that the team will explore in model development.

4.0 SOFTWARE DEVELOPMENT

The approach to implementation of ABM3 starts with the current release version of ActivitySim, version 1.0.3. SANDAG has developed a prototype version of 1.0.3 that works with their land use, synthetic population, and network level-of-service data (MGRA, TAZ, and TAP). RSG has also implemented the cross-border model with the same set of inputs and source code. RSG made several changes and extensions to the ActivitySim package to implement the cross-border model (see https://github.com/SANDAG/activitysim/pull/9). These revisions and extensions are currently being finalized for contribution to the ActivitySim package via a pull request. A similar exercise will need to be completed for ABM3 ActivitySim software development.

The migration of ABM2+ to an ActivitySim-based ABM3 will be done in phases. A phased approach is suggested to accommodate the cost and schedule risk inherit in software development. Upon completion of each phase, the project team will review the actual to estimated level of effort and assess project resources available for work in the next phase.

- Phase 1 is focused on integration and continued setup of the existing SANDAG ActivitySim models – the existing 3 zone system prototype model and the cross-border model. Starting from the 3-zone system prototype and cross border model, RSG will setup the tour and trip mode choice models and transit virtual path builder, including new modes and expression files. RSG will also make necessary improvements within the level-of-effort (LOE) estimate below to get this starting point for the model system up and running. This first phase is scheduled for three months.
- Phase 2 is focused on revising the resident demand model to include the "must have" features in Table 1. This phase will likely include additional revisions to the prototype 3 zone system model not yet identified. This second phase is schedule for six months.
- Phase 3 is focused on additional revisions to the resident demand model for the "nice to have" features in Table 1. Additional discussion with SANDAG is required to delineate "must have" features from "nice to have" features. This third phase is schedule for three months.
- Phase 4 is focused on programming the special market demand models – the internal-external, airport, and visitor models. This fourth phase is schedule for nine months.
- Phase 5 is functionality that will be refactored at a later time. The existing programs will be used in the interim.

Table 3 presents the draft phases and estimated level-of-effort (LOE) for development of ABM3. The estimates include design of the ActivitySim component, software programming for simulation and estimation mode, testing, verification, inline code documentation, and incorporation of improvements to the ActivitySim package, as well as updates to the example_sandag included with ActivitySim. They do not include hours for creation of model expression files, model calibration, or estimation, including estimation notebooks/larch integration.

TABLE 3: SOFTWARE DEVELOPMENT PHASES

Demand Model	Component (Table 1 Item #)	Phase 1	Phase 2	Phase 3	Phase 4	Phase 5	LOE Hours
		Existing Programs	Must-have	Nice-to-have	Special Market Models	Later	
Resident demand	Existing SANDAG ActivitySim 3 zone system prototype and cross border model integration, mode choice model setup, and transit virtual path builder setup	✓					160
	Household level expansion factors (1)		✓				40
	Walk and bike time and logsum calculator in Python / ActivitySim (2)			✓			360

	Disaggregate accessibilities (3)		✓				120
	Pre-processor parking costs (4)		✓				20
	Two stage auto ownership (5)			✓			24
	Transponder ownership (6)		✓				24
	Vehicle type model (7)		✓				20
	Parking reimbursement costs (8)			✓			20
	Work location choice size terms by occupation (9)		✓				20
	School location choice not constrained by district (10)		✓				4
	Work and school location choice		✓				24

	shadow pricing generalized (11)						
	Coordinated Daily Activity Pattern Model with joint travel episodes (13)			✓			64
	School pickup/dropoff Model (14)			✓			160
	Simultaneous joint tour frequency (15)			✓			80
	AV availability/ allocation model (16)			✓			16
	Tour and Trip Mode choice VOTs and AVs (17)		✓				40
	Clear time-of-day periods (18)		✓				16
	Stop frequency intermediate stops on drive transit tours (19)			✓			64

	Disaggregate mode choice utility diagnostics (20)			√			16
	Migrate micromobility choice model post-processor to within ActivitySim models (21)		√				40
Internal-External demand (12)					√		
	Trip time of day choice				√		24
	Trip destination choice				√		24
	Trip mode choice				√		24
	Write trip tables				√		16
Airport demand					√		
	Generate airport parties				√		16

	Trip destination choice				✓		24
	Trip mode choice				✓		24
	Write trip tables				✓		16
Cross-border demand	Existing ActivitySim model integration	✓					16
Visitor demand					✓		
	Tour enumeration				✓		16
	Tour time of day choice				✓		24
	Tour destination choice				✓		24
	Tour mode choice				✓		24
	Tour stop frequency				✓		24
	Trip purpose				✓		24
	Trip location choice				✓		24
	Trip time-of-day				✓		24

	Trip mode choice				✓		24
	Trip micromobility choice				✓		24
	Write trip tables				✓		16
TNC fleet routing (22)						✓	200
Private AV routing (23)						✓	200
DTA model converter						✓	80
Total Hours		176	344	804	416	0	2,220

5.0 MODEL ESTIMATION, CALIBRATION & VALIDATION, AND SENSITIVITY TESTING

This task will be performed in Year 2 of the project. RSG will develop and use a systematic approach that will employ automated procedures in model estimation, calibration and validation. For model estimation, RSG will use ActivitySim's estimation mode when possible and practical or ALOGIT for models that ActivitySim is not capable of estimating in a timely manner. For model calibration and validation, RSG will use automated summaries already integrated in the ABM2+ (HTML visualizer and validation summaries).

The following sub-sections provide details on our approach to the three model development components.

5.1 MODEL ESTIMATION

The RSG team will compile all estimation data and prepare the data for use in ActivitySim's estimation mode. The dataset includes, but is not limited to, the 2016-2017 San Diego travel behavior survey, the 2019 California SB1 TNC survey, the 2015 and/or 2021 transit on-board surveys, Census/ACS/CTPP data, and 3rd party passive data. Estimation mode is a useful feature of ActivitySim that did not exist in the original CT-RAMP model software. In estimation mode, data is prepared in the same format that ActivitySim requires to run a model component. All utility expression variables required for the model are created by ActivitySim and the choice model is estimated using Larch which relies upon the scipy Python package. Although many variables can be prepared ahead of ActivitySim, certain variables such as mode choice logsums used in destination choice are calculated within the ActivitySim software. This procedure then eliminates the need to develop such code outside the ActivitySim package.

It is preferable to use transit on-board data for the purpose of mode choice estimation, since household survey data typically does not include enough transit records to estimate significant transit parameters. However, mixing random (household survey) and choice-based (transit on-board survey) samples requires careful consideration in estimation. Typically, we develop utility adjustment parameters to account for the statistical bias in mixing these datasets; Mark Bradley is an expert in choice model estimation and will provide oversight and guidance on this task.

Typically, models are estimated in reverse order from the order in which they are applied. In other words, in the resident models, the trip mode choice models would be estimated first, followed by intermediate stop destination choice models, followed by stop frequency, and so on until the first models in the model system are estimated. After each model is estimated, it would be implemented so that the logsums feeding up into the next higher level are consistent with the final implemented model form. There are three key aspects to this work that bear mentioning. First, we do not consider a model implemented until it has been thoroughly debugged. This involves running ActivitySim in debug mode for one or more households to ensure that variables are being calculated and coefficients are being applied correctly. Second, some of the variables may require special functions implemented in the ActivitySim software. An example of such functions is the function used to calculate residual time windows after previous tours have been scheduled. Again, these functions will be tested and debugged. Third, the utility expressions will be vetted by the software team (Ben, Jeff, and Max) to ensure that they are implemented efficiently. We have found that efficient implementation of estimated models in ActivitySim can save significant runtime.

RSG will document model estimation results in a technical memorandum and commit all code used to estimate data to GitHub. RSG will deliver estimation datasets to SANDAG.

Table 4 lists all existing and proposed ABM3 sub-model components and indicates whether they will be estimated. The table also provides details on model structure in terms of model form, decision-making unit, and number of alternatives. RSG will evaluate each sub-model component in terms of variables included, reasonableness of parameters, and match of model outcomes to local data and create an efficient model estimation based upon our analysis.

TABLE 4: SANDAG ABM3 COMPONENT ESTIMATION

NUMBER	MODEL COMPONENT	ESTIMATION	MODEL STRUCTURE		
			Form	Decision-Making Unit	Alternatives
1	Long-Term Models				
1.1	Workplace location choice	✓	MNL	Workers	MGRAs
1.2	School location choice	✓	MNL	Students	MGRAs
1.3	Work From Home	✓	MNL	Workers	2 (true or false)

2	Mobility Models				
2.1	Free Parking Eligibility	✓	MNL	Person	2 (has free parking or not)
2.2	Auto ownership	✓	NL	Household	4 (0,1,2,3+ autos)
2.3	+ Transponder ownership			Household	2 (Yes or no)
2.4	Vehicle type **(+ AVs)**				
2.5	Parking reimbursement (**+partial**)	✓		Workers & students	3 (full, partial, none) + subsidy percent
2.6	Telecommute Frequency	✓	MNL	Workers with work location outside home	4 (0 days, 1 day, 2 to 3 days, 4+ days)
2.7	Transit subsidy		MNL	Person	2 (Yes\No, + subsidy percentage if yes)
2.8	Transit pass ownership	✓	MNL	Person	Yes\No; also requires analysis of On-board data to determine effects of pass ownership on fare
3	Daily Models				

3.1	Coordinated daily activity pattern (CDAP) type	✓	MNL	Household	363 across all household sizes
3.2	Mandatory tour frequency	✓	MNL	Person	5 (1 Work Tour, 2 Work Tours, 1 School Tour, 2 School Tours, 1 Work/1 School Tour)
3.3	Mandatory tour scheduling	✓	MNL	Person	190 (combinations of tour departure hour and arrival hour back at home)
3.4	+ School pickup/dropoff	✓	MNL	Household	157 (combinations of up to 3 students escorted in combinations of bundles across 2 potential drivers, as either a stop on the drivers mandatory tour or as a pure escort tour)
3.5	Joint tour frequency	✓	MNL	Household	21 (No Tours, 1 Tour

					segmented by purpose, 2 tours segmented by purpose combination)
3.6	Join tour composition	✓	MNL	Joint tour	3 (Adults-only, Children-only, Adults + Children)
3.7	Joint tour participation	✓	MNL	Person	2 (Yes or No)
3.8	Joint tour destination choice	✓	MNL	Joint tour	MGRAs
3.9	Joint tour scheduling	✓	MNL	Person	190 (combinations of tour departure hour and arrival hour back at home)
3.10	Individual non-man. tour frequency	✓	MNL	Person	89 (Correspondin g to most frequently observed combinations of number of individual maintenance and discretionary tours by purpose)

3.11	Individual non-man. tour destination choice	✓	MNL	Person	MGRAs
3.12	Individual non-man. tour scheduling	✓	MNL	Person	190 (combinations of tour departure hour and arrival hour back at home)
3.13	At-work sub-tour frequency	✓	MNL	Person	6 (None, 1 eating out tour, 1 business tour, 1 maintenance tour, 2 business tours, 1 eating out tour + 1 business tour)
3.14	At-work sub-tour primary destination	✓	MNL	Person	MGRAs
3.15	At-work sub-tour scheduling	✓	MNL	Person	190 (combinations of tour departure hour and arrival hour back at home)
4	Tour Level Models				
4.1	Tour mode choice (+TNC,	✓	NL	Person	13

	micromobility, AVs)				
4.2	Intermediate stop frequency	✓	MNL	Person	Maximum 6 total, 3 per tour direction
5	Trip Level Models				
5.1	Trip purpose				Lookup from observed frequency distribution
5.2	Trip destination choice	✓	MNL	Person	MGRAs
5.3	Trip scheduling		MNL	Person	Lookup from observed probabilities
5.4	Trip mode choice (+TNC, micromobility, AVs)	✓	NL	Person	13
5.5	Auto trip parking location choice				MGRA

Note: +component is addition to current ActivitySim software; MNL – Multinomial logit model; NL – Nested logit model

5.2 MODEL CALIBRATION AND VALIDATION

RSG will calibrate and validate the model base year. The model base year will be decided in discussion with SANDAG staff and will be based on research of other agencies approach for incorporating pandemic effect in their model base year. The observed data sources will include but not limited to travel surveys, ACS/Census data, and traffic and transit counts. There is a possibility of additional data availability (e.g., transit on-board survey, new census) at the time of this task which is scheduled to happen in the second year. RSG will explore new data sources at that time and utilize in our model development whenever possible.

As described in Section 2.2, RSG will also explore possibilities of using big data and innovative modeling techniques, such as AI and ML, in calibrating and validating the model. RSG will utilize SANDAG's ABM visualizer and automated highway and transit validation summaries to guide the model calibration and validation.

Below (Table 5) are some example summaries that we typically use for an ActivitySim model calibration, for each model component, along with the sources for the summaries. Note that model components that rely upon observed distributions from survey data, such as the timing of intermediate stops on tours, are not listed, as it is assumed that the input distributions for these models will be created from the survey data and therefore will not need to be calibrated.

TABLE 5: MODEL CALIBRATION SUMMARIES

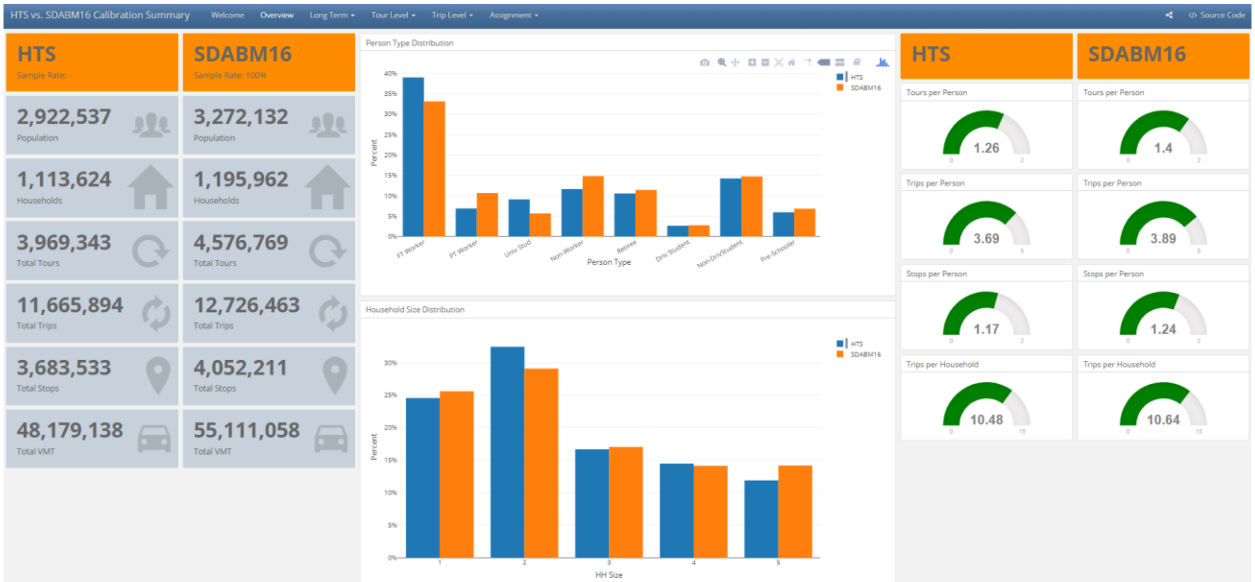
Model Component	Calibration Summary
AUTO OWNERSHIP	Households by autos owned and number of workers (Census, ACS PUMS) Households by autos owned and household income (Census, ACS PUMS) Households by autos owned and district (CTPP, ACS 5-year summaries)
PARKING REIMBURSEMENT MODEL	Workers of level by parking reimbursement and district (household travel survey)
TELECOMMUTE FREQUENCY MODEL	Telecommute frequency by occupation / industry group and other household / person characteristics (Household travel survey)
TRANSIT PASS OWNERSHIP	Pass ownership rate by income, person type, auto sufficiency (Household travel survey)
WORK LOCATION CHOICE MODEL	Home to work average distance and distance frequency distribution (Household travel survey) Workers by place of residence and place of work, district level (Household travel survey, CTPP, ACS 3- and 5-year summaries, Big Data)

	Work from Home (Household travel survey, Big Data)
UNIVERSITY, SCHOOL LOCATION CHOICE	Home to school average distance and distance frequency distribution (Household travel survey) Students by place of residence and place of school, district level (Household travel survey)
COORDINATED DAILY ACTIVITY PATTERN MODEL	Share of persons by activity pattern and person type (Household travel survey) Share of households by presence of fully joint tours and household size (Household travel survey)
MANDATORY TOUR GENERATION MODEL	Share of mandatory tour generation model alternatives by person type (Household travel survey)
FULLY JOINT TOUR GENERATION/COMPOSITI ON AND PARTICIPATION MODELS	Share of fully joint tour generation/composition alternatives by household size (Household travel survey) Share of fully joint tours by number of persons participating (Household travel survey)
INDIVIDUAL NON-MANDATORY TOUR GENERATION MODE	Share of non-mandatory tours by purpose, number, and person type (Household travel survey) Total number of tours by person type (Household travel survey)
NON-MANDATORY TOUR LOCATION CHOICE	Home to primary destination average distance and distance frequency distribution (Household travel survey) Tours by origin and primary destination district (Household travel survey)
TOUR TIME-OF-DAY CHOICE	Share of tours by departure, arrival, and duration half-hour period and purpose (Household travel survey)

TOUR MODE CHOICE	Tours by tour purpose, mode and auto sufficiency (Household travel survey, transit on-board survey) Tours by tour purpose, mode and origin/destination district (household survey, transit on-board survey)
INTERMEDIATE STOP FREQUENCY	Share of tours by number of outbound and inbound intermediate stops and tour purpose (Household travel survey) Number of trips per tour and person type (Household travel survey)
INTERMEDIATE STOP LOCATION CHOICE	Intermediate stops by tour purpose and out-of-direction distance (Household travel survey) Intermediate stops by distance to tour origin and primary destination (Household travel survey)
TRIP MODE CHOICE	Trips by tour purpose, tour mode and trip mode(Household travel survey)

Since working on the SANDAG AB model, we have developed an ABM visualizer (see Figure 2) that compares two scenarios according to a wealth of summaries. The ABM visualizer will be used to compare the survey scenario to the updated model scenario. The tool summarizes all aspects of an AB model output (long-term choice models, mobility models, day pattern models, tour frequency, destination, time-of-day and mode choice, joint tour models, as well as intermediate stop frequency, destination, departure time, and trip mode models). The visualizer will be a central part of the model estimation, calibration, and validation assistance workflow since it will be updated with each revision to either the target data or the model to check results across all model components. The visualizer is automated within the SANDAG ABM2+ system. RSG will maintain the same workflow in the ABM3 as well for an automated generation of calibration summaries in every model run.

FIGURE 2: SANDAG ACTIVITY-BASED MODEL VISUALIZER



The results from this comprehensive set of comparisons will inform a reasoned re-estimation and calibration process involving the limited adjustment of constants to ensure the best possible fit to observed data while maintaining the ability of the model to appropriately respond to inputs.

A meaningful model validation involves comparing model outputs to independent data sources, such as traffic counts and transit boardings. Matching base year traffic counts and boardings is extremely important to build credibility in the model forecasts. However, one must be careful not to introduce meaningless calibration factors just to ensure a better match to traffic counts. Deviations from traffic counts must always be used as an indication of some potential upstream model error that needs to be addressed. RSG will utilize highway and transit validation summaries that are automated within the SANDAG's AB model system. The validation summaries provide detailed comparison of model outputs with observed traffic counts and observed transit. Some of the summaries include:

- Percent gap by facility type, volume group, and key highway corridors
- Percent root mean square error by facility type, area type, and volume group
- Estimated auto VMT versus observed VMT
- Estimated boardings versus transit counts regionally, and by sub-mode and route

RSG will document the final calibration and validation results in a technical memo and provide all calibration and validation files and scripts to SANDAG.

Model Sensitivity Testing

Sensitivity testing is a fundamental component of the development of a new modeling system. The purpose of sensitivity testing is to understand model response to changes in inputs. Sensitivity testing involves systematically varying one or more model inputs to understand how the model responds to those changes. It is fundamentally different from model calibration and validation, which involves comparing goodness-of-fit of model output against observed data using a fixed set of inputs.

The RSG team proposes the following tests for analyzing model sensitivities to transportation network, services, demographics, and land-use changes of interest in SANDAG.

Network Scenarios: This involve changes to the road, transit, and/or non-motorized network. Examples of network scenarios include:

- Major new transit system expansion
- Road capacity expansion

Land-Use Scenarios: This is a broad group of sensitivity tests involving the analysis of changes in land-use on model outputs. Examples of land-use scenario tests include the following:

- Analysis of a new major employment center
- Analysis of changes in parking cost
- Analysis of a new mixed-use or transit-oriented development

Demographic Scenarios: This involve systematically changing the controls to population synthesis, to change the characteristics of the synthetic population. Examples of demographic scenarios include:

- Aging households
- Income shifts

What-if Scenarios: These involve changing assumptions around telecommuting, modal preferences, and other 'non-observed' attributes of travel behavior that could lead to significant impacts in outcomes. Examples include

- Telecommute participation
- Transponder availability
- Shared-TNC mode preference
- Autonomous vehicle fleet penetration

Sensitivity testing is an excellent way to learn how to change model inputs, run the travel model, and analyze results. The RSG team will provide guidance and direction to SANDAG staff who will lead the model sensitivity runs. RSG will provide scripting and analysis support as necessary to ensure that useful insights can be obtained from model results. Depending upon the results of the tests, we may want to modify the model design or parameters to ensure reasonable results.

5.3 MODEL INTEGRATION

This section describes the plan for the overall modeling system integration.

Model Run and Data Management

The ABM2+ model system is run through a combination of EMME and DOS programs, with data managed in EMME, OMX, and text-based formats. RSG will update the existing EMME-based Python runner to directly run the Python-based ActivitySim model components. All the DOS batch/command files used for the CT-RAMP/Java-based models will be removed/rewritten in Python. All existing model inputs and outputs will be revised to conform to ActivitySim input formats, which are OMX files, CSV files with headers, and YAML files. Any input / output transformation will be done with pre / post processing scripts to keep the ActivitySim model components as generic as possible. Network related data such as skim matrices and demand matrices will be stored in EMME. ActivitySim outputs data in either CSV format or HDF5 format, which is the same data storage technology that ActivitySim and PopulationSim use for data pipelining. Each model scenario will be stored in a separate folder, with a programs, inputs, and outputs folder, consistent with ActivitySim design. Visualization and reporting will work with the OMX, CSV or HDF5 format data. RSG may integrate the planned ActivitySim visualizer being developed by the consortium if available in time and sufficiently capable for SANDAG's needs.

Land-Use Model Integration

Currently, SANDAG has a consultant under contract to create an updated version of a subarea forecasting model which is a systematic upgrade of the existing subarea land use modeling that produces the synthetic population and land use inputs for ABM2+ (and eventually ABM3). The model is expected to be sensitive to transportation accessibilities produced by ABM3 as well. Each of these topics is described in more detail below.

Microzone input data

The current microzone data file is shown in Table 6. Fields that are not being used by ABM2+ or are planned for removal in ABM3 are denoted with strikethrough. These include households by income range, school district codes, hotel rooms by type, parking cost and supply variables, and density variables now computed by Python. We anticipate new, simplified parking cost and supply variables as part of the parking model simplification described above. These are likely to be daily parking cost and number of total spaces, which would be an optional variable.

We recognize that categories of employment are subject to change given the land-use model development effort currently underway. Employment categories are primarily used in destination choice model 'size term' equations, which can be thought of as trip attraction equations used in a gravity model. Each tour and trip purpose is attracted to a different combination of these variables. Files containing size terms in the current ABM2+ model can be found on github ttps://github.com/SANDAG/ABM/tree/ABM2_TRUNK/uec). They include:

- *Accessibilities.xls*: See 'size terms - work' for work location choice size terms (segmented by occupation category of the worker), 'size terms - school' for school location choice size terms, and 'size terms - nonmandatory' for tour destination choice size terms for other purposes.
- *SlcSoaSize.xls:* See 'slc size terms' for intermediate stop location choice model size terms.
- *VisitorDestinationChoiceSample.xls*: See 'SizeTerms' for visitor tour and stop destination choice size terms.
- *CrossBorderDestinationChoiceSample*: See 'size_terms' for cross-border travel model tour and stop destination choice size terms.

RSG will need base-year (2019) land-use data for model estimation by June 2022, including employment data in categories consistent with the land-use model.

TABLE 6: MICROZONE DATA FILE

Column Name	Description
mgra	MGRANumber
taz	TAZ Number
hs	housing structures
hs_sf	single family structures

Column Name	Description
hs_mf	multi family structures
hs_mh	mobile homes
hh	total number of households
hh_sf	number of households - single family
hh_mf	number of households - multi family
hh_mh	number of mobile homes
gq_civ	GQ civilian
gq_mil	GQ military
i1	Number of households with income less than $15,000 ($2010)
i2	Number of households with income $15,000-$29,999 ($2010)
i3	Number of households with income $30,000-$44,999 ($2010)
i4	Number of households with income $45,000-$59,999 ($2010)
i5	Number of households with income $60,000-$74,999 ($2010)
i6	Number of households with income $75,000-$99,999 ($2010)
i7	Number of households with income $100,000-$124,999 ($2010)
i8	Number of households with income $125,000-$149,999 ($2010)

Column Name	Description
i9	Number of households with income $150,000-$199,999 ($2010)
i10	Number of households with income $200,000 or more ($2010)
hhs	household size
pop	total population
hhp	total household population (exclude gq pop)
emp_ag	Agriculture
emp_const_non_bldg_prod	Construction Non-Building production (including mining)
emp_const_non_bldg_office	Construction Non-Building office support (including mining)
emp_utilities_prod	Utilities production
emp_utilities_office	Utilities office support
emp_const_bldg_prod	Construction of Buildings production
emp_const_bldg_office	Construction of Buildings office support
emp_mfg_prod	Manufacturing production
emp_mfg_office	Manufacturing office support
emp_whsle_whs	Wholesale and Warehousing
emp_trans	Transportation Activity
emp_retail	Retail Activity
emp_prof_bus_svcs	Professional and Business Services

Column Name	Description
emp_prof_bus_svcs_bldg_maint	Professional and Business Services (Building Maintenance)
emp_pvt_ed_k12	Private Education K-12
emp_pvt_ed_post_k12_oth	Private Education Post-Secondary (Post K-12) and Other
emp_health	Health Services
emp_personal_svcs_office	Personal Services Office Based
emp_amusement	Amusement Services
emp_hotel	Hotels and Motels
emp_restaurant_bar	Restaurants and Bars
emp_personal_svcs_retail	Personal Services Retail Based
emp_religious	Religious Activity
emp_pvt_hh	Private Households
emp_state_local_gov_ent	State and Local Government Enterprises Activity
emp_fed_non_mil	Federal Non-Military Activity
emp_fed_mil	Federal Military Activity
emp_state_local_gov_blue	State and Local Government Non-Education Activity production
emp_state_local_gov_white	State and Local Government Non-Education Activity office support
emp_public_ed	Public Education K-12 and other

Column Name	Description
emp_own_occ_dwell_mgmt	Owner-Occupied Dwellings Management and Maintenance Activity
emp_fed_gov_accts	Federal Government Accounts
emp_st_lcl_gov_accts	State and Local Government Accounts
emp_cap_accts	Capital Accounts
emp_total	Total employment
enrollgradekto8	Grade School K-8 enrollment
enrollgrade9to12	Grade School 9-12 enrollment
collegeenroll	Major College enrollment
othercollegeenroll	Other College enrollment
adultschenrl	Adult School enrollment
ech_dist	Elementary school district
hch_dist	High school district
pseudomsa	Pseudo MSA -
	1: Downtown
	2: Central
	3: North City
	4: South Suburban
	5: East Suburban
	6: North County West
	7: North County East

Column Name	Description
	8: East County
parkarea	Category determining functionality of parking models –
	parkarea field codes
	1: Trips with destinations in this MGRA may choose to park in a different MGRA, parking charges apply (downtown)
	2: Trips with destinations in parkarea 1 may choose to park in this MGRA, parking charges might apply (quarter mile buffer around downtown)
	3: Only trips with destinations in this MGRA may park here, parking charges apply (outside downtown paid parking, only show cost no capacity issue)
	4: Only trips with destinations in this MGRA may park here, parking charges do not apply (outside downtown, free parking)
hstallsoth	Number of stalls allowing hourly parking for trips with destinations in other MGRAs
hstallssam	Number of stalls allowing hourly parking for trips with destinations in the same MGRA
hparkcost	Average cost of parking for one hour in hourly stalls in this MGRA, dollars
numfreehrs	Number of hours of free parking allowed before parking charges begin in hourly stalls
dstallsoth	Stalls allowing daily parking for trips with destinations in other MGRAs
dstallssam	Stalls allowing daily parking for trips with destinations in the same MGRA

Column Name	Description
dparkcost	Average cost of parking for one day in daily stalls, dollars
mstallsoth	Stalls allowing monthly parking for trips with destinations in other MGRAs
mstallssam	Stalls allowing monthly parking for trips with destinations in the same MGRA
mparkcost	Average cost of parking for one day in monthly stalls, amortized over 22 workdays, dollars
zip09	2009 Zip Code
parkactive	Acres of Active Park
openspaceparkpreserve	Acres of Open Park or Preserve
beachactive	Acres of Active Beach
budgetroom	Number of budget hotel rooms
economyroom	Number of economy hotel rooms
luxuryroom	Number of luxury hotel rooms
midpriceroom	Number of midprice rooms
upscaleroom	Number of upscale rooms
hotelroomtotal	Total number of hotel rooms
luzid	Land-use zone ID
truckregiontype	Region type code used for truck model
district27	27 district system
milestocoast	Distance (miles) to the nearest coast

Column Name	Description
acres	Total acres in the mgra (used in CTM)
effective_acres	Effective acres in the mgra (used in CTM)
land_acres	Acres of land in the mgra (used in CTM)
MicroAccessTime	Micro-mobility access time (mins)
remoteAVParking	Remote AV parking available at MGRA:
	0 = Not available
	1 = Available
refueling_stations	Number of refueling stations at MGRA
totInt	Total intersections (optional)
duden	Dwelling unit density (optional)
empden	Employment density (optional)
popden	Population density (optional)
retempden	Retail employment density (optional)
totintbin	Total intersection bin (optional)
empdenbin	Employment density bin (optional)
dudenbin	Dwelling unit density bin (optional)
PopEmpDenPerMi	Population and employment density per mile (optional)

Population Synthesis

PopulationSim can run with household and person controls specified at multiple levels of geography. Table 7 compares the marginal controls across various travel models and shows the geographic resolution at which the controls were specified. All models in the table except the SEMCOG model use PopulationSim to generate synthetic population.

The total number of households control is specified at the lowest geography for all models. SEMCOG uses UrbanSim's PopGen based population synthesis process which operates at Block Group level; however, the model operates at TAZ level. Other household-level controls include household size, household income, number of workers, and presence of children in the household. On the person side, generally a persons-by-age-group control is included at a higher geography (or lower if data is available). A number-of-workers-by-occupation-type control is included in models where the work location choice submodule is segmented by occupation types, as is the case for ABM2+ and planned for ABM3.

RSG and SANDAG will need to decide the control variables and level of geography to be used for the synthetic population.

TABLE 7: MARGINAL CONTROLS COMPARISON

Control Variable	Categories	Portland Metro	SOABM[2]	MTC TM1	MTC TM2	Met Council[3]	SEMCOG
Household Level							
Total Households		MAZ	MAZ	TAZ	MAZ	TAZ	Block Group
Dwelling Type	SF, MF, MH, Duplex	MAZ	MAZ				
Household Size	1,2,3,4,5,6,7,8+	Tract	TAZ	TAZ	MAZ	TAZ	Block Group
Vehicles	0,1,2+						Block Group
Household Income	0-$25K, $25K-$50K, $50K-$75K, $75K-$100, $100K+	Tract	TAZ	TAZ	TAZ	TAZ	Block Group

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[2] Southern Oregon Activity-Based Model (SOABM)

[3] Metropolitan Council (MPO for Twin Cities of Minneapolis & St. Paul, Minnesota)

Control Variable	Categories	Portland Metro	SOABM[2]	MTC TM1	MTC TM2	Met Council[3]	SEMCOG
Number of Workers	0,1,2,3+	Tract	TAZ	TAZ	TAZ		Block Group
Presence of children	Yes, No	Tract	TAZ		TAZ		Block Group
Householder age	(15,24], [25,44], [45,64], 65+						Block Group
Household race	White, Black, Asian, Other						Block Group
Person Level							
Person Age	0-5, 6-12, 13-15, 16-17, 18-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, 85+	Region	Region	TAZ	TAZ	TAZ	Block Group
Person race	White, Black, Asian, Other						Block Group
Gender	Male, Female					TAZ	Block Group
Student Status	Student, Non-student					TAZ	

Control Variable	Categories	Portland Metro	SOABM[2]	MTC TM1	MTC TM2	Met Council[3]	SEMCOG
Employment Status	FT worker, PT worker					TAZ	
Occupation Type	Management, Sales, Production, etc.	Region	Region		County		
Total Population						Region	
GQ Controls							
Total GQ households			MAZ	TAZ	MAZ		
GQ Type	University, Military, Other Non-Intst.		MAZ	TAZ	MAZ		

Land-use accessibilities

Currently, ABM2+ creates aggregate accessibilities for use in PECAS. These accessibilities are created by running an aggregate mode choice model for every microzone-pair and averaging the utilities (mode choice logsums) for all microzone-pairs within each land-use zone (LUZ) pair. Note that this method does not take into account weighting by households in origin microzones or employment in destination microzones. The result is an averaged utility at the LUZ level. There are currently seven logsum segments written by the model:

- LS_0_PK: Averaged mode choice logsums for 0-auto households traveling in the peak period
- LS_1_PK: Averaged mode choice logsums for 1-auto households traveling in the peak period
- LS_2_PK: Averaged mode choice logsums for 2+ auto households traveling in the peak period
- LS_0_OP: Averaged mode choice logsums for 0-auto households traveling in the off-peak period
- LS_1_OP: Averaged mode choice logsums for 1-auto households traveling in the off-peak period
- LS_2_OP: Averaged mode choice logsums for 2+ auto households traveling in the off-peak period
- All_PK: Averaged mode choice logsums for all households traveling in the peak period

The simple mode choice model used for these calculations excludes many of the explanatory variables used in the actual travel model. In the ABM3 model, we propose to implement a disaggregate mode and destination choice logsum calculator that would utilize the actual tour mode choice model for a synthetic population created specifically to cover all of the market segments for which logsums are required. Since the ABM3 design will produce disaggregate destination choice accessibilities by household type, a re-design of the land use model accessibilities integration is needed. RSG will discuss this topic with SANDAG and propose a final land use accessibilities module programmed with ActivitySim that integrates with the updated subarea forecasting model.

Network Editing Integration

If SANDAG revises the TCOVED-based processes, RSG will work with the team to understand the differences and will draft a revised model integration plan. Depending on the scope of the revisions, the RSG team will implement a revised solution within project resources.

Aimsun Model Integration

As mentioned above, the SANDAG DTA model in Aimsun software utilizes input trip tables and trip lists from the ABM2+ travel demand model. A Java program reads output files from a model run and processes the files to create a trip list for assignment. Conversion of this program to Python is listed in Table 3 but may be beyond the available resources for this project. It is likely that the current Java program can be adapted to use ActivitySim outputs with limited changes.

6.0 EMERGING MODES, TECHNOLOGIES, AND RISK/WHAT-IF ANALYSIS

Constant changes in technology related to travel modes and choices create a clear need for model flexibility and adaptability. Assumptions of the adoption and penetration of technological changes to the transportation modes, infrastructure and use patterns need to be applied, reevaluated and changed as technology and adoption develop further.

In the last decade, behavior and future mindedness in decision making with relation to vehicle ownership and car use has shifted as new options and technologies have become available. The use of ride hailing and ride sharing services have introduced new alternatives into the choice set of decision-making processes. Looking forward, developments in autonomous vehicles have the very real potential to upset both the way in which individuals interact with vehicles as drivers, but also as households make long term decisions. The combination of ride-hailing and autonomous vehicle penetration may have impacts on household vehicle ownership and even residential and work locations. However, it is not just the personal vehicle that is being revolutionized in the transportation realm. Technological and business/policy developments in both bicycles and scooters have not only increased the availability of alternative modes, but also have altered the functionality of these modes, such as increasing their range and reducing physical demands of operation through electric propulsion.

In addition to existing modes that are being upset by recent technological advances, new alternatives such as Urban Air Mobilities (UAM) may be closer to reality. Advances in batteries and mobile storage technologies have already shifted the fueling options for personal vehicles, and are changing the composition of small aircraft. This opens doors for the operation of air taxis, running services that operate in mid-range distances (100-200 miles), that would otherwise require an hour to several hours to overcome by ground networks.

As developments in this arena continue to progress, it is expected that the relationship between households and mode choice as well as vehicle ownership will continue to be transformed. As with many travel demand model assumptions, for most of these advances in transportation technology, the question is not about if it will happen, the question is about when, how, and the magnitude of the influence. It is therefore imperative that the ABM3 framework include functionality to create a variety of potential futures with respect to these emerging modes and technologies. Utilizing a scenario manager to build a suite of potential outcomes will be pivotal in deploying models that explore the range of uncertainties regarding these emerging technologies. Attributes of the alternatives, as well as market penetration and other key assumptions can be altered within the scenario manager to create a variety of possible portraits of the future of transportation.

6.1 TRANSPORTATION NETWORK COMPANIES

Current status and modeling

Transportation Network Companies (TNCs) have perhaps the longest tenure (in the aforementioned list of emerging modes), in the constantly evolving discussion of newest modes in transportation. The onslaught of competition to traditional taxi modes in the early 2010s from companies such as Uber and Lyft changed the way in which on-demand car services operated. Private companies have further revolutionized the on-demand taxi service in their efforts to match riders and drivers efficiently. Shared ride services have utilized cell phones to geographically match closest drivers to riders, but have also begun matching riders to each other when shared services are desired. From a modeling perspective, TNCs operate in a similar fashion to taxi services, and have indeed taken a portion of the market share that taxis once exclusively held. However, there are small, nuanced differences in the behaviors of taxi services and TNC providers that must be recognized. Unlike taxi services where most hailing occurs at points of interest or in heavily populated areas, TNC services operate as a distributed business which is more effective at attracting riders from less dense areas. The distributed business model is made possible through the use of a smart-phone application (or app) that links drivers to riders.

There are two types of ridesharing trips; one in which the TNC is used all the way from the origin to the destination, and another in which the TNC is used as a leg in a transit trip, also known as first/last mile transit. TNCs can also be operated by privately held companies such as Uber and Lyft, or via public-private partnerships such as Via. From a user perspective, it makes little difference 'who' operates the service. What matters to the user is the quality of service provided by the operator; in other words, the wait time, travel time, cost, reliability, ease of requesting a ride, whether the fee paid includes the cost of transit if transferring, whether the ride is shared with other travelers, and so on. Branding and visibility of the service may also play a role though there is little research or evidence to suggest what effect that might have on demand.

TNC mode choices are accounted for in two separate areas of the model. First, hailed rides are included in the mode choice model, as a modal alternative that competes with or provides access/egress to other modes. Origin-destination hailed ride modes include traditional taxi, single-payer TNC, and shared TNC. First/last mile transit is represented as TNC-access transit mode. However this model suffers from a short-coming in that TNC is only available at the home end of a transit trip. We plan to make TNC available as both an access and an egress mode in ABM3 (see ABM3 Design).

Second, a taxi/TNC routing model handles generating vehicles and routing those vehicles to serve the generated demand. Another model handles allocation of privately held AVs to intra-household AV trips. This model considers storage location logistics and unmanned trips. The status of TNCs in transportation, and specifically TNCs related to activity based models has previously been reviewed in detail for SANDAG in a white paper4. Further elaboration of the literature on TNCs can be found in this resource.

The current SANDAG ABM2+ model shares many features of treatment of TNC modes in other activity-based models including DaySim and CT-RAMP. The DaySIM framework (detailed in the Github repository documents) makes available paid shared ride as a mode choice and adds TNC modes in linked trips utilizing public transit systems. In the first instance of TNC use (paid shared ride availability) parameters of the model include a mode specific constant, extra cost per mile on the trip, fixed costs per trip, an age coefficient, and a density coefficient.

An accurate portrait of TNC availability (or wait time) is necessary to model modal demand. As mentioned earlier, one way in which TNC availability has been estimated is by using a proxy of density as used in the recent DaySIM and SANDAG ABM2+ updates. In this approach, a density coefficient is created and applied using the number of jobs and households within a geographic buffer around the origin of the trip (or tour) parcel or microzone. This is used as a proxy for where the TNC vehicle is most likely available and relates to the wait time incurred for the vehicle at the trip origin. Although this approach can provide some level of TNC availability, a network supply model to provide more accurate TNC availability would be best.

One alternative would be to limit the routing model to a specific vehicle fleet and iterate the routing model with the demand model. However, this would increase model runtime. Another option would be to hardcode wait times based on observed data (see below).

Data Needs, Assumptions and Limitations

In addition to the TNC availability data needs, TNC user data needs to be utilized. Much of these data needs can be provided by the 2018/2019 survey of TNC use completed by RSG studying the San Diego, Los Angeles and San Francisco regions. In this data collection effort, 2,092 persons were sampled within the San Diego region, leading to 12,551 completed travel days, and 1,368 trips using TNCs. This data should be analyzed to determine observed origin-

[4] RSG in cooperation with DPC. Whitepaper on Modeling of Autonomous Vehicles, Transportation Networking Company Modes, Fast Fixed Guideway Transit and Telecommuting. Prepared for Sandag in July, 2019.

destination patterns, wait times, person-level ridership characteristics, and other aspects of the TNC travel market. The 2017 National Household Travel Survey contains data on frequency of TNC use in a month, and data on trips that used TNC modes and might be used to supplement the TNC survey in San Diego.

There are several assumptions that will need to be made in modeling TNC use. Available data, although richer than previous data available, still does not provide a complete and exhaustive portrait of the availability and use of TNCs within the model region. Survey data has implicit error, and any error in the data will be compounded in subsequent model estimations. Additionally, assumptions will need to be made pertaining to the adoption of autonomous vehicles for TNC use. Market penetration, user acceptance, and policies/ regulation will need to be made to inform the model of possible scenarios. Additional considerations of TNC impact include household level decisions, most primarily the influence of TNC availability and AV technology in household vehicle ownership.

Despite debate about whether it competes or complements public transit service, recent studies have indicated that the majority of ride-hailing trips do have a public transport alternative and that the out-of-vehicle time, as well as in-vehicle time, are significant in this mode choice. It may also be significant in mixed-mode commuting, in which more than one mode is used, which is increasingly well socialized in journey planning applications. Mixed-mode journeys are characterized by access, egress or intermediate trip legs used together with public transit, and may include park-and-ride, kiss-and-ride, ride-hailing to / from transit, bike-to-ride or other mode combinations. If this is of interest, Emme 4.6 targeted Fall 2021 will include specific support to accommodate mixed-mode journeys within transit assignment, allowing intermodal combinations at any node.

6.2 ELECTRIC BICYCLES AND SCOOTERS

Current Status and Modeling

Electric bicycles and scooters (collectively referred to as micro-mobility modes) provide potential to fill in gaps left in transit services as they provide an alternative for the first and last mile of services. In many cases, micro-mobility modes replace walking or other active modes for transit access and egress. Electric bicycles and scooters can be either private or a part of the shared economy. Privately owned electric bicycles and scooters will have some influence in the distance, time or feasibility of a trip, but will still be restrained by storage needs at either end of the trip, and are not a very large component in the overall transportation landscape. Conversely, scooter and bike share options offer users ultimate flexibility, as the user does not need to consider how to store or carry their personal bicycle or scooter with them when conducting a multimodal trip. While electric bicycles have made a slow and steady introduction into the market, electric scooters have had a volatile tenure in the transportation industry. Due in part to the lack of physical infrastructure needs in order to penetrate the market, many instances of scooter sharing seemingly popped up overnight, and in most cases without collaboration from cities. The lack of planning, and agreement with city governance led to the immediate ban of many scooter programs, and a lengthy reintroduction through an application process, planning and adherence to regulations. Because of the nuanced entry into the transportation landscape, data on scooter use is still very minimal. A more complete review of scooters and bike share in transportation was prepared in a white paper prepared for SANDAG on micromobilities.

Micro-mobility and dockless bike share systems were modeled in the previous iteration of the Activity Based Model (ABM2+) as a mode choice for trips as well as access and egress modes for transit trips. The method for estimating micro-mobility mode shares is described above in Section 2.1 on Mobility Hubs. The drawback of this approach is that the mode choice model only sees an improved accessibility when the micro-mobility utility is better than that of walking; which is very rare due to the large negative alternative-specific constant associated with the use of e-scooters for most travelers. As a consequence, modeled elasticities with respect to changes in micro-mobility availability and/or cost are limited. We plan to change this by making micro-mobility modes an explicit part of the mode choice model.

Data Needs, Assumptions and Limitations

There are several data requirements for modeling e-scooter and e-bicycle use. The groundwork for many of the data needs and assumptions has already been laid in the last iteration of the model. The average speed, variable and fixed costs (rental fees), rental time (time allocated to unlocking vehicle with a mobile device), value of time, search/access time and a non-included attributes penalty (time 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) will be considered in ABM3, similar to ABM2+. Data for these attributes will need to be either obtained from data or assumed. Additionally, data from the recent TNC survey as well as a targeted micro-mobility survey in Portland can serve as sources of data for model calibration in the mode choice estimation.

Limitations in the assumptions of positioning and availability of modes might also need to be considered, as the exact location as well as the size of the fleet of vehicles is unknown. Behaviorally, adoption and willingness to use micro-mobilities, especially in light of arising alternatives via autonomous vehicles, might shift and evolve as the transportation landscape changes, which will be difficult to estimate and reflect in the mode choice parameters.

6.3 AUTONOMOUS VEHICLES

Current status and modeling

There has been much interest in the progress of autonomous vehicle technology and the future of driverless cars in transportation. Varying levels of automation of autonomous vehicles have and will continue to comprise a growing portion of the current vehicle fleet. Test vehicles are currently in operation and being utilized in an ever-growing market, and the interest and trust in the technology are improving. In addition, policies and protocols for operation continue to be defined and amended to improve safety and efficiency. A full review of autonomous vehicles and studies incorporating autonomous vehicles in modeling can be found in the white paper produced under previous model improvement contracts.

The timing and manner in which autonomous vehicles will enter the market is still unclear. Modeling improvements undertaken to reflect the increasing potential of autonomous vehicles, and the interplay between AV and TNCs have included a suite of potential scenarios under which autonomous vehicles are integrated into the vehicle fleet. Scenarios range, with focus on levels of automation in vehicles, levels of connectedness of infrastructure, composition of the AV fleet (privately owned or TNC operated), and composition of the fleet with each level of automation.

Rashidi et. al.[5] in a recent publication conducted a review to summarize studies about connected and autonomous vehicles (CAVs) and provide a condensed report of the current dialogue. In this paper, they provide a quantitative bibliometric review of articles (including many conference proceedings) and book content and retrieved over 6,000 publications for analysis between 1999 and 2018. From these papers, common themes were identified, and further explored using publication year to identify current emerging themes. From the quantitative analysis, the authors identified four key emerging topics to explore in further, qualitative depth. These four topics were: 1) key drivers and limiting factors for CAV adoption, 2) multitasking and

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[5] Rashidi, T, Najmi, A., Haider, A., Wang, C. & Hosseinzadeh, F. (2020) What we know and do not know about connected and autonomous vehicles, Transportmetrica A: Transport Science, 16:3, 987-1029, DOI: 10.1080/23249935.2020.1720860

impact on VOT/VOR, 3) adoption scenarios and rates, and 4) expected impacts. Their work highlights many of the current unknowns and the complexity of the future of CAV. The potential of CAVs to add convenience, increase safety and contribute to time savings, along with the increasing interest and use of Mobility as a Service (MaaS) may contribute to driving the adoption of CAVs. However, CAVs face the hurdle of public and social acceptance, consumer willingness to pay, intervening opportunities in other mode developments, and a large number of technological, safety, infrastructure and regulatory development needs in order for implementation to be a reality. There are few value of time studies on CAV use. The study areas of these efforts are across the globe and consider specific instances of CAVs shared or private), but due to the lack of studies, there are limitations to the transferability of findings to a local market. The authors also found that possible scenarios of CAV adoption rates and impacts on travel demand are varied. Figure 3 and Figure 4 from Rashidi et al. provides a succinct review of the studies examined and the findings from these studies with regards to CAV impacts on travel demand and adoption rates.

FIGURE 3: SUMMARY OF STUDIES ANALYZING CAV IMPACTS ON TRAVEL DEMAND

Table 6. Summary of studies analysing CAV impacts on travel demand and a summary of consequences of such adoption.

Study authors	Summary of predicted impacts
Litman (2018)	Factors increasing vehicle travel likely to outweigh factors decreasing vehicle travel, resulting in worsened congestion
Gruel and Stanford (2016)	Scenario 2: Significantly higher levels of VKT with negative consequences on land use and public transport Scenario 3: Higher levels of VKT, however, increase in travel not as dramatic as Scenario 2
Childress et al. (2015)	Increase in vehicle travel is accommodated by increase in road capacity. However, when parking cost is reduced, significant increase in VKT and Vehicle Hours Travelled (VHT) observed.
Auld, Sokolov, and Stephens (2017)	VKT and Average Travel Time increase significantly in all modelled scenarios
Anderson et al. (2016)	VKT and Congestion likely to significantly increase if CAVs adopted as an add-on to current vehicle ownership and usage trends. Impact on VKT and Congestion unclear if CAVs adopted primarily as shared mobility services
Levin and Boyles (2016)	271% increase in trips, however, this increase is mostly accommodated by the increase in road capacity and only a modest decrease in link speed was observed
Correia and Van Arem (2016)	resulting additional travel could largely be accommodated within the network without increasing congestion significantly
Kloostra (2017)	Increase in road capacity, with 11.7% decrease in travel time at 90% penetration and a 0.5% increase in travel time at 10% penetration
Llorca, Moreno, and Moeckel (2017)	Shared CAVs would result in increased VKT, however, this adoption model also corresponded with decreased overall congestion
Moreno, Michalski, and Moeckel (2018)	Shared CAVs would result in increased VKT of up to 8%, primarily due to empty running of CAVs
Truong et al. (2017)	4.14% increase daily trips due to entirely new trips and 5.24% increase in car trips due to trip diversions from other modes in Victoria, Australia
Harper et al. (2016)	Upper bound of 14% increase in VKT due to elderly people gaining access to easier mobility
Perrine, Huang, and Kockelman (2018)	CAVs likely to result in significant decrease in Air Travel for inter-city trips in favour of CAVs

Source: Rashidi et al., 2018

FIGURE 4: SUMMARY OF STUDIES PREDICTING CAV ADOPTION

Table 4. Summary of studies predicting CAV adoption with some notes on limitations and approaches.

Study authors	Prediction	Notes
	Research papers	
Litman (2018)	Optimistic – 50% of total vehicle travel in the 2040s Pessimistic – 30% of total vehicle travel in the 2040s	Noted that too early to accurately predict adoption, thus breaking predictions down into optimistic and pessimistic scenarios
Bansal and Kockelman (2017)	Pessimistic – 25% of vehicle fleet by 2040 Moderate – 43% of vehicle fleet by 2040 Optimistic – 71% of vehicle fleet by 2040	Study based on a stated willingness to pay survey in the US
Lavasani, Jin, and Du (2016)	36% market share by 2040, and 84% by 2050	Utilised a Bass Diffusion adoption curve based on Hybrid Electric Vehicle sales in the US
Wadud (2017)	Early adoption to centre around high-income households and commercial vehicles	Study based on a cost of ownership and operation analysis
Talebian and Mishra (2018)	Adoption dependent on rate of price decrease. Could reach between 90% and 15% adoption rate as soon by 2050	Utilised the theory of diffusion of innovations to predict adoption rates.
	Private Publications	
KPMG (2015)	100% of vehicle sales by 2030	Based on adoption trends of L1 and L2 autonomous vehicle technologies
Mosquet et al. (2015)	5 and 25% of vehicle sales by 2020 and 2035 respectively	
IHS (Markit 2016)	5% of new car sales by 2030	
McKinsey Consulting (2017)	30-100% of new car sales by 2040	

Source: Rashidi et al., 2018

Data Needs, Assumptions and Limitations

In order to develop a model of AV use, there are several key data requirements. As aforementioned, these data requirements are largely unknown and will likely require many assumptions in order to estimate the impact of AVs. Additionally, there is not a common consensus on the adoption and outcomes of AVs in the future, or the way in which attributes of AV modes should be modeled in choice models. As mentioned in Table 1, in ABM3 AV ownership will be modeled in the vehicle type model, and not the auto ownership model as it is in the current ABM2+ implementation. Additionally, the AV availability/allocation model from ABM2+ will be condensed and handled within the vehicle type model as well in ABM3. Model improvements for ABM2+ included scenarios of 20 and 50% private AV ownership, and changes in the mode parameters for in-vehicle time, parking costs, auto operating costs and terminal costs for privately owned AVs mode choice. Many of the needs for further model enhancements will likely be met in the form of assumptions rather than specific data. Previous studies can serve as a basis for forming scenarios of adoption of CAVs and model parameters catered to the San Diego area.

6.4 URBAN AIR MOBILITY

Current status and modeling

Urban Air Mobilities are perhaps the most novel of the emerging modes in transportation. Urban Air Mobilities include future on-demand air transportation for urban mid-distance trips and drone delivery services. Aspirational distances for urban air taxi services approach 200 miles, although battery life and requirements for reserves on battery life currently limit that goal. The emergence of UAM in transportation as a viable alternative has and will continue to make forward progress, although the technological, infrastructure and policy developments that will enable a system for service need a sizable amount of progress for implementation.

A report prepared by NASA in November 2018[6] outlined three UAM use cases: Last mile delivery, air metro, and air taxi scenarios. In the case of last mile delivery services, packages under five pounds would be delivered rapidly when online orders are placed via drones. In the air metro case, autonomous air vehicles would be used in a service that is on predetermined routes, with scheduled times and serve more densely populated areas of cities. Vehicles would carry an average of three passengers, although the vehicle capacity would be between 2 to 5 passengers. In the third case, air taxis would provide door to door services and would be similar to TNC car services. Rides are unscheduled, on demand and not on fixed routes, using autonomous vehicles and accommodate between two and five passengers, with an average of one passenger per trip. In this third case, technology requirements would include vertical take-off and landing aircraft (VTOLs).

NASA also developed surveys, collected data and created models of consumer willingness to pay, and technology adoption using data from five representative cities from the largest 15 cities (San Francisco, Dallas, New York, Washington D.C. and Detroit). Findings indicate that delivery services may have a viable market in 2030, air metro services may have a viable market in 2028, and air taxis are unlikely to be ubiquitous and profitable by 2030, but may have a niche

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[6] NASA (2018) Executive Summary presentation on Urban Air Mobility (UAM) Market Study https://www.nasa.gov/sites/default/files/atoms/files/uam-market-study-executive-summary-v2.pdf

market or some localized version of an air taxi. This finding is in part attributed to the high cost of vertical take-off and landing infrastructure. Of the 2,500 respondents, 25% reported that they felt comfortable with unmanned aerial technology, and 25% reported that they would not use eVTOLs or Unmanned Aircraft Systems at all when services become widely available. Although the NASA report provides three probable use cases, there are additional possibilities in the way in which UAMs will evolve into services. Uber Elevate (which was acquired by Jovy Aviation in late 2020) for instance outlines services that include intra-city flight using UAM that is seamless with the first and last mile services of Uber ground services. Furthermore, they acknowledge that initially, VTOLs are unlikely to operate as a door to door service, and will more likely operate out of existing or centralized infrastructure (heliports or airports that have capacity for UAM vehicle landing and takeoff). Additional vertiport or vertistops may be integrated, but the early iterations of services would be mainly out of existing infrastructure.

Data Needs, Assumptions and Limitations

Data on urban air mobilities is sparse. Moreover, there is little certainty about how most UAM will actually penetrate the market. Policies ensuring safety, distribution of externalities and environmental impact have yet to be fully defined in most cases. This produces a plethora of data needs and unknowns, and forces many assumptions due to lack of data and certainty. For this reason, the data needs section will be combined with assumptions and limitations for this emerging mode for the sake of fluidity and avoidance of redundancy.

There are several use cases that have specific data needs and assumptions. Each use case has very specific and unique data needs associated with it.

Last mile delivery: In order to estimate the impact of last mile deliveries, data is required about deliveries expected by drone services. It is also important to consider whether these deliveries are happening as a substitution for a different delivery mode, or whether they are an addition (for instance if the parcel would have been delivered by USPS which is still delivering other mail). Additionally, data regarding market penetration and what services will utilize these delivery methods (parcel delivery, food delivery, etc) is necessary to determine the extent of trips utilizing unmanned delivery systems.

Passenger urban air services: The most fundamental step in modeling passenger urban air mobilities is determining in what manner urban air mobilities will take place. This is a big unknown as the technology and development stages are in their infancy. A portion of the trips taken for specific distance thresholds can potentially be determined using cell phone data (for instance, flights from San Diego to Los Angeles for connecting flights may potentially be rerouted to an air taxi, as well as trips utilizing Amtrak services or a car at similar distances. A portion of these trips could potentially be mined using cell phone data for some basis of assumptions of market potential. Knowing the total number of trips taken within distances that could be served by urban air mobilities only supplies a portion of the data needs. Willingness to adopt these modes, and comfort with the technology is another unknown. In the case of point-to-point urban air mobilities at existing transportation hubs (airports for instance), the origin and destination of the air portion of the trip would be known. These services will still need a multimodal trip composition for the first and last mile component.

There has been an uptick in recent work in Urban Air Mobilities, and specifically computational modeling of UAM. Garrow et al (2021)[7] conducted a review of current UAM, electric vehicle and autonomous vehicle articles (between 2015 and 2020) and compared the UAM literature with Electric Vehicle/Autonomous Vehicle literature to identify emerging and future trends in research topics. In this work, they reviewed nearly 800 articles in the AIAA publication database and Scopus. They then analyzed these articles with respect to demand modeling, infrastructure integration and operations discussions for UAM and EV/AV. They found that the discussion within the UAM and ground transportation communities has been divergent with respect to demand modeling. Within the UAM literature, the discussion focused on determining whether there are viable markets for UAM and how they differ across cities, while ground transportation research is focused on predicting how individuals will respond to different operational, pricing, and policy measures related to AV. This is potentially a reflection of the early nature of the research and the institutions in which research articles are being written. Of the 554 authors and co-authors of the papers on UAM, 44 percent are affiliated with an academic institution, 31 percent are associated with NASA, and the remaining 25 percent of authors are associated with U.S.-based and international companies and research agencies. Significant technical challenges must be overcome for UAM to become feasible, and proof of a market is needed in order to encourage the initial capital investment to create such systems. Considering the development to deployment timeline of similar emerging modes in transportation, it is likely that there will be considerable time before passenger mode choice options include UAM.

Though the research in UAM has been focused largely on establishing proof of markets, and technological advances to make electric air vehicles feasible, there has been some research

[7] Garrow, L., German, B., and Leonard, C. (2021) Urban Air Mobility: A Comprehensive Review and Comparative Analysis with Autonomous and Electric Ground Transportation for Informing Future Research. Paper submitted to Transportation Research Part C Special Issue on Urban Air Mobility

exploring the human dimensions and AB modeling of UAM. For instance, Rothfield et al. (2018)[8] used MATSim to create an AB model of Urban Air Taxis. In this modeling effort, the authors used a modified version of the AV simulation framework within MATSim to model an air taxi system. The rationale behind this is that the Urban Air Taxi system would work similarly to an on-demand vehicle transport system using AVs. The problem is solved in both cases using the Dynamic Vehicle Routing Problem. Major differences between the AV and UAM functions include the necessity for VTOL infrastructure, management of airspace and aerial networks, and the varying nature of the UAM fleet properties and composition (different fleets have different max speeds, distance, capacity, etc). For the model, UAMs utilized airspace along a defined network to mimic the ground network characteristics. The study also utilized a stated preference survey conducted in Munich about flying taxis. UAM stations were given locations and vehicle capacities, and UAM vehicles were given passenger capacities, cruising speed, VTOL speed, maximum range, beginning and end times of daily operations, and a starting location for overnight parking. Networks were defined with links and nodes, where links had origin and destination nodes, length, throughput capacity (vehicles in a predefined time frame), and maximum free flowing speed. While this is a substantial step forward in modeling UAM in the transportation network, this does not consider the passenger elements of UAMs and is focused on the routing problem.

Boddupalli et al (2020)[9] conducted an online stated choice experiment in five US cities (Atlanta, Boston, Dallas- Ft. Worth, Los Angeles, and San Francisco) to better understand the passenger elements of UAMs. In this research, the authors develop a mode choice model for traditional auto, transit and air taxi for commute trips. This work focuses in part on understanding passengers' value of time and building an understanding of the distribution of value of time, rather than assuming one value of time across all individuals. It should be noted that their survey only included individuals who were full time workers, traveled to a work location outside the home at least two days per week, and had an annual income of $100K or more. A priority was placed on individuals with a one-way commute time of 30 minutes or more. The authors

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[8] Rothfield, R., Balac, M., Ploetner, K., and Antoniou C. (2018) Agent-based Simulation of Urban Air Mobility Presented at the 2018 Modeling and Simulation Technologies Conference of the American Institute of Aeronautics and Astronautics. Paper 2018-3891

[9] Boddupalli, S., Garrow, L., German, B. (2020) Mode Choice Modeling for an Electric Vertical Takeoff and Landing (eVTOL) Air Taxi Commuting Service in Five Large U.S. Cities. Draft submitted to Transportation Research Part A.

estimated several models (multinomial logit, hybrid multinomial logit with an attitudinal component, panel mixed logit with random taste parameters to account for a distribution of value of time, and hybrid multinomial logit with random taste parameters and attitudes) to understand the nuances of mode choice. They found that, consistent with research on other emerging modes, individuals who are younger, make and have tech-savvy attitudes are more likely to select air taxi. They also found that air taxi preferences are polarized, with a significant portion of the respondents not being interested in the air taxi mode choice option. The authors also found that while the median in-vehicle value of time was $29/hour, 10% of their survey respondents had a value of time higher than $70/hour. This work highlights the need for consideration of those in the market who would never use an air taxi, as well as a distribution of value of time for those who would consider using this emerging mode rather than focusing on key socio-demographic attributes that contribute to the likelihood to choose an air taxi mode.

6.5 ELECTRIC VEHICLES

A vehicle type model component is currently under development by the ActivitySim consortium. This model would run after auto ownership and create an enumerated list of vehicles by body type, age, and fuel type for each household. A vehicle allocation model would run prior to tour and trip mode choice, indicating which vehicle would be used should auto be chosen for the tour. The vehicle type information would affect the mode choice utility; for example auto operating cost would reflect fuel type of the vehicle. If the vehicle is an AV, the travel time sensitivity and parking cost would be affected (similar to treatment in ABM2+). If an electric vehicle, the auto operating cost would be affected. After the model system is run, vehicle miles of travel will be assigned to each vehicle and used to estimate greenhouse gas emissions.

Electric vehicles have a specific mileage range after which they must be charged. Electric vehicle ranges are constantly improving. According to a 2021 survey of electric vehicles by Edmunds[10], the range of electric vehicles varied from 150 miles (for a 2020 Mini Cooper SE) to 345 miles (2021 Tesla Model 3 Long Range). According to an analysis by the Office of Energy Efficiency and Renewable Energy (2017) the longest range of an electric vehicle was 94 miles, and the median range across all electric vehicles was 71 miles. In 2017, the median range increased 61% to 114 miles and the maximum range increased 256% to 335 miles. Auto manufacturers are also working on electric vehicles whose batteries can be quickly swapped out for fresh batteries. Based on this, we believe that vehicle charging stations will be irrelevant to most electric vehicle owners in the near future, with the exception of travelers making long-

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[10] https://www.edmunds.com/car-news/electric-car-range-and-consumption-epa-vs-edmunds.html, accessed September 21, 2021

distance trips and commercial vehicle drivers. We believe most owners will charge their vehicles at home overnight, unless vehicle charging stations are conveniently provided at the workplace (though this is unlikely to affect traveler behavior). If electricity is provided at a subsidized cost, a household may be more likely to own an EV. This can be done by adjusting the vehicle type model to represent increased EV ownership resulting from such a policy, but would require the user to specify the assumed increase in ownership.

Note that the taxi/TNC routing model takes into account a user-specified maximum vehicle range and schedules re-fueling/re-charging stops between pick-ups and drop-offs when a vehicle reaches the maximum of that range. The model assigns the re-fueling/re-charging location to the closest microzone with a gas station as listed in the input microzone file. It is possible to use such data for a revised commercial vehicle model as well, though that is beyond the scope of this effort.

Currently, vehicle types are not assigned separately in highway assignment. Testing policies related to allowing electric vehicles to drive for free or at reduced costs on managed lanes would require separating electric vehicles from other vehicles as a separate assignment class in the model. This would effectively double traffic assignment runtime and the memory required to hold skims in memory, unless other assignment classes are collapsed. An alternative approach would be to rely on a disaggregate assignment software such as AimSun or MatSIM for testing such a policy. The implementation of one of these models is beyond the scope of this project but we look forward to discussing further with SANDAG.

6.6 SCENARIO MANAGER FOR WHAT-IF SCENARIOS

Each of these emerging modes and technologies is in constant evolution. Because of the large number of possible scenarios for each of these modes, a scenario manager is a natural way in which to keep track of and apply different instances of a new transportation landscape. A centralized repository of assumptions around these emerging technologies, similar to the TNC and AV variables in the current ABM2+ model. These assumptions can then be systematically modified to better understand how they affect system performance.

7.0 SERVICE BUREAU ADAPTION

RSG is currently updating the Service Bureau ABM2+ Sub-Regional Applications to provide automated processes and enhancements. RSG will review these enhancements in the context of ABM3 and identify any adjustments that are needed to ensure that Service Bureau projects are applied consistently.

Service Bureau applications primarily involve preparing model runs for transportation analyses for the following types of studies conducted for local agencies and consultants:

- Land use plans such as General Plans and Community Plans which require traffic forecasts, VMT analyses, and other outputs from the model.
- Roadway corridor studies which require traffic forecasts, VMT analyses, select link analyses, and other outputs from the model.
- Transit corridor studies which require ridership forecasts and traffic forecasts.
- Transportation impact analyses for land development projects which require traffic forecasts, select zone analyses, and analyses of VMT/resident and VMT/employee.

Some difficulties recently experienced in responding to Service Bureau requests include the following:

- There is some variability in outputs of separate model runs with identical inputs. Although this variability is inherent to the ABM modeling process, it would be desirable to have an improved understanding of the extent of variability of outputs based on different input parameters. The commercial vehicle model in particular has shown high variability that can produce illogical results. Reducing this variability could help Service Bureau clients in interpreting the results of model runs and could also help SANDAG modeling staff in preparing model runs that would be most useful to clients.
- Preparing model runs that require changes in socioeconomic data has been challenging, particularly when Service Bureau clients wish to model changes expressed in residential units and square feet of commercial development of various types. This information then needs to be converted to population and employment data for input to the model. SANDAG has recently updated conversion factors based on available data and provided some automation of this process but additional review of select land use types may be warranted.
- Use of the model to determine VMT/resident and VMT/employee values for land development projects is a relatively new application of the model based on changes in the California Environmental Quality Act (CEQA). The changes were required from the implementation of SB 743 in July 2020. Service Bureau clients and SANDAG modelers

are continuing to redefine methodologies and calculation strategies for these outputs from the model. In addition, handling of VMT/resident and VMT/employee calculations for external trips has been a challenge since residents outside the San Diego area are not explicitly included in the modeling process and tours are terminated at the regional boundaries.

We will consider additional enhancements for model usability, 1-hour peak hour traffic analysis and reducing commercial vehicle model variability (which we have identified as a potential issue for the ABM2+ project). RSG will consider all recommended changes in the ABM3 structure, resident and special market models to determine if there is any effect on the subarea model applications.

Recent enhancements to ABM2+ have started to address some of the challenges described above. During the development of ABM3, consideration will be given to additional improvements as well as monitoring of Service Bureau requests to determine any new issues that arise.

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the science of insight

55 Railroad Row

White River Junction, VT 05001

802.295.4999

www.rsginc.com