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Hybrid agent based simulation with adaptive learning of travel mode choices for University commuters (WIP)

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Keywords

Traffic Simulation, Machine Learning, Agent Based Simulation, Travel Mode Choice

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Hybrid Agent based Simulation with Adaptive Learning of Travel Mode Choices for University Commuters

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Abstract

This paper presents a methodology for developing a hybrid agent-based micro-simulation model to capture the impacts of commuter travel mode choices on a University campus transport network. The proposed methodology involves: (i) developing realistic population of commuter agents (students and staff); (ii) assigning activity lists and travel mode choices to agents using machine learning method; and, (iii) traffic micro-simulation of the study area transport network. This furthers the understanding of current transport modal distributions, factors affecting the travel mode choice decisions, and, network performance through a number of hypothetical travel scenarios.

1. INTRODUCTION

1.1. Motivation

Commuter travel behaviour and its impact on the transportation system in and around university campuses present unique challenges for policy makers. These environments are characterized by varying weekly and yearly peak periods. Often, university campuses are the largest employers in small to medium size cities. Therefore, it is critical to examine University commuters' travel patterns to ensure the network is adequately servicing the population. The impacts of planned transport policies and its emergence over time present complexity and uncertainty that is best analyzed using simulation models. Building simulations incorporating agent-based models (ABMs) will help the transport policy planners and decision makers to better understand travel patterns, travel demand/supply, and to explore hypothetical policy scenarios. The intention of this model is to predict commuter travel behavior and transportation system utilization in response to changes in policy, university land use, commuter demographics, and socioeconomic conditions.

1.2. Literature review

Data gathering of university related travel behavior traditionally relied on the university wide travel surveys to identify travel demand and supply [Abiola

and Ayodeji 2012]. In these surveys, questionnaires are designed to gather preferences in transport modes, and commuter attitudes towards existing or planned transport options. Although these surveys provide greater understanding of existing travel patterns and perceptions; they lack the predictive capability to analyze future travel scenarios. These scenarios can affect infrastructure and policy changes through an intra-year and inter-year population changes.

1.2.1. Agent based modeling for transportation systems

University campuses are complex transportation networks. As such, the performance of the network is influenced by individuals and choice behaviors. The complexity of these environments is influenced by interactions among heterogeneous agent types (e.g. staff, student, visitors), between agents and their environment (e.g. road network, access to travel modes), and the emergence of behaviors over time. Given these complexities, ABMs are best suited to simulate these complex interactions.

ABMs attempt to model the complexity of social systems with individual level representations of interacting autonomous agents [Gilbert 2008; Gilbert and Troitzsch 2005; Macal and North 2006]. The behavior of any system is a result of the interactions amongst its components [Macal and North 2006; Ackoff 1971]. Transport networks are no different, in that their performance is a product of network component interactions. In this case, agent based models assume each commuter is an autonomous agent with certain attributes and states. In the simulated environment, agents interact with other agents and the environment to make autonomous rational travel decisions, pro-act or react given previous experiences and communications with other agents [Gilbert and Troitzsch 2005, Woolridge and Jennings 1995]. Over time, these agents evolve continuously based on their interactions and time-based feedbacks. Agent based models have been predominantly used in modeling the travel behavior of individuals in cities to inform transport and urban planning decisions [Vaughn et al., 1999; Barrett et al., 1995]. The value of these models lies in the prediction of emergent system behavior that would be difficult (if not impossible) to ascertain with analytical methods [Gilbert and Troitzsch 2005].

1.2.2. Modeling travel mode choices

Travel behavior has been comprehensively studied in the transportation research area. In particular, travel mode choice has been predominantly studied [McFadden 1973; Koppelman and Wen 1998], primarily using discrete choice models. Discrete choice models include probit model [Gaudry 1980]), multinomial logit (MNL) model [McFadden 1973] and nested logit model [Daly & Zachary 1979]. These approaches have limitations such as i) specific model structure needs to be specified in advance, which ignores partial relationships between explanatory variables and travel modes for subgroups in a population; ii) inability to model complex non-linear systems, which represent complex relationships involved in human decision making; and iii) they check only for conditions that hold across an entire population of observations in the training dataset and patterns cannot be extracted from a subgroup of observations. These limitations are overcome by using machine learning based methods such as decision trees (DT) and artificial neural networks (ANN). Research in travel mode choice literature has proven superior performance of machine learning methods over traditional methods for travel mode choice [Xie et al. 2003; Reggiani & Tritapepe 1998; Cantarella et al., 2003; Shmueli et al. 1996]. Despite the inherent advantages of machine learning methods, they are rarely used for simulating agent's travel mode choice. Conceptual decisions remain unexplored, such as; (i) decision whether to implement supervised or non-supervised learning approaches, and (ii) choosing a learning algorithm. For instance, ANN are adequate at classifying large amounts of data, however, with the resulting ANN model it is difficult to determine how classification decisions are made (black box type model); DTs, provide structure to how decisions are made (black box type model), but are not good at classifying continuous data. Therefore, further research is needed to operationalise these models and methods in simulating agent decisions in ABMs for transportation system simulations.

1.2.3. Traffic Micro-simulation models

Another method for simulating the travel of individuals in the transport network of a city or a region is micro-simulation models [Balmer et al., 2008; Barrett et al., 1995]. Micro-simulation traffic models are capable of highly detailed analysis of traffic flow through a transport network such as congestion profiles of a street in the road network. Although, micro-simulation models are better suited to represent and define the structure of transport system; ABMs are usually better suited to capture the impact of 'behaviours' on the transport network, justifying the methodology. That is, model agent's travel behaviour and its evolution over time using ABM; and, simulate traffic flows based on the travel decisions made by agents using micro-simulation models.

The main contributions of the paper are:

- To predict commuter travel behaviour and transportation system utilization in response to changes in University travel policies, university land use, student and staff demographics, and socioeconomic conditions.
- To integrate agent based and traffic micro-simulation models for modelling travel behaviours of university commuters (student and staff)
- To model adaptive travel mode choices with the help of machine learning approaches for university commuters.

2. CONCEPTUAL MODEL

The proposed modeling methodology includes the following individual interacting methods and conceptual modeling components: (i) synthetic population; (ii) travel diary assignment; (iii) adaptive travel mode choice learning and prediction; and (iv) traffic micro-simulation. The proposed methodology with individual methods and data sources are illustrated in Fig. 1.

In order to perform agent based simulations, at each time step t , a realistic synthetic population ($CurrPop(t)$) is needed that encapsulates demographic and behavioral heterogeneity of university commuters as state variables. The population is initialized with a list of states derived from anonymous university records (student and staff). The purpose of the data is to inform agent attributes as the agent population is initialized and aged.

In this research, five individual types and their characteristics will inform agent attributes. These are: Full time student; Part time student; Academic staff; General staff; and, Others (includes private enterprises or University tenants). Each agent $i \in (1,2,3, \dots, N)$ in above five types will have following attributes ($indAttrb^t(i)$):

- (i) Age
- (ii) Employment level
- (iii) Session address (aggregated to Australian Statistical Geography Standard Statistical Area Level 1 (SA1))
- (iv) Array list of preferred destination zones inside study area
- (v) Parking permit type
- (vi) Faculty and School Affiliation
- (vii) Car access
- (viii) Time spent on campus
- (ix) Frequency of travel to campus in a week

Once the synthetic population is created, each agent is assigned a travel activity list, referred in this study as a travel diary. The travel diaries assign origin, destination, travel mode, departure time, and other essential individual-level information prior to trip

initiation. In this study, all agents are assigned only work or study related round trips from their home location to a set of destination zones at the university campus. Spatially, the study area (University campus and adjacent surrounding areas) will be divided into several origin and destination zones based on entry

points into the network and bus station or car parking facilities, respectively.

Therefore, all agents will be assigned two types of trips in a day (if they are making trip to university):

(i) From Home location to Work/Study locations (set

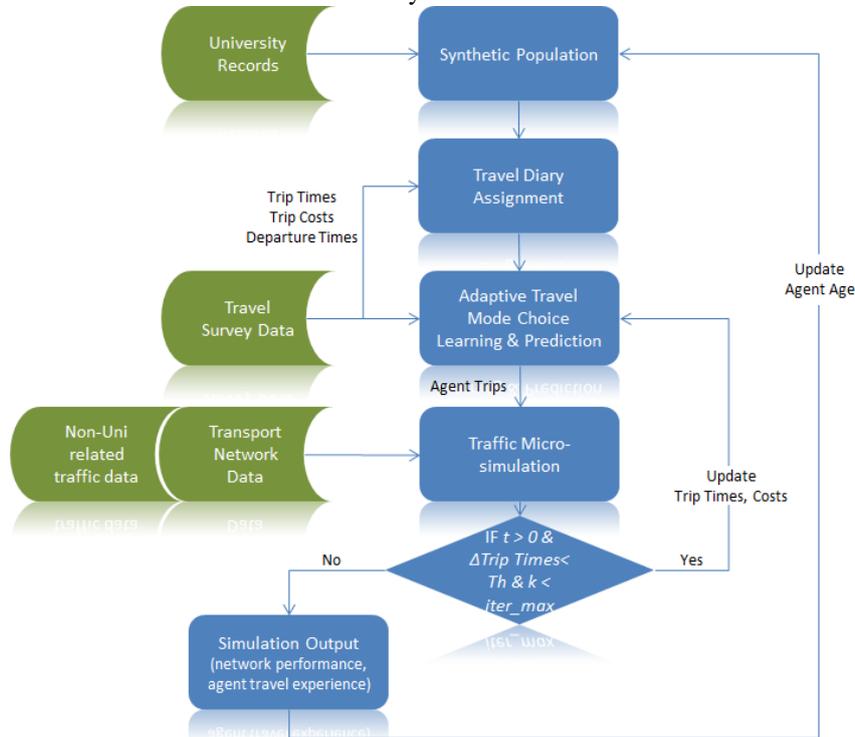


Figure 1: Conceptual illustration of the model

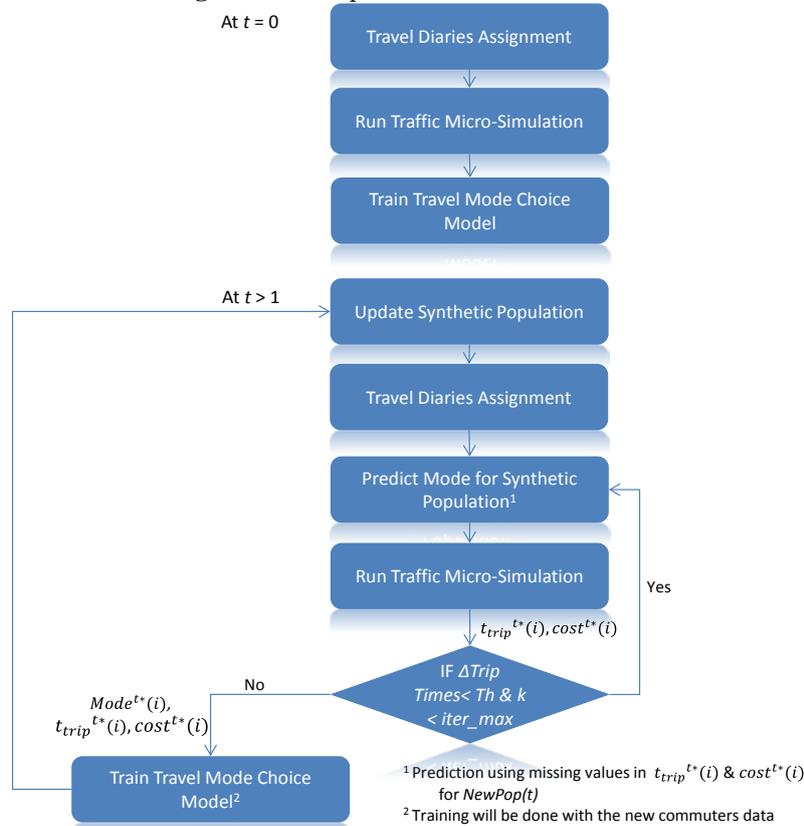


Figure 2: Adaptive learning for travel mode choices in the simulation model

¹ Prediction using missing values in $t_{trip}^{t^*}(i)$ & $cost^{t^*}(i)$ for $NewPop(t)$

² Training will be done with the new commuters data

of destination zones at the study area)
(ii) From Work/Study location to Home location

At time step $t = 0$: once origin location ($O^0(i)$) and destination location ($D^0(i)$) for i^{th} agent trip is defined, departure time ($t_{dep}^0(i)$), estimated travel mode ($Mode^0(i)$), estimated trip time ($t_{trip}^0(i)$) and estimated trip cost ($cost^0(i)$) will be initially (at time step $t = 0$) assigned to each trip based on existing activity lists and trip time statistics from the university travel survey (see Fig. 2). These initial agent trips are used for running the traffic micro-simulation model to capture the real trip times ($t_{trip}^{0*}(i)$) and real trip costs ($cost^{0*}(i)$). Then, the adaptive travel mode choice model (f^0) is trained with the help of these trip related data ($indAttrb^0(i), O^0(i), D^0(i), t_{dep}^0(i), t_{trip}^{0*}(i), cost^{0*}(i), Mode^0(i)$).

At time step $t > 0$,

The travel mode choice for each agent is predicted using an iterative process starting with f^{t-1} . In each case, $t_{trip}^{t*}(i)$ and $cost^{t*}(i)$ for agents retained at time step t from time step $t - 1$ (i.e., $CurrPop(t - 1) - LeavingPop(t)$) are first initialised based on $t_{trip}^{(t-1)*}(i), cost^{(t-1)*}(i)$, i.e.,

$$t_{trip}^{t*}(i) = t_{trip}^{(t-1)*}(i), cost^{t*}(i) = cost^{(t-1)*}(i) \quad (1)$$

for any $i \in (CurrPop(t - 1) - LeavingPop(t))$

Travel mode choices are predicted using f^{t-1} with the attributes $indAttrb^t(i), O^t(i), D^t(i), t_{dep}^t(i), t_{trip}^{t*}(i), cost^{t*}(i)$. Due to the influx of new commuters ($NewPop(t)$) at each time step t , the $t_{trip}^{t*}(i), cost^{t*}(i)$ values for agents in $NewPop(t)$ may not be available. Therefore, a method has been adopted to compute missing values and use that data for travel mode choice prediction for new commuters, i.e.,

$$Mode^{t*}(i) = f^{t-1}(indAttrb^t(i), O^t(i), D^t(i), t_{dep}^t(i), t_{trip}^{t*}(i), cost^{t*}(i)) \quad (2)$$

Once $Mode^{t*}(i)$ is evaluated for each agent in $CurrPop(t)$, traffic micro-simulation is run to obtain the new trip times and trip costs. If the changes in $t_{trip}^{t*}(i)$ in k^{th} and $(k - 1)^{\text{th}}$ iteration is less than threshold Th or $k > iter_max$; then the resulting $Mode^{t*}(i), t_{trip}^{t*}(i), cost^{t*}(i)$ for $i \in NewPop(t)$ are used for further training the model (f^t). This iterative process induces adaptive travel mode choice decisions over time.

The traffic micro-simulation model enables the simulation of each agent's movements from origin to destination based on its mode, and departure time to determine transport network performance. These agent movements are simulated on the transport network to obtain the detailed congestion profiles and

other traffic performance parameters such as public transport usage, car park occupancy vs. hours of a day. In order to simulate traffic in and around university campus, two types of trips are considered:

- (i) University related trips – will be captured from the travel diaries and travel mode choice output
- (ii) Non-University related trips – traffic generated by other commuters using the road network in study area but are not represented in the synthetic population, replicated from traffic count data

All trips are simulated by traffic micro-simulation software over a number of representative days (semester, non-semester days, weekend, weekdays, etc.).

3. SOFTWARE ARCHITECTURE

A survey of existing transport modelling and pedestrian simulation software packages indicated a lack of adequate existing software that would enable addressing the research questions presented. The main research questions presented in this paper are: (i) Integrate Agent based modelling and traffic micro-simulation models to observe travel behaviour of agents (university commuters) travelling to and from major university campus; (ii) Model the travel mode choice decisions of individual agents using the classification model (based on machine learning algorithm) derived from university travel survey dataset. Therefore, a customised software platform was designed. Figure 3 illustrates the software architecture for simulation model. Major software tools used in developing the simulation model include; the Java, Transims, PostgreSQL databases and Yellowfin Business Intelligence and data visualisation software. The functions of each are briefly discussed in the following subsections:

Java: The general-purpose, concurrent, object-oriented programming language is used to implement algorithms managing the synthetic population, travel diaries assignments, and travel mode choices. The Eclipse Integrated Development Environment (IDE) is used as main development platform.

Transims: a set of software tools to perform transportation system analyses based on a cellular automata microsimulator. It receives information from the Java and Postgres database to simulate individual agent's travel patterns and their multi-modal transportation activities. The results of analysis performed on Transims are recorded in the output database.

PostgreSQL: an open source object-relational database system, which is used to record (i) inputs to the model; (ii) intermediate data; and, (iii) model outputs. The main database tables are:

1. Central Configuration – stores all the parameters required to run the simulation model
2. Commuter Records – stores university commuters raw dataset

3. Synthetic Population – stores synthetic population generation at each model run
4. Transport Survey – stores university travel survey
5. Trip timeplans – stores trip time tables for each agent trips
6. Output metrics – stores the simulation model output data

YellowFin: Yellowfin is business intelligence and data visualisation software used to represent congestion profiles on the road network, travel mode patronage, public transport usage, and car park occupancy profiles.

4. WORK IN PROGRESS CASE STUDY

The case study involves simulation of the travel behavior of university commuters to and from

Wollongong campus of University of Wollongong (UOW) in New South Wales, Australia. At UOW, limited parking facilities and land space constraints guide policy design to enable greater use of public transport by students and staff. This study will enable the exploration of alternative parking permitting configurations as well as the incentive scheme efficiency in increasing public transport usage by commuters.

This study will largely utilize data available from UOW Transport Questionnaire Survey conducted in 2011 by Facilities Management Division of UOW; traffic counts data from local government Road and Maritime Services (RMS), and, UOW students and staff records.

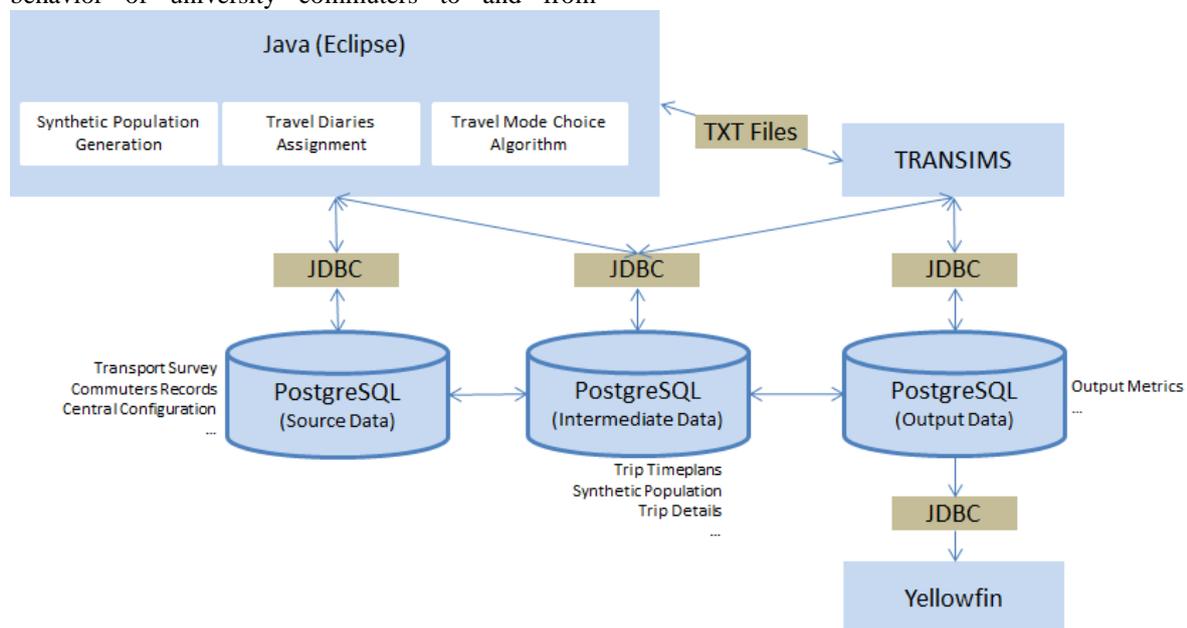


Figure 3: Software architecture for simulation modeling

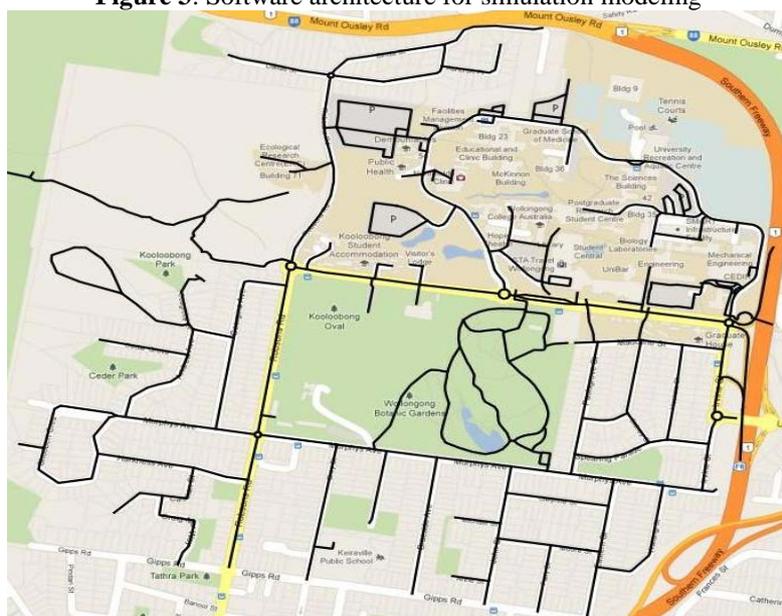


Figure 4: Study area (Source: Google Maps) for simulation modeling and transport network considered (solid black lines)

As with any simulation modelling activity, the modelling scope has to be defined. The model will include the base case simulation scenario of the UOW commuters to and from Wollongong campus. This simulation scenario will illustrate the commuter patterns and travel behaviour during a typical semester and non-semester week. The main model outputs will enable the analysis of:

- (i) Congestion profiles of the roads in and around study area (university campus)
- (ii) Hourly parking facilities occupancy in and around study area (university campus)
- (iii) Daily profile of bus utilization

The study area for this research is shown in Figure 4. It covers most of the possible routes for coming to campus and going out of the campus. This map also illustrates the transport network that will be considered in this research.

5. CONCLUSION

This paper presents a simulation modeling framework and software architecture to analyze the impact of travel mode choices of commuters on university transportation network performance. The proposed methodology involves building realistic synthetic population of university commuters, assigning travel diaries, predicting travel mode choices based on adaptive machine learning, and traffic micro-simulation to assess transport network performance. The future research of this simulation modeling framework will include; an estimation of overall Carbon Dioxide emission due to travel mode decisions, dynamic agent decision strategies on travel mode choice, and alternative infrastructure configurations to enable higher public transport patronage.

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