USTM Resiliency Sensitivity Analysis

Gregory Macfarlane[a,*], Natalie Gray[a]

[a]*Civil and Environmental Engineering Department, 430 Engineering Building, Provo, Utah 84602*

Abstract

This is where the abstract should go.

Keywords: Sensitivity Analysis Resiliency Latin Hypercube Sampling

1. Questions

There exists uncertainty in travel demand models. This is known by transportation planners but the majority do not use any particular method to quantify it. This uncertainty exists to some extent by the variance among input parameters. A coefficient of variation can be used to approximate the standard deviation of the inputs, which then provides a range of values that are possible for model input (Zhao and Kockelman, 2002). A sampling method can then be used to determine the possible combinations of parameter variance. Two popular sampling methods are Monte Carlo simulation and Latin Hypercube sampling. Monte Carlo simulation is capable of providing full variance probability, but requires large computations to be effective on a large scale model (Yang et al., 2013). Latin Hypercube sampling reduces the amount of variants needed, but the amount of reduction is unknown. ~~but the question arises if the same result be achieved with fewer samples, and how many samples is that?~~

The research questions are therefore:

Hypothesis??

- Using a dummy travel demand model, can Latin Hypercube sampling simplify the iterations needed to approximate random sampling methods (e.g., Monte Carlo simulation)?
- Does this method of sampling have few enough iterations for statewide model application?

2. Methods

To examine the effects of parameter input sensitivity, a 25 zone dummy model was created using data from https://github.com/ActivitySim/activitysim. The skims data was ~~read in~~ used to get the values between zones for the distance, the single occupancy vehicle (SOV) AM time, the walk distance, and the ~~AM time for walk to~~ walk to local bus total AM in vehicle time.

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*Corresponding Author

Email addresses: `gregmacfarlane@byu.edu` (Gregory Macfarlane), `nat.gray2000@gmail.com` (Natalie Gray)

Table 1: Mode Choice Coefficients

Name	HBW	HBO	NHB
CIVTT	-0.0450	-0.0350	-0.0400
CCOST	-0.0016	-0.0016	-0.0016
CWALK1	-0.0900	-0.0700	-0.0800
AUTOCOST	18.3000	18.3000	18.3000

Table 2: Mode Choice Constants

Name	HBW	HBO	NHB
K_TRN	-0.5140	-0.9853	-1.3020
K_NMOT	1.7602	0.5448	-0.5359

~~local bus total in vehicle time.~~ Auto time is simplified using the SOV AM time, nonmotorized uses walking distance multiplied by a factor of average walking speed, and transit time uses the walk to local bus time. The activitysim household data **, as given in the GitHub Activity Sim Repository,** is also used and then organized so that it is capped at 4 persons, 3 vehicles, and 2 workers per household. If the value is larger than that capacity ~~is~~ **it** is marked as the high values.

Activitysim doesn't have trip productions so nhts2017 data https://github.com/byu-transpolab/nhts2017 can be used to approximate them. Only weekday trips are used and the household sizes, vehicles, and workers are capped to the same extent as the activitysim households. The data is summarized by household sizes, vehicles and workers, and the weighted mean of each trip purpose is taken. The three trip purposes used are Home Based Work, Home Based Other, and Non-Home Based. The nhts2017 approximated productions are then applied to each household based on size, vehicles, and workers.

Next mode choice parameters (constants and coefficients) are generated. The base values were obtained from the USTM Resiliency model. These values are shown in Table 1 and Table 2.

A coefficient of variation is used to identify a standard deviation for each parameter. A set coefficient of variation of 0.30 is used for all six parameters. The standard deviation is equal to 0.30 multiplied by the mean, where the mean values are the base scenario parameters. (SD = CV*mean).

The random sampling uses the R function of rnorm.

```
rnorm(1, mean_value, 0.30*mean_value).
```

Ten random samples are taken, and the same function format is used for each of the six variables. **Latin Hypercube** ~~Latinhypercube~~ sampling uses the lhs package in R. Since this package only chooses variables on a zero to one scale, the values given ~~the~~ use the function   **FIX!**
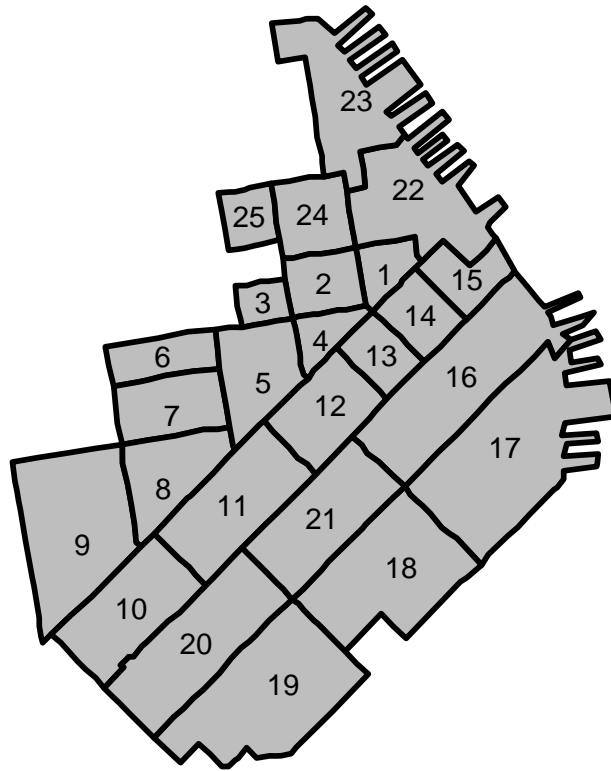
Figure 1: TAZ Map with ID

```
qunif(X[,1], mean_value-0.30*mean_value, mean_value+0.30*mean_value)
```
FIX!

to put the random sampling on the right scale needed for the given parameter. This is then applied for all six parameters for the five samples of ~~latinhypercube~~ **latin hypercube** sampling.

Now the mode choice logsum can be calculated for each of the list types and their iterations.

The utility ~~equations~~ **equations** are as follows:

```
drive_utility = (coeff_ivtt*auto)+(coeff_cost*auto_cost*DIST)
nonmo_utility = (k_nmot + 20*(coeff_walk1*nonmotor))
trans_utility = k_trn + (coeff_ivtt*transit)
```

These utilities are then exponentiated, added together, and the natural log is taken to get a logsum value for every origin and destination pair.

The shapefile for the dummy model is shown in Figure 1.

~~The initial model was run, the change was calculated on a random selection basis, and then using latin hypercube sampling, to see if latin hypercube sampling can estimate uncertainty in fewer runs.~~

The initial model was ran using the base parameters. Then the same model was ran again using the randomly sampled parameters and with the latin hypercube sampled parameters. The method of uncertainty estimation can then be analyzed.

3

Match Tenses!!

3. Findings

Which describes the results of what you found.

References

Yang, C., Chen, A., Xu, X., and Wong, S. (2013). Sensitivity-based uncertainty analysis of a combined travel demand model. *Transportation Research Part B: Methodological*, 57:225–244.

Zhao, Y. and Kockelman, K. M. (2002). The propagation of uncertainty through travel demand models: an exploratory analysis. *The Annals of regional science*, 36(1):145–163.