Combinatorial tour mode choice

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Abstract

In most Activity-Based Models (ABMs) in practice mode choice decisions are modeled in two steps. First the entire-tour mode combination is predicted based on the location of the primary destination of the tour (at this step the modeled tour is largely treated as a simple round trip). Secondly, a detailed trip mode is predicated conditionally upon the tour mode and given the specific origin and destination location for each trip.

The mode choice model applied for the ABMs recently developed for the Maricopa Association of Governments (MAG) and Ohio state DOT (ODOT) has a different structure where the tour-level and trip-level choices are integrated in a network combinatorial representation. The model considers all feasible trip mode combinations on the tour (in a similar way how a path dependent shortest path is built in a transportation network) and the tour mode combination emerges as the joint choice of trip modes. This model formulation imposes a lot of additional constraints compared to the two-step structure and in particular, with respect to the conditional linkages between different trip mode choices within the tour. This structure explicitly tracks the car status at origin and destination of each trip and constraints multi-model combinations such as park and ride to consider a logical location of the parking lot.

In terms of practical application, this approach suites some of the recent ABMs developed in practice where tour formation sub-model precedes tour mode choice in the model chain and eventually both models are equilibrated.

Keywords: Tour mode choice, trip chaining, stochastic network shortest path

Objectives, Motivation, and Statement of Innovation

In most Activity-Based Models (ABMs) in practice mode choice decisions are modeled in two steps. First the entire-tour mode combination is predicted based on the location of the primary destination of the tour (at this step the modeled tour is largely treated as a simple round trip). Secondly, a detailed trip mode is predicated conditionally upon the tour mode and given the specific origin and destination location for each trip.

The mode choice model applied for the ABMs recently developed for the Maricopa Association of Governments (MAG) and Ohio state DOT (ODOT) has a different structure where the tour-level and trip-level choices are integrated in a network combinatorial representation. The model considers all feasible trip mode combinations on the tour (in a similar way how a path dependent shortest path is built in a transportation network) and the tour mode combination emerges as the joint choice of trip modes. This model formulation imposes a lot of additional constraints compared to the two-step structure and in particular, with respect to the conditional linkages between different trip mode choices within the tour. This structure explicitly tracks the car status at origin and destination of each trip and constraints multi-model combinations such as park and ride to consider a logical location of the parking lot. In terms of practical application, this approach suites some of the recent ABMs developed in practice where tour formation sub-model precedes tour mode choice in the model chain and eventually both models are equilibrated.

Analysis of impact of trip chaining on mode choice has a long history and many interesting descriptive observations as well as modeling attempts. There is a clear common denominator across multiple studies that in general complexity of the tour in terms of number of stops works in favor of auto modes and walk (if the distances are short and walk is available) but negatively affects propensity to use transit [1,2,5,6,7,8,9,14]. However, the number of stops is not an ultimate measure of the tour complexity from the mode choice perspective. In recent publications [3,7], some finer location patterns were considered and it was shown that a complex tour with multiple stops can be efficiently implemented by transit if the activity stop location corresponds to location of transit stations. In particular, a multi-destination transit tour pattern with possible walks between the intermediate destinations was found frequent [3].

The intention of the current research is to model the observed effects associated with tour complexity and mode choice explicitly as a rational chain of mode choices of the traveler through the entire tour.

Tour mode combinations

In the current research, 14 trip modes (m) were defined as shown in Table 1 and for each tour the mode label (1-14) was assigned using predetermined priority rules that were used for both processing the HTS data and processing the model output in all steps of model estimation and validation. Analysis of the observed trip mode combinations in the HTS for both MAG and three Ohio regions have shown similar patterns. In most cases (more than 70%) and especially for simple 1-destination tours (with 2 trips), trip mode was the same for all trips on the tour. However, there was a substantial number of cases, and especially for complex multi-destination tours, where the tour mode combination included more than one mode for the following reasons:

- Asymmetric tours with outbound and inbound main modes not being equal, for example, when the traveler was driven as HOV-passenger in one direction and used transit in the opposite direction,

- Variety of transit modes used for different trips on the same tour; in the current research this variety was somewhat suppressed by defining only 2 principal transit modes (conventional and premium); it could be presented in full with more detailed classification of transit modes (local bus, express bus, LRT, BRT, subway, rail, etc),

- Frequent car occupancy change (SOV, HOV/2, HOV/3, etc) from trip to trip on auto tours; a systematic strong pattern was observed with occupancy most frequently growing towards the home end of each half-tour. In the outbound direction, car occupancy is most frequently maximal when the tour starts from home and it gradually decreases towards the primary destination due to the possible drop-offs of passengers. In the inbound direction, car occupancy most frequently minimal at the primary destination and it gradually increases towards the arrival back home due to the possible pick-ups of passengers.

- Bi-modal tours such as Park-and-Ride (PNR) and Kiss-and-Ride (KNR) with stops. One frequent case includes starting from home with a child, dropping off a child at school, then parking a car at transit station, going to work by transit, going back to parking station by transit, taking the car from the parking lot, stopping for shopping, and then going back home. This PNR tour would include the following sequence of trip modes "HOV-driver, PNR, reversed PNR, SOV". Another frequently observed case includes some activity at the parking location. The first trip would be SOV with shopping at the destination and parking a car. The second trip can be on transit to a different destination, third trip will be on transit back to the parking lot, taking the car and continuing by SOV back home. This PNR tour would include the following sequence of trip modes "SOV, transit/walk, reversed PNR".

- Non-motorized trips on motorized tours. Many cases of walk trips were observed on motorized tours including both auto and transit tours. Walk trip sub-chains on motorized tours are frequent when the primary destination is in a dense urban area such as CBD.

Car status and feasible combinations of trip modes

One of the key factors in formulating a consistent model for tour mode combination is to properly track car use across the sequence of trips. In the proposed model structure car status plays a role of a "glue" that allows to stitch available trip modes in a feasible string. At any trip origin or destination the car status (s) is classified into 4 possible states:

1. "Car from home" which means that until this point the car was used on all preceding trips and has never been parked outside home, hence car is available for the subsequent trip.
2. "Car parked" which means that car was used originally (at least for the first trip from home) but is was subsequently parked outside home on one of the preceding trips, hence car it is not available for the subsequent trip until it has been taken from the parking lot.
3. "Car from parking" which means that car was parked earlier on this tour but then it was taken from the parking lot and is available for the subsequent trip.
4. "No car on tour" which means that car was not used for the very first trip on the tour and hence it is not available for any sub sequent trip.

Tracking car status at trip origin and destination provides many logical constraints on the trip mode choice as shown in Table 1 below. Taking into account that car status at a trip destination defines car status at the origin of the subsequent trip, this creates a formal framework for description of all possible feasible trip mode combinations for a tour.

Table 1: Feasible combinations of trip origin car status, trip mode, and trip destination car status

Car status at trip origin				Trip mode	Car status at trip destination			
1=Car from home	3=Car from parking	2=Car parked	4=No car on tour		1=	3=	2=	4=
X	X			1=SOV/driver	X	X	X	
X	X			2=HOV2/driver	X	X	X	
X	X			3=HOV3+/driver	X	X	X	
			X	4=HOV/passenger				X
		X	X	5=Conventional transit/walk		X	X	X
			X	6=Conventional transit/KNR				X
		X		7=Conventional transit/PNR		X		
		X	X	8=Premium transit/walk		X	X	X
			X	9=Premium transit/KNR				X
		X		10=Premium transit/PNR		X		
		X	X	11=Walk		X	X	X
		X	X	12=Bike		X	X	X
			X	13=Taxi				X
			X	14=School bus				X

Model formulation for feasible tour mode combination

Tour mode combination represents a sequence of modes and car statuses

$$\{s_0, m_1, s_1, m_2, s_2 \ldots, m_t, s_t \ldots, m_T, s_T\} \tag{1}$$

Where:

$t = 1,2,\ldots,T$ =   trips on the tour in a sequential order,

$m = 1,2,\ldots,M$ =   set of all available modes

m_t =   mode for the given trip

$s = 1,2,3,4$ =   car status (1=from home, 2=parked, 3=from parking, 4=no car)

s_t =   car status at trip destination

s_{t-1} =   car status at trip origin

Tour mode combination is considered feasible obeys the system of logical constrains imposed across multiple dimensions. Basic feasibility rules are further applied a framework of sequential joint choice of mode and destination car status $\{m_t, s_t\}$ for each trip conditional upon the car status at the trip origin s_t. The availability rules can be formalized in a set of the following matrices with binary values (1=feasible, 0-infeasible):

A_{s_{t-1},s_t} =   car status switching rules between trip origin and destination,

B_{s_{t-1},m_t} =   feasible combinations of trip origin car status and trip mode (Table 1),

D_{m_t,s_t} =   feasible combinations of trip mode and trip destination car status (Table 1).

Given these basic rules the set of available joint alternatives for trip mode and destination cars status given the trip origin car status can be formalized as

$$(m_t, s_t | s_{t-1}) = \{m_t, s_t | A_{s_{t-1},s_t} = 1, \ B_{s_{t-1},m_t} = 1, D_{m_t,s_t} = 1\} \tag{2}$$

There are also additional rules that truncate the possible combination of trip modes but they are imposed using the same technique. In particular, and based on the observed tour mode combinations, it was useful to specify these feasibility matrices separately for outbound and inbound half-tours as well as constrain the number of car status switches for 2 to 3 and from 3 to 2 as well as request that the car taken from home should always arrive back home. Also, it should be noted that the described logical constraints are combined in model estimation and application with the usual trip-level mode constraints (for example, transit availability) and individual constraints (car availability, driver license, joint travel, etc) that further truncate the set of possible mode combinations.

It is useful to present the feasibility constraints as a decision making tree where the variety of available modes for each subsequent trip is branched out of the chosen modes and corresponding car statuses for

the previous trips. An example of a full tree with 3 modes (1=SOV, 2=conventional transit/walk, 3=conventional transit/PNR, where the number of modes was reduced solely for illustration purposes) and 4 car statuses is shown in Figure 1 below for a 3-trip home-based tour. In this example, we assume that first two trips are in outbound direction where PNR with switching to car status 2 (car parked) is available while the third trip is inbound direction where only a reversed PNR with switching to car status 3 (car from parking) is available. Note that only two car statuses (1 and 4) are available from the beginning of the tour (origin of first trip) and only three car statuses (1, 3, and 4) are available for the end of the tour (destination of the last trip).

Figure 1: Feasible combinations of trip modes and car statuses on a 3-trip tour
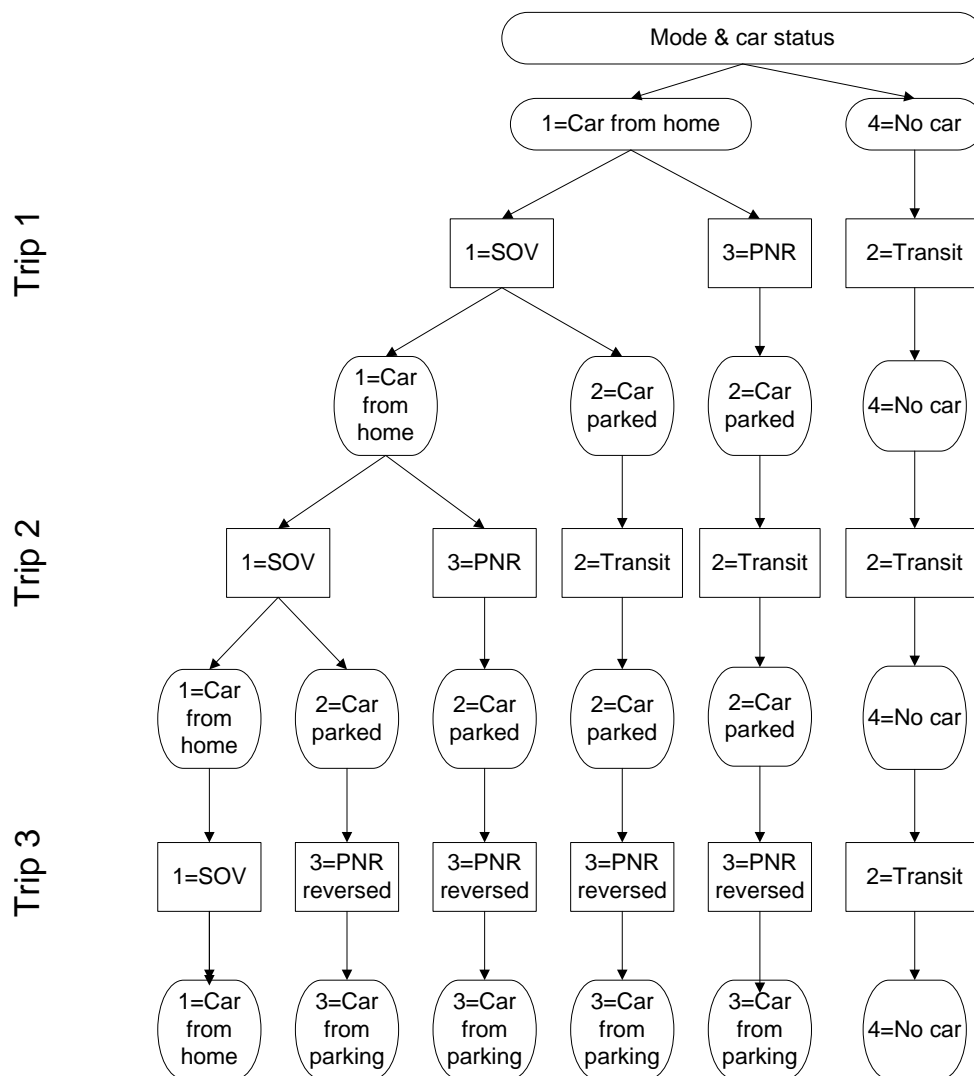
This simple example illustrates the importance of a proper constraining of trip mode and car status combinations. While a simplified Cartesian consideration of all possible trip modes results in 3^3=27 combinations, the actual number of feasible combinations with a logical car tracking is only 6.

Specifics of (observed) trip mode utility function

The observed portion of trip mode utility $V_t(m)$ is estimated statistically based on the observed modes in Household Travel Survey (HTS). In many respects this utility is similar to a standard tour or trip mode choice model since it includes a wide spectrum of explanatory variables such as LOS attributes (time and cost components), individual attributes (such as income, car availability, age) and trip/tour attributes (travel purpose at trip origin and destination, primary purpose of the entire tour, escorting or joint travel arrangements). It can be said that majority of the mode preferences can be captured at the trip level while the most essential inter-trip constraints within the tour are accounted through car status tracking.

However there are two important specifics of the trip mode utility structure that are not part of a standard mode choice estimation since they stem from the specific structure of proposed combinatorial model. The first aspect relates to entire-tour (path-based) effects and transaction costs associated with mode switches. These utility components essentially make the utility $V_t(m)$ dependent on the modes chosen for the previous trips that can be formalized as $V_t(m_t|m_1, m_2, \ldots, m_{t-1})$. The most statistically significant mode transaction effects included:

- Transit mode switching penalties that reflect fare discounts and/or transit pass consideration and make transit mode fare for the given trip a function of the previously chosen transit modes.
- Car occupancy switching penalties that reflect systematic car occupancy changes by direction (even w/o explicit school escort arrangements) where passenger drop-offs (decreasing car occupancy) happen mostly in the outbound direction (from home), while passenger pick-ups (increasing car occupancy) happen mostly in the inbound direction (towards home).
- PNR symmetry, i.e. taking a car from the same parking lot it was originally parked; this utility component is not a statistically estimated penalty but a constraint on how LOS variables are calculated for the reversed PNR trip. Distance, travel time, and cost for inbound reversed PNR are conditional upon the chosen parking location in the outbound PNR trip. Since choice of the both the outbound and reversed PNR trips are optimized in a "branching" procedure in model application, the choice of PNR lot is also somewhat optimized in the combinatorial mode choice although it is different from an explicit choice of PNR location as described in [9].

The second aspect is that the utility function for each trip and mode should be structured in such a way that it would always be negative $V_t(m) < 0$. This is essential for an efficient application algorithm that borrows from the network shortest path techniques. It is of course always possible to ensure negativity of mode utilities by adding an arbitrary large negative number (say, -99) to all of them across the board. However, this would make the absolute scale of all mode utilities dominate the differences between them that would reduce the efficiency of the branching algorithm although it does not affect the result (the shortest path remains the same). Thus, for the most efficient application it is essential to set the utility scale in such a way that all of them would be negative and also the best one would be close to zero as much as possible. For this reason, the mode utility structure and estimation were specified to have only negative constants and negative coefficients on positive variables (such as ravel time and cost).

Model estimation as recursive logit model

It is possible to estimate this model by an explicit enumeration of all possible mode combinations for each tour. This however, would require forming a choice model with a very large set of alternatives (at least for some tours with 3+ trips) and this set would be further exploding exponentially if the mode details are added (for example, more detailed list of transit modes) despite the fact that the mode combination tree is substantially truncated by the feasibility rules and car status tracking. To overcome this problem and take advantage of the network analogy between the mode choice and route choice we apply an innovative approach that was suggested for estimation of route choice models in a large network where a complete enumeration of all paths is infeasible [3, 4].

The essence of this approach is that the choice framework is limited to a single trip and considers only a limited set of trip modes at a time (analogous to considering only a set of links outgoing from a single note in the network route choice context). However, this single-trip choice is put in a context of backward conditionality (this trip choice is conditional upon trip choices made for the previous trips) and forward thinking (this trip choice takes into account the approximate utility of the rest of the tour until arrival back to the tour origin. This can be formalized as recursive equation pertinent to dynamic programming [3, 4] in a particular case where the underlying choice model is multinomial logit.

$$W_t(m_t) = V_t\big(m_t\big|m_1, m_{2,\dots}, m_{t-1}\big) + \ln\big[\sum_{m_{t+1}} W_{t+1}(m_{t+1})\big] + \varepsilon_t(m_t)$$

Where:

$W_t(m_t)$ =   estimated "dynamic" utility associated with trip mode choice.

In practical model estimation, an exact formulation of the forward-thinking terms $W_{t+1}(m_{t+1})$ is difficult to use without a complete enumeration of all possible mode combinations and iterative recalculation of these terms based on the estimations results for $V_t\big(m_t\big|m_1, m_{2,\dots}, m_{t-1}\big)$. This can be done in model application when the set of coefficients is fixed but not in the model estimation. Thus, a manageable approximation is used for the forward-thinking term $W_{t+1}(m_{t+1})$. In the network route choice framework, the approximation used was the shortest path from link m_{t+1} to the final destination based on the distance only [3, 4]. In the mode choice framework, we used the shortest generalized cost (weighted time and cost with predetermined coefficients) function for this purpose. It also proved to be possible to estimate this model with a complete direct calculation of all logsums for the subsequent trips due to a relatively small size of the corresponding network. However, it proved to be a very time-taking iterative process that involves recalculation of all logsums for all observation and corresponding nodes in the network representation for each step in the model estimation when a new coefficient is added or the values of the other coefficient change. A more efficient matrix algorithm was suggested recently for handling the value functions in the estimation of a recursive logit model for network route choice that could be tried for combinatorial mode choice in future [4]. Further details of the model estimation cannot be reported in the paper due to the size limit but are available from the authors by request.

Model application as stochastic network shortest path problem

Network representation of the tour mode combination choice model allows for application of an efficient network Shortest Path (SP) algorithm that does not require a full enumeration of all mode combinations and additionally does not require a computationally expensive evaluation of trip mode utility functions for all nodes of the path tree (Figure 1) as far as the systematic utility function for each trip and mode is kept negative $V_t(m) < 0$. Since the underlying choice model is stochastic, in the model application random terms are generated and used in the SP building. This can be done in two possible ways that have relative pros and cons.

The first method that is less consistent with the model estimation but allows for a very simple way to account for differential mode combination similarities is based on logit random terms $\varepsilon(m)$ generated for each individual and mode by drawing from the Gumbel distribution that a subsequently added to each trip utility. Logit random terms can originally be positive and negative, thus they are subsequently normalized by making the largest one equal to zero and all others negative (by subtracting the largest error term from all others). Thus, with the addition of random terms the trip mode utility functions are still guaranteed to be negative:

$$U_t(m) = V_t(m) + \varepsilon(m) < 0 \ .$$

The choice of the mode combination that has the maximum total utility is then implemented by applying a standard Dijkstra SP algorithm in the network of feasible trip mode combinations where each node corresponds to a trip-level alternative combination of mode and car status at the destination. The Dijkstra algorithm does not evaluate each and every path and link. It selectively branches from the attractive node (with the highest current utility) and requires evaluation of the mode utilities only for the trip outgoing from this node with the mode set constrained by the car status at trip origin.

A frequent case with the mode combination presented in (Figure 1) in a practical application will be that the combination with all trips made by 1=SOV and car status equal to "1=Car from home" be optimal. In most cases the Dijkstra algorithm would evaluate four alternatives for the first trip and identify the "1=SOV/1=Car from home" as the most attractive one. Then this alternative will be re-chosen for the second trip and third trip without branching out of the other nodes since their utility will not be competitive after evaluation of the first trip.   Thus, in terms of the number of utility calculations, that is the most time-taking component of the entire model, only 6 utilities will be evaluated out of 16.

The second method is fully consistent with the model estimation but is more difficult with respect to accounting for differential similarities between different mode combinations beyond the underlying MNL framework. In this method, logit random terms are generated for each mode combination (route in the network) $\varepsilon(r)$. Mode combinations (r) are not enumerated in advance, thus the random terms cannot be generated and normalized in advance to be negative. In the Dijkstra SP algorithm, trip mode (link) utilities are processed without random terms, but in the very end each labeled SP is added a random term that can be thought of as an extra link added to each route in the network. The value of the random term is generated on the fly when each final node is reached. In order to guarantee that the random terms are negative (that is necessary for the Dijkstra SP algorithm based on utility maximization)

the following special normalization is applied. For each individual record, an expected maximum value across all routes $\varepsilon = \max_r\{\varepsilon(r)\}$ is generated first. Given the properties of the Gumbel distribution It is drawn from the same Gumbel distribution but with shift of mean by $\ln(R)$ where R correspond to the estimated number of routes that is easy to calculate for the network representation of this type without an explicit enumeration of all routes. Subsequently, when error terms are generated for each labeled route on the fly they are drawn conditionally on the generated maximum mad made negative by subtracting the expected maximum.

Treatment of differential similarities between tour mode combinations

Similar tour mode combinations (overlapping routes) taking into account by having the random error term generated for each mode and trip combination $\varepsilon_{nt}(m)$, i.e. link in the network representation. Overlapping routes will have more common random terms and will be more correlated. Accounting for route overlapping in a microsimulation framework is easier to implement through generating and additive-by-link error term rather than through a complex entire-route random term. A similar approach was used to resolve the route overlapping problem in network route choice [11].

In order to illustrate this approach consider the following three alternative mode combinations out of the six feasible alternatives presented in Figure 1 with the corresponding error terms:

1. SOV, SOV, SOV: $\varepsilon_{t=1}(m=1) + \varepsilon_{t=2}(m=1) + \varepsilon_{t=3}(m=1)$
2. SOV, transit, reversed PNR: $\varepsilon_{t=1}(m=1) + \varepsilon_{t=2}(m=2) + \varepsilon_{t=3}(m=3)$
3. Transit, transit, transit: $\varepsilon_{t=1}(m=2) + \varepsilon_{t=2}(m=2) + \varepsilon_{t=3}(m=2)$

Mode combinations 1 and 3 are very different and do not have common error terms. Their combined error terms are independent. Mode combinations 1 and 2 have a partial similarity (first trip is by SOV) that is expressed in a common term $\varepsilon_{t=1}(m=1)$ that creates a certain correlation between the two combined error terms. Similarly, mode combinations 2 and 3 have a partial similarity (second trip is by transit) that is expressed in a common term $\varepsilon_{t=2}(m=2)$ that creates a certain correlation between the two combined error terms. In general, the more common modes are shared between the tour mode combinations the more correlated (similar, competing) they become.

Model Validation

The developed model was applied and validated as part of the new ABMs developed for the metropolitan regions of Phoenix, AZ region and Columbus, OH with generally very good results. A detailed comparison between model results and expanded HTS was done for validation:

- Replication of 14 tour mode shares by 7 aggregate tour types and travel purposes (1=work, 2=university, 3=school, 4=escorting, 5=individual non-mandatory, 6=joint non-mandatory, 7=at work),
- Replication of 14 trip mode shares by 7 aggregate tour types and travel purposes,
- Replication of 14 trip mode shares by 14 tour modes,

- Replication of trip-length distribution by trip mode.

Due to space constraints, it was not possible to show all validation results. For analysis and comparison to the HTS, each tour was assigned a single tour mode based on the predetermined priorities of trip modes. Tour mode, in this case, was the emerging property of the model. Instead of showing aggregate tour mode share for all tours, the focus was on how tour characteristics affect the emerged tour mode. As an example,

Figure 2 shows the aggregate tour mode share for the model and expanded HTS for two tour types: 1) work tours without escorting, and 2) work tours with escorting. An escorting stop on commute tours can affect the mode consideration for subsequent trips on the tour. In this particular example, it is easier to take transit if there are no escorting stops on the tour and, thus, a higher share of transit for work tours without escorting stops was expected.

**Figure 2: Tour mode split for work tours for Columbus, OH**
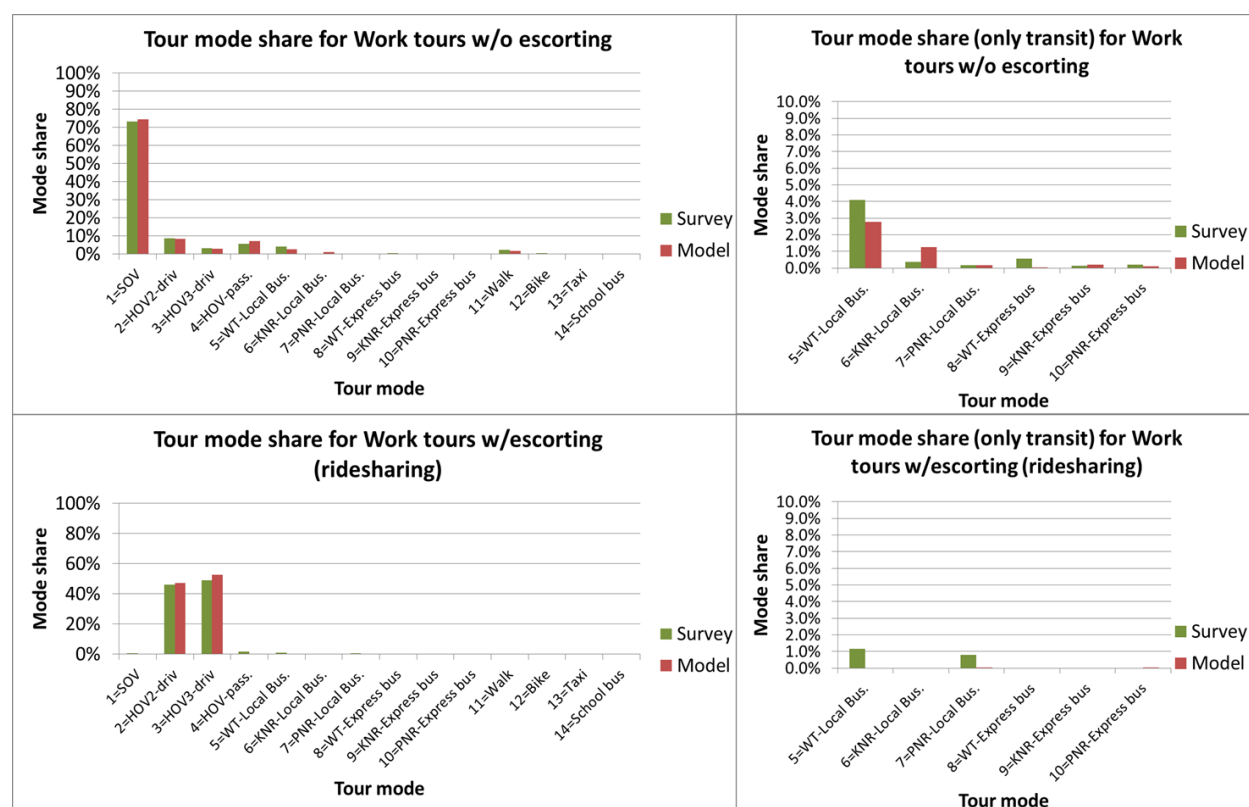
Another important aspect of validation of the combinatorial mode choice mode relates to replication of the observed mode choice patterns by tour complexity. For this analysis we combine all tours by purpose but segment them into three groups by number of destinations. Simplest tours have only one destination and include two trips (to and from the destination). Tours with two destinations have three trips. Tours with three or more destinations have four or more trips respectively. It was important to

analyze how the combinatorial model would capture the observed differences across these tour-complexity categories. The corresponding observed statistics and modeled output are compared in Figure 3. There is a clear observed pattern in the survey that can be summarized as follows:

- Auto occupancy grows with tour complexity. When the number of destinations grows, the SOV share becomes less significant while the HOV2 and HOV3 shares become more substantial for drivers. Interestingly, and seemingly counter-intuitive the share of auto passenger tours stays similar across all tour-complexity categories. However, all this has a behavioral explanation. Multi-destination tours are associated with a higher probability of shared rides. One frequent type of multi-destination tours includes escorting stops where certain members of the travel party are picked-up or dropped-off (partially-joint tours). The second frequent type constitutes a fully-joint tour where all members of the travel party participate in all activities together. Since the tour auto occupancy is defined by the highest occupancy across all trips, multi-destination tours of the first type have a higher probability to have at least one trip with higher car occupancy. For example, a tour with two or more escorted passengers will always have two or more escorting stops in addition to the primary destination. However, the fact that the HOV passenger was the chosen mode for one of the trips does not automatically make the entire passenger tour HOV-passenger. For the escorted passenger, there can be a "leakage" to transit modes if this person used transit for one of the other trips due to the established rules of tour mode assigning. This explains why at the tour level the share of HOV drivers might be higher than the share of HOV passengers. For tours of the second type (fully-joint tours) there are always consistent numbers of HOV-driver and HOV-passenger tours. For fully-joint tours, it is also a positive correlation between car occupancy and tour complexity. Bigger travel parties are also associated with more substantial coordination and longer activity durations.
- Lower share of transit and non-motorized modes when tour complexity grows. These effects are logical and largely relate to the limited transit availability and non-motorized availability. It is enough for one trip on the tour to have transit not available or non-motorized distance longer than the reasonable walking threshold in order for these tour modes not to be chosen. It is also known that perceived convenience of auto modes grows with the tour complexity due to the accumulated factors (such as number of transit boardings and wait time) that essentially have a non-linear impact on tour mode choice.

As was discussed in the previous sections the combinatorial tour mode choice model accounts for these factors but not in an explicit way. For example, the limited transit and non-motorized mode availability is accounted through possible trip mode combinations. At the tour level, it is not controlled and arises from the application of mode combination rules to each individual tour. It can be seen, that the model captures the observed effects quite well. The alternative explicit approach to capture the impacts of tour complexity would require a certain over-specification of the tour mode choice utility with additional constants by tour complexity categories.
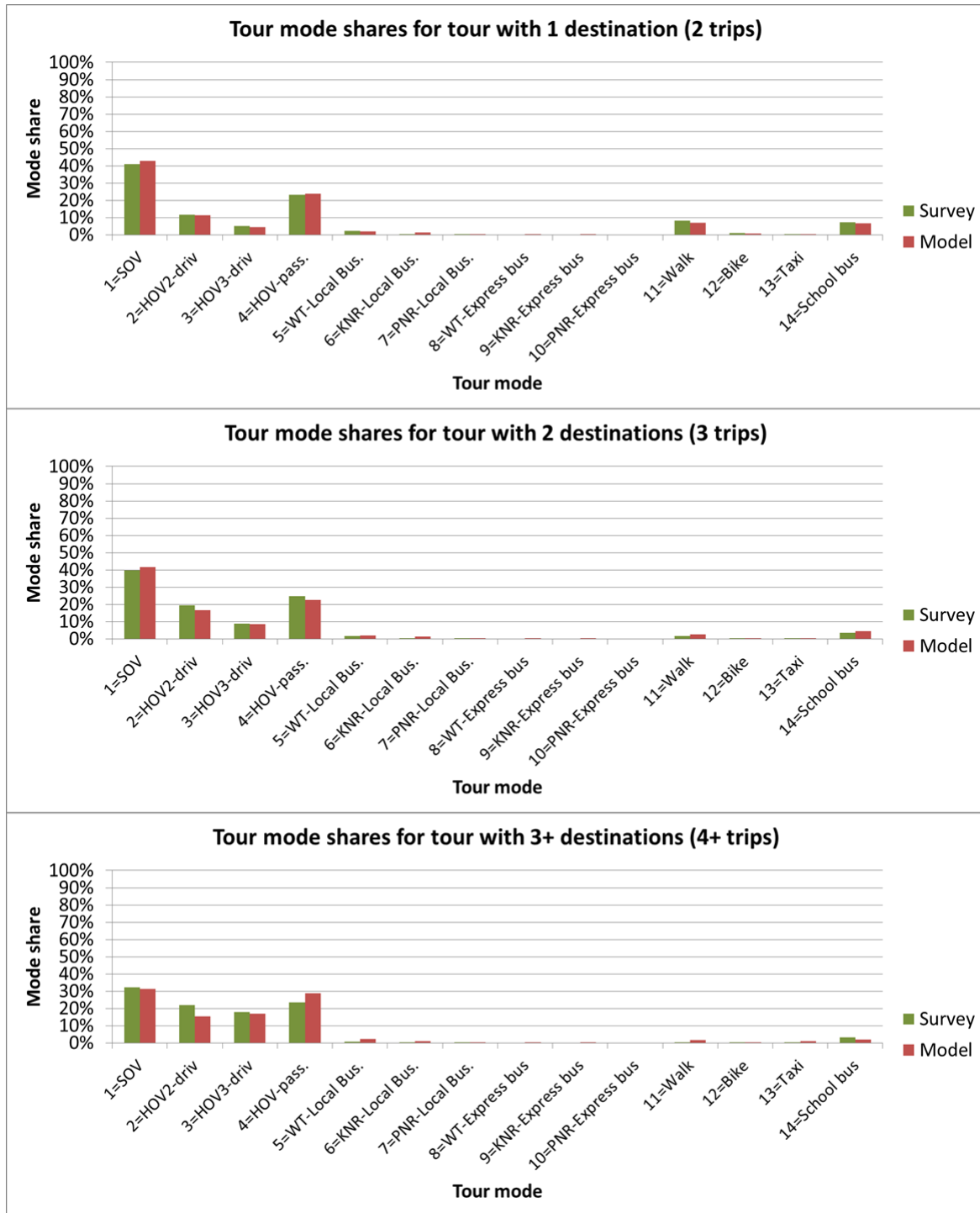
One of the unique features of the validation analysis done for the mode choice model was the validation of trip length distribution by trip modes. The mode choice tendency is different for different trip length and, thus, it is very important to compare the trip length by trip modes with the HTS. Figure 4 shows the average distance by trip modes for the model and the survey in addition to the trip mode shares. First of

all, it can be observed that aggregate trip mode share in the model is similar to the HTS. But, more importantly, the average trip distance by mode in the model is very close to the HTS, and the relative average trip distance is very logical, especially, when local and express bus are compared. Express buses are generally used for long distance as they do not make frequent stops and the travel time saving by taking express bus over local bus is higher. Thus, express bus trip distance is expected to be longer that local bus trip distance.

Figure 4: Average trip length by trip mode
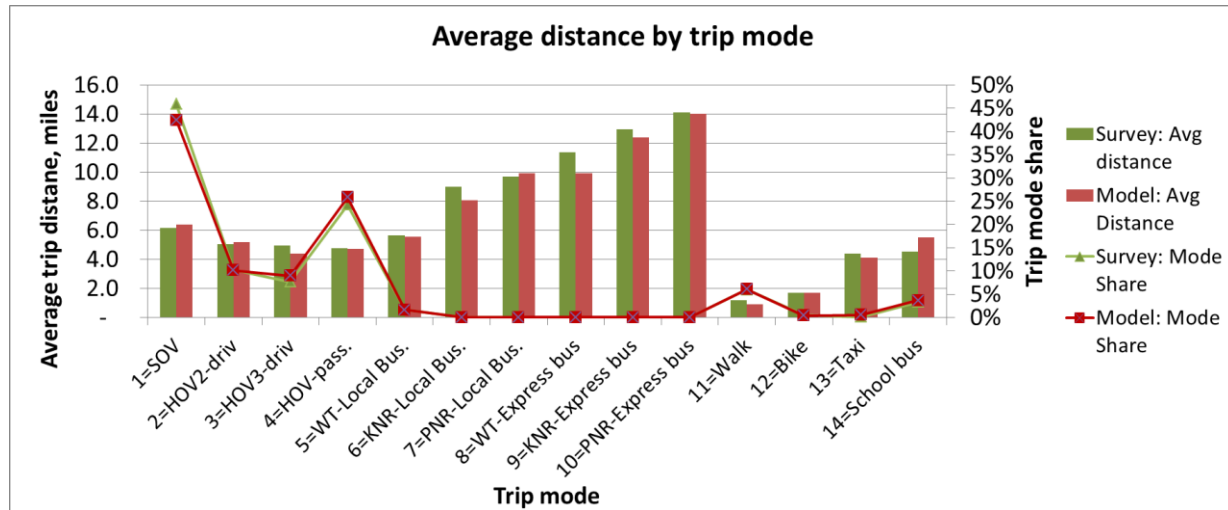
Combinatorial mode choice placement in the ABM system

Application of the proposed combinatorial tour mode choice model is conditional upon prediction of locations for all destination of the tour. This structure suits well the new ABM design applied for the MAG and Ohio ABMs where this model is combined with a tour-formation model applied earlier in the model chain at each model system iteration [10]. Probably the most interesting and promising direction in this regard is how these two models can be internally equilibrated to ensure both upward and downward integrity in the model system. This issue is beyond the scope of this paper but the overall equilibration strategy can be described as follows (the upper-level set of models that correspond to long-term choices and activity generation is omitted for brevity):

1. Specify initial travel impedance
2. Tour formation model to identify tour structure and sequence of stops for each tour
3. Tour formation model to identify location for each stop on the tour
4. Tour start-end time-of-day choice model
5. Combinatorial mode choice model
6. Within-tour activity time allocation and trip departure time
7. Network simulation
8. Feedback loop 1 to step 4
9. Feedback loop 2 to step 3
10. Feedback loop 3 to step 2

Conclusions

This research was intended to fill certain gaps in the structure of tour-based mode choice models and take advantage of several parallel developments in route choice models that are essentially tackling similar problems:

- Ensure a full consistency between the tour-level and trip-level mode choice models and with a consideration of actual locations of all stops on the tour,
- Take into account multiple combinatorial constraints on available trip modes with an explicit tracking of car status at each trip end,
- Integrate multi-modal combinations, and specifically, PNR lot location choices into the trip mode choice structure in a consistent way for the entire tour,
- Avoid an explicit enumeration of all possible trip mode combinations in the model application by applying an efficient network shortest path algorithm,
- Avoid an explicit enumeration of all possible trip mode combinations in the model estimation by applying a parsimonious choice set structure for each trip,
- Account for differential similarities between trip mode combinations ("tour mode overlaps") by simulating correlated error terms for tour modes from trip-mode error terms.

Application of the developed model as part of the operational ABMs in practice showed promising results. The model replicated the observed patterns of mode choice by different tour and trip types quite well. It should be specifically mentioned that the model successfully captured several effects (such as impacts of tour complexity on mode choice) in an uncontrolled fashion as emerging through the micro simulation with the realistic constraints on trip mode availability.

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