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Evaluating the effect of time-dependent utility on the performance of the route choice model

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1. Introduction

Route choice models play an important role in transport applications such as travel demand estimation, as they are a core to the traffic assignment process. Various studies have exploited the information from real observations to capture the route choice behaviour of pedestrians, cyclists, cars, trucks etc. The attribute and model selections for these studies are based on the application as well as the availability of the dataset.

Dhaker (2012) and Parady et al. (2021) provided an overview of empirical route choice studies with their corresponding utility variables and model selection. The review suggested that the existing route choice studies mainly consider distance and travel time variables with limited heterogeneity such as free-flow time (FFT), or average travel time. Yao and Bekhor (2020) highlighted that although these studies exist, they cannot be directly utilized for modelling the route choice behaviour for large urban networks. Some of the key issues pertaining to the applications of the route choice models are a) limited dataset availability (Prashker and Bekhor, 2004) (***issue 1***), b) over-reliance on simplistic evaluation measures (Parady et al., 2021) (***issue 2***), and c) lack of spatial and temporal variability in the observed dataset and utility specification (de Jong and Bliemer, 2015)(***issue 3***).

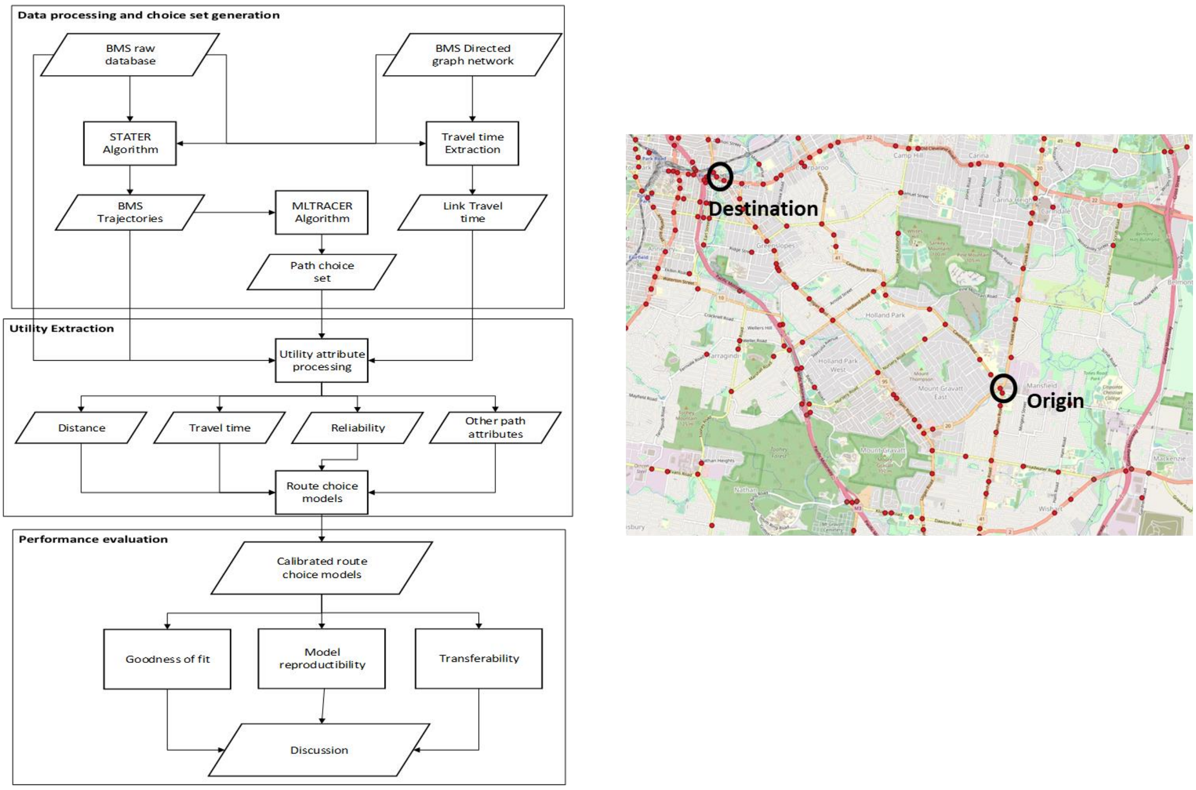
A potential solution to this problem is including the real and historical traffic state dynamics in the SRC-based modelling such that the stochastic models can appropriately estimate the route choice proportion for changing traffic conditions. This research aims at evaluating the effect of such real-time and historical traffic state information on the performance of the route choice models. For this, the study utilizes the Bluetooth trajectories and corresponding traffic state information from Brisbane OD pairs, currently utilized for congestion evaluation. The Bluetooth dataset possesses challenge in regard to lower sample size and noisy observations. However, the large network of Bluetooth MAC Scanners (BMS) and large travel time and speed repository provide an ability to identify such outliers or interpolate such missing information, hence resulting in this research.

This study evaluates the performance of route choice models using a large trajectory and traffic state dataset (addressing issue 1). The study specifically focuses on evaluating the impact of time-dependent utility attribute information on the performance of the route choice models (addressing issue 3). Further, to assess the model application regarding the practical application, the performance is evaluated based on a) goodness of fit measure, and b) model generalization capabilities of the estimated route choice models (addressing issue 2).

This research aims at applications involving real-time simulation such as Aimsun Live or a digital twin modelling of a city, which utilizes the dynamic traffic assignment (DTA) framework for travel demand estimation. Accordingly, multinominal logit-based route choice models are evaluated with simplistic parameters that can be pre-specified or provided in real time to the simulation software.

2. Proposed Framework

Brisbane city is highly equipped with over 1200 Bluetooth MAC Scanners (BMS), which provide seamless data of the Bluetooth equipped vehicles on the road network. This data presents an opportunity to understand travel behaviour and evaluate network performance by tracing an individual vehicle at multiple road locations. We use this information from BMS scanners to develop modelling inputs and then utilize them for evaluating the route choice models. Figure 1 (a) shows the data-driven framework, consisting of the steps involved in this evaluation process.



(a) (b)

Figure 1 Data-driven route choice model evaluation framework.

The framework in Figure 1 consists of three main sections: a) data processing and route choice set generation ***(refer to section 3),*** b) extracting utility parameters for the observed trips ***(refer to section 4)***, and c) performance evaluation of the calibrated route choice models ***(refer section 5)***. The first part of the framework explains the process of Bluetooth trajectory and path generation methods adopted from the literature. The second part of the framework deals with the utility estimates for the paths in the choice set. Lastly, the performance evaluation section provides a comparison among the identified models. The proposed framework is utilized to evaluate the route choice modelling performance for an OD pair shown in

3. Bluetooth trajectories and path choice set

3.1 Trajectory aggregation

This study uses the Bluetooth trajectories constructed using the STATER algorithm for route choice modelling (Advani et al., 2021). Each trajectory corresponds to a trip and consists of the trip's origin, destination, departure and arrival times, travel time, and the path sequence. The origin and destination of a trip correspond to the first and last BMS at which the vehicle is observed. As the Bluetooth scanners are densely placed, this study aggregated the trajectories originating and ending within same Statistical Analysis -1 (SA-1) level zones. The aggregated trajectories are then utilized to generate the path choice set and for route choice modelling.

3.2 Path choice set generation

Recent studies such as Yao and Bekhor (2020) and Chintan et al. (2021) proposed trajectory-based clustering techniques to identify the path choice set using data-driven techniques. We use the MLTRACER algorithm by Chintan et al. (2021) to generate the path choice set between the zonal boundaries of the OD pair. The algorithm provides a flexibility of identifying optimal essential paths using an error minimization approach and clusters highly spatially similar paths into a single set.

4. Utility specification and model testing

Choice modelling requires information on the attributes of the chosen and non-chosen alternatives. This study utilizes the trajectory and traffic state information from Bluetooth dataset to extract the path utilities. For this, the utility is defined based on distance, travel time, path size, speed and travel time-based reliability and delay variables. Further, these utility variables are considered at different heterogeneity (aggregated resolution) as summarized in Figure 2.

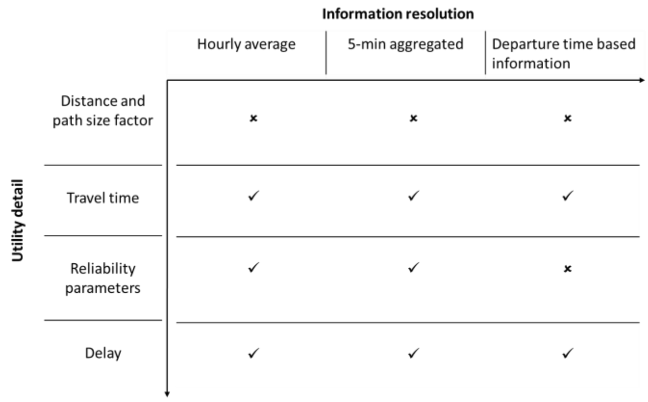


Figure 2 Utility specifications and time resolution

Here, the distance and path size parameters are time independent while all other parameters can have different information resolution. This study considers three levels of information resolution i.e., hourly averaged, five-minute averaged, and departure-based information (to nearest 5 min information). The utility variables are aggregated over similar day types and time period for the paths in the choice set (e.g., average travel time for path 1 on Monday 6-7 am). Based on the above information, models in Table 1 are tested to comprehend the effect of utility attributes and its corresponding time resolution information on the performance of route choice models.

Table 1 Overview of model selection

Model	Sub-Model	Attributes	Interpretation
1	1a	distance, path size factor, hourly average travel time	Evaluating effect of travel time resolution
	1b	distance, path size factor, five min average travel time	
	1c	distance, path size factor, departure-based travel time	

2	2a	distance, path size factor, hourly average speed	Evaluating the effect of speed-based hourly averaged reliability
	2b	distance, path size factor, travel time, hourly averaged stdev speed	
	2c	distance, path size factor, travel time, hourly average cov speed	
3	3a	distance, path size factor, travel time, five min average speed	Evaluating the effect of speed-based five-min averaged reliability
	3b	distance, path size factor, travel time, five min average stdev speed	
	3c	distance, path size factor, travel time, five min average cov speed	
4	4a	distance, path size factor, travel time, hourly averaged stdev travel time	Evaluating the effect of travel time-based hourly averaged reliability
	4b	distance, path size factor, travel time, hourly average cov travel time	
5	5a	distance, path size factor, travel time, five min averaged stdev travel time	Evaluating the effect of travel time-based five-min averaged reliability
	5b	distance, path size factor, travel time, five min averaged cov travel time	
6	6a	distance, path size factor, travel time, reliability, hourly average delay	Evaluating effect of travel delay at various time resolutions
	6b	distance, path size factor, travel time, reliability, five min average delay	
	6c	distance, path size factor, travel time, reliability, departure time-based delay	

The model evaluation in Table 1 consists of six models, each focusing on different aspects of utility specification or the time resolution. Here, model 1 evaluates the effect of travel time resolution on the model performance using the log-likelihood estimate. The results of model 1 are utilised to choose the optimum travel time resolution, which is then fixed along with distance and path size attributes to test the effect of reliability in models 2 to 5. The best performing utility attributes from models 2 to 5 are then considered in addition to different travel time delay resolution in model 6. In this study, the outputs are presented for the best performing sub-model under each main model for all various OD pairs.

5. Results

This section provides results on the model performance using goodness of fit measures and model generalisation capabilities. The goodness of fit is evaluated using Log-likelihood, AIC and BIC, as they are well established parameters in literature. Further the model generalisation capability is tested using 5-fold cross validation, where a stratified sampling process used to assign the trajectories into five set. The cross-validation results are evaluated using out of sample Log-likelihood, MAE based on First Preference Recovery (FPR), and MAE based on aggregated market share. Table 2 presents the goodness of fit results and Table 3 presents the 5-fold validation test results for the OD pair considered in Figure 1 (b).

Table 2 Goodness of fit results for the best performing route choice models

Co-efficient	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
Distance	-1.01	2.62^{**}	-1.1	2.77^{**}	-0.71	$1.83^{.}$	-0.82	2.25^{*}	-1.39	3.53^{***}	-0.93	2.24^{*}
Path size factor	-1.69	4.37^{**}	-0.29	0.61	-0.81	$1.85^{.}$	-1.04	2.3^{*}	-2.45	6.04^{***}	-0.44	0.85
Travel time at departure	-0.42	10.17^{***}	-0.45	8.94^{***}	-0.43	9.96^{***}	-0.46	9.89^{***}	-0.42	10.51^{***}	-0.13	0.68
Hourly average stdev speed			-0.45	5.34^{***}							-0.42	4.75^{***}
five-minute averaged speed					-0.21	3.83^{***}						
hourly averaged cov _tt							-8.31	7.63^{***}				
five-minute average stdev tt									0.22	3.97^{***}		
departure delay											-0.36	$1.73^{.}$
Log-likelihood	-486.33		-468.64		-477.43		-470.62		-477.63		-466.59	
AIC	978.66		945.29		962.87		949.23		963.26		943.18	
BIC	990.27		960.74		978.33		964.68		978.71		962.5	

Significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Most models in Table 2 possess desirable magnitude and direction for variables except for Model 2 to 5, which have unexpected magnitudes for average speed and travel time standard deviation. Model 1 output provides an expected behaviour that individuals consider departure-based travel time information over the everyday travel time information. Models 2 to 5 suggest that the inclusion of speed/ travel time reliability certainly improves the route choice models. Therefore, real time simulations can utilise the historical travel time information in model enhancement. Further in regards to reliability aggregation, hourly average information provides better fitness and behaviour interpretation than the five minute aggregated information, probably because individuals cannot perceive reliability information at such aggregation level. Lastly, the departure delay is significant for model 6, then any other aggregated delay measure, and suggest that individuals provide more importance to departure delay than the travel time.

Table 3 5-fold cross-validation aggregated results

Model	LL	MAE (FPR)	MAE (Prob)
1a	-110.57	25.94%	1.30%
1b	-110.38	12.79%	3.43%
1c	-97.37	68.10%	3.12%
2a	-97.08	6.92%	2.50%
2b	-94.00	5.45%	1.30%
2c	-94.52	5.55%	1.42%
3a	-95.73	6.12%	1.90%
3b	-96.78	6.47%	2.80%
3c	-96.20	5.47%	2.56%
4a	-94.52	4.76%	1.22%
4b	-94.33	5.76%	1.26%
5a	-96.93	6.10%	2.32%
5b	-96.44	5.66%	2.44%
6a	-94.01	5.44%	1.29%
6b	-94.14	8.05%	2.44%
6c	-93.64	4.31%	1.29%

In regard to model generalization, the model enhancement trend based on out of sample likelihood is almost similar as Table2, with model 6 performing best compared to other models. In terms of MAE, interesting observations are made as FPR based MAE is best for model 6c, while model 4a provides a better MAE for aggregated probability. The results from Table 2 and 3 suggest that an aggregated model evaluation considered in this study can provide a better inference and application to the route choice modelling.

6. Conclusion

Advancement in the data collection techniques have provided an opportunity to collect real time and historical travel information. The trajectory information in aggregation to network traffic state can be utilised to model the route choice behaviour for practical applications such as real-time travel demand modelling. This study demonstrates one such process of evaluating the route choice model using trajectory and traffic state information from Bluetooth dataset. The aim is to evaluate the effect of information resolution on the performance of route choice model. For this, three different aggregated level of information i.e., departure based, hourly averaged, and five-minute averages are considered. Further, the work utilises the large travel time database to evaluate the effect of various reliability parameters on the route choice behaviour. Six models were tested for an OD pair using the model fitness and generalisation capabilities. The results suggested that including reliability information essentially improves the goodness of fit and model prediction capabilities. Furthermore, the cross-validation results suggested that the goodness of fit parameters do not essentially explain the overall model and generalisation based on MAE and other aspect provide better idea of the practical consideration of route choice models. The study is currently performed for one OD pair but will be extended to more OD pairs to evaluate the transferability capability of the route choice models.

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