The Effects of Mode Choice Model Consistency between Activity-based Models and Microsimulation Tools

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Abstract

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Keywords: Accessibility Passive Data Location Choice

1. Question

In recent years, there has been variation in how the mode choice is estimated within activity-based travel demand modeling. Originally, Bhat and Koppelman (1999) stated that travel demand models should use individual trips as the primary unit of analysis, and to calculate mode at a trip level. More recently, Eluru et al. (2010) developed a joint multiple discrete continuous extreme value (MDCEV) framework to model the individual's mode choice (among other decisions). Hasnine and Nurul Habib (2021) listed differing estimation techniques found in activity-based models, some of which include tour-based modeling, nested model structures, iterative and dynamic processes, and simply calculating the mode choice elsewhere and feeding it in as an input. Variation amoung activity-based models has always existed.

Like with activity-based models, mode choice estimation in microsimulation tools is not universal. W Axhausen et al. (2016) explain that mode choice in MATSim is chosen using the Charypar-Nagel Utility Function, where agents pick the best alternative based on their uniquely calculated utility score. Alternatively, Ciari et al. (2008) proposed introducing multinomial logit models on the subtour level to increase mode choice estimation accuracy in MATSim. In addition, BEAM originally used a Latent Class Choice Model as its mode choice structure, but then switched to a simple multinomial logit model. Alternatively, Barth et al. (2020) proposed that BEAM implements a fundamental influencing factor (FIF) mode choice model instead. As can be seen with MATSim and BEAM, no current common ground has been established in mode choice model structure among microsimulation tools.

Since there is no way to model human behavior perfectly, it does not seem ideal to develop one universal technique to estimating mode choice. However, a useful advancement in travel demand modeling could be to align the internal structure of mode choice in microsimulation with mode choice in activity-based models. Oftentimes, the outputs of activity-based models are used as the inputs to microsimulation tools. Yet, the way mode choice is estimated in a microsimulation tool rarely matches that of its parent activity-based model. This heterogeneity of estimation between models may lead to increased variability in the final microsimulation results.

We hypothesize that a microsimulation tool with a mode choice structure that mimics that of its parenting activity-based model more accurately simulates the distribution of mode choice across a population. In addition, we explore which population characteristics within the mode choice model has the most significant effect in estimating realistic results.

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2. Methods

In our research, the input population used to model behavior corresponds to individuals in the Salt Lake City, Utah, US Region. The activity-based model used to generate the microsimulation input data is ActivitySim (act, 2021). The microsimulation tool used to generate travel behavior data is BEAM (bea, 2021).

ActivitySim implements a multifaceted mode choice model that is dependent on trip, tour, and purpose. One model determines the primary mode for each tour and a separate model determines the mode for each trip. In addition, each modal decision is dependent on the current tour purpose value. Contrastingly, BEAM's default mode choice structure uses a simple multinomial logit model, independent of tour purpose value. Therefore, in order to test our hypothesis, we aligned the mode choice structure of BEAM (a microsimulation tool) with that of ActivitySim (an activity-based model).

To closely align the mode choice structure of BEAM with ActivitySim, we changed much about the code structure inside of BEAM. More specifically, we wrote code that forced modal decisions to be based on tour purpose values. We also implemented the use of ActivitySim's path, person, and location utility parameter values to calculate modal alternative probabilities. These simple steps allowed us to create consistency between an activity-based model and a microsimulation tool.

To test the effectiveness of our calibrated mode choice model, we conducted five different test scenarios within BEAM and compared their outputs with eachout. Each test scenario that we simulated used a multinomial logit function to determine modal probabilities. Although all used a multinomial logit function, each scenario used a different utility function to predict behavior.

The first sceneario we ran used the default BEAM structure. This represented a model with an inconsistent mode choice structure (1). The next three scenarios we ran used a purpose based model with part of ActivitySim's utility function (either using the path (2), person (3), or location type (4) variables). These represented models with semi-consistent mode choice structures. The last scenario we ran used a pupose based model with ActivitySim's complete utility function. This represented a model with a consistent mode choice structure (5). Simplified versions of the utility function used in each of the scenarios can be seen in the following equations.

Eq 1: BEAM's Default Utility Equation

$$V_j = ASC_j + \beta_c(c) + \beta_t(t) + \beta_{xfer}(xfer) \tag{1}$$

where

- j is the modal alternative,
- c is the cost,
- t is the travel time, and
- $xfer$ is the number of transfers.

Eq 2: Utility Equation using ActivitySim's Path Variables

$$V_j = \beta_{t_v}(t_v) + \beta_{t_w}(t_w) + \beta_{t_e}(t_e) + \beta_{tr_p}(tr_p) + \beta_{xfer}(xfer) + \beta_{w_{dis}}(w_{dis}) + \beta_{b_{dis}}(b_{dis}) + \beta_{d_{dis}}(d_{dis}) \tag{2}$$

where

- j is the modal alternative,
- t_v is the in vehicle travel time (mins),
- t_w is the wait time (mins),
- t_e is the egress time (mins),
- tr_p is the proximity to transit (miles),
- $xfer$ is the number of transfers,
- w_{dis} is the walk distance (miles),

- b_{dis} is the bike distance (miles),
- d_{dis} is the drive distance (miles),
- β_{tr_p} differs between origin/destination and length, and
- $\beta_{w_{dis}}$, $\beta_{b_{dis}}$, and $\beta_{d_{dis}}$ differ between lengths.
- *Note:* All β values differ between mode and tour purpose.

Eq 3: Utility Equation using ActivitySim's Person Variables

$$V_j = ASC_{auto} + \beta_c(c) + \beta_{ag}(ag) \tag{3}$$

where

- j is the modal alternative,
- ASC_{auto} is the alternative specific constant that differs between modal alternative and auto ownership dependency,
- c is the cost, and
- ag is the age grouping (if the person is between 0-10 or 16-19 years old).
- *Note:* All β values differ between mode and tour purpose.

Eq 4: Utility Equation using ActivitySim's Location Variables

$$V_j = \beta_{zdi}(zdi) + \beta_{cbd}(cbd) \tag{4}$$

where

- j is the modal alternative
- zdi is the zonal density index,
- cbd is a classifier for zones labeled as central business district, and
- β_{zdi} differs between origin/destination.
- *Note:* All β values differ between mode and tour purpose.

Eq 5: Utility Equation using All of ActivitySim's Variables

$$V_j = Eq:2 + Eq:3 + Eq:4 \tag{5}$$

where

- j is the modal alternative.

3. Findings

To effectively compare the differences between the five scenarios that we ran, we calculated how the mode choices were distributed across the population. The modal shares of each scenario were compared with each other and with the actual modal share of the region. These findings were generated from the events files created by BEAM.

The first modal share we found was the total modal share of the population. Figure 1 displays the percentage of each modal alternative calculated by each different scenario. The actual modal share of the region is shown by the horizontal lines. We hypothesized that the ActivitySim All model (5) would produce the most accurate mode choice results. Surprisingly, however, Figure 1 shows that this was not the case. Instead, the Beam Default MNl model (1) produced the closest approximation of total modal share.

In addition, we analyzed subsections of the modal share with respect to the vehicle ownership status of each agent. Figure 2 displays how modal share is affected by vehicle ownership. Again, we were incorrect in our hypothesis that the ActivitySim All model (5) would align closest to the target shares. In general, none of the models gave an accurate representation of the modal share. Although, the Person model (3) provided the closest approximation for the auto deficient population, the Path model (4) provided the closest approximation for the auto sufficient population, and the BEAM Default MNL model (1) provided the closest approximation for the no auto population.

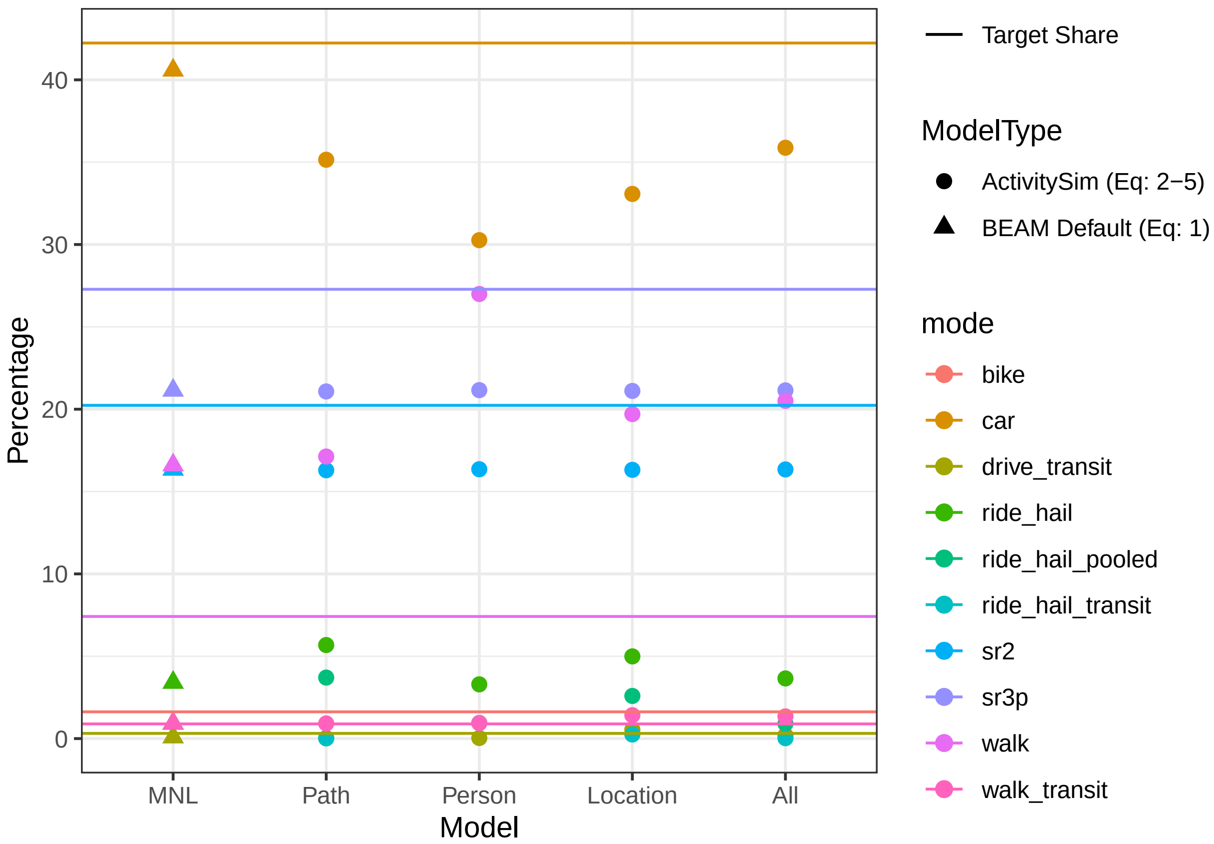

Figure 1: The Total Modal Split of each Scenario compared with Real World Data.

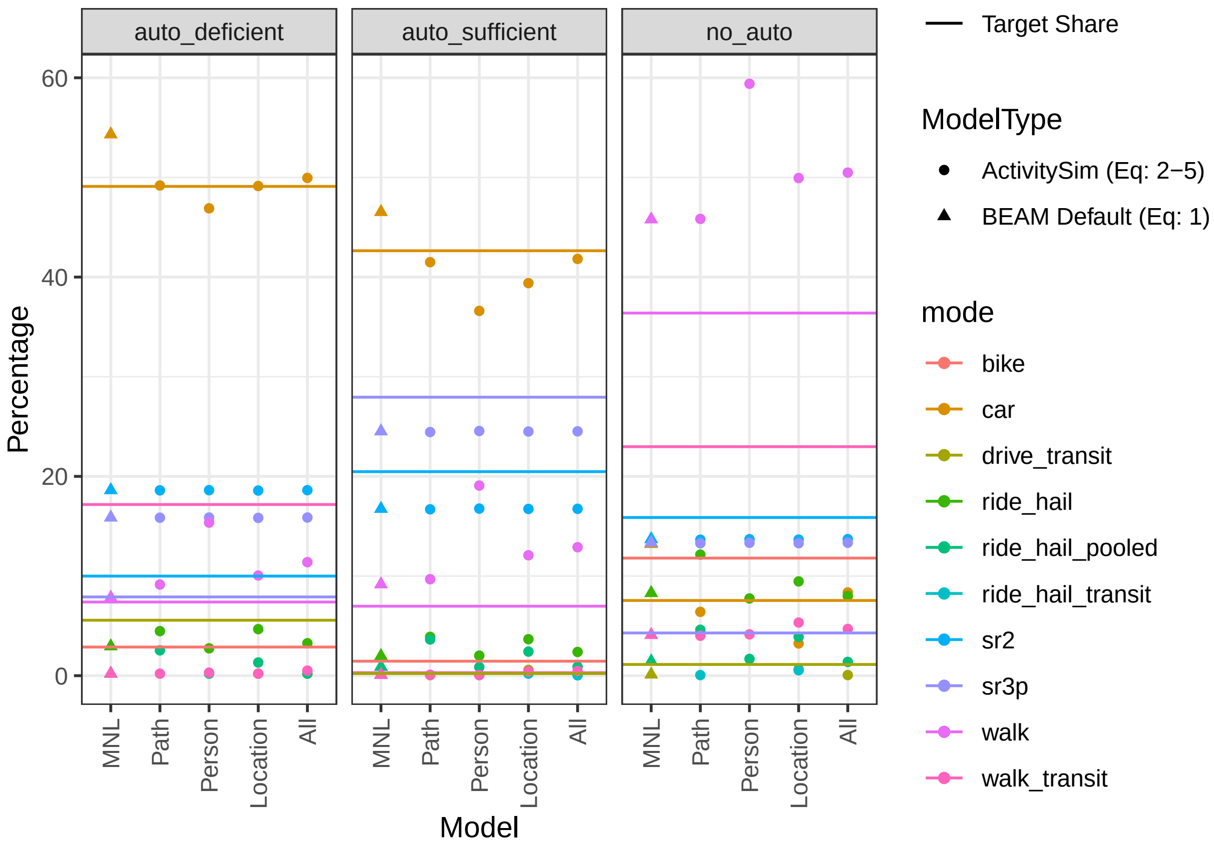

Figure 2: The Modal Split by Vehicle Ownership of each Scenario compared with Real World Data.

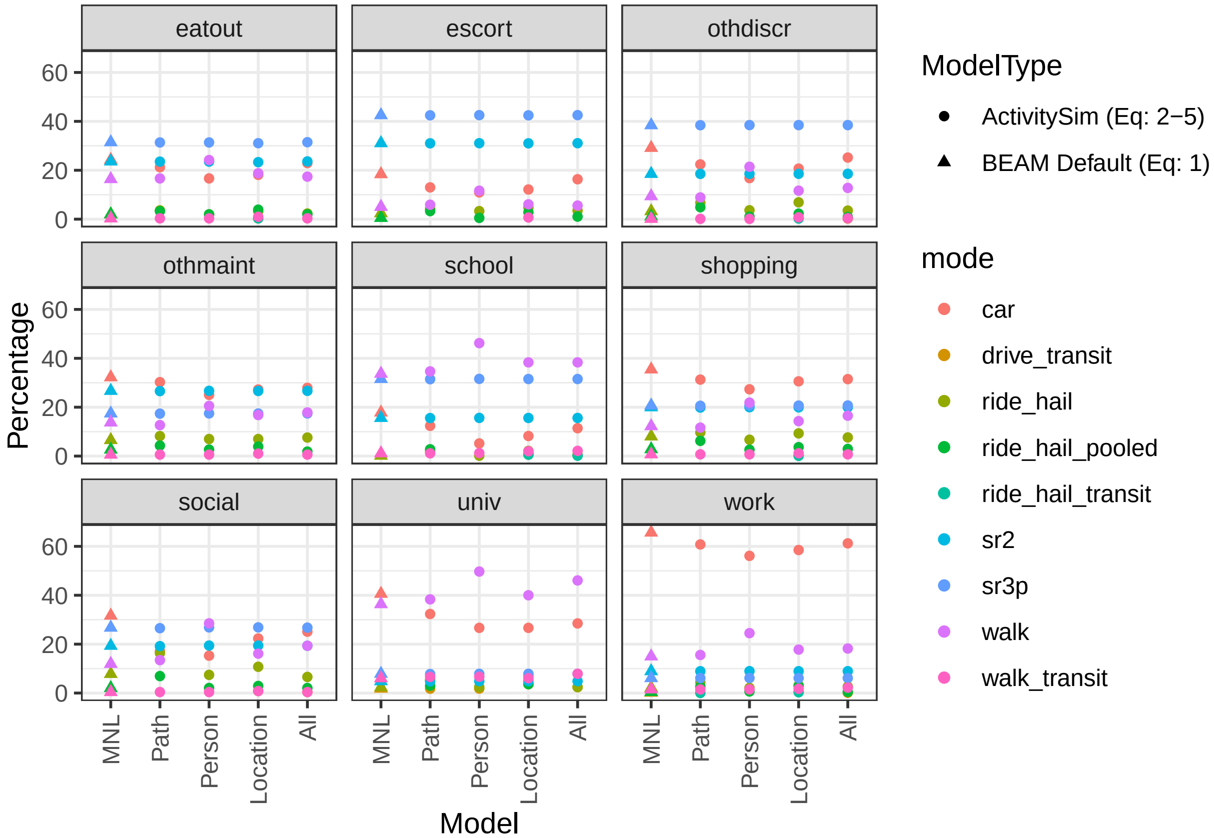

Figure 3: The Modal Split by Tour Purpose of each Scenario.

3.1. Additional Analysis

Overall, it can be seen that a microsimulation tool with a mode choice structure that mimics that of its parenting activity-based model does not seem to more accurately simulate the distribution of mode choice across a population. This can be verified by examining the comparison modal share graphs; the All model does not seem to most accurately predict actual modal shares.

Although this is true, we see that the variables relating to Person types have the most significant effect in estimating realistic results. The Location and Path variable tyes seemed to predict relatively little in comparison to the Person types. This can be verified by examining the comparison modal share graphs; the Person variable seemed to be the most different when compared to the other factors.

In conclusion, we suggest that future analyzts attempt to rerun a similar scenario that has been presented. Unfortunately, sufficient model calibration was not able to be completed. With a more accurately calibrated scenario, we hypothesize that a microsimulation tool with a mimiced mode choice structure will more accurately simulate the mode choice of a population. We also advise analyzts to pay special attention to Person varaible types, as they have a greater affect in modal decisions than other variable types.

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