Towards an Agent-Based Model of Passenger Transportation

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Abstract. An agent-based simulation model for supporting the decision making in urban transport planning is presented. The model can be used to investigate how different transport infrastructure investments and policy instruments will affect the travel choices of passengers. We identified four main categories of factors influencing the choice of travel: cost, time, convenience, and social norm. However, travelers value these factors differently depending on their individual characteristics, such as age, income, work flexibility and environmental engagement, as well as on external factors, such as the weather. Moreover, instead of modeling the transport system explicitly, online web services are used to generate travel options. The model can support transport planners by providing estimations of modal share, as well as economical and environmental consequences. As a first step towards validation of the model, we have conducted a simple case study of three scenarios where we analyze the effects of changes to the public transport fares on commuters' travel choices in the Malmö-Lund region in Sweden.

Keywords: Multi-agent based simulation · Traveler behavior modeling · Passenger transport · Impact assessment · Web services

1 Introduction

The design of a "greener" transport system can be supported by a wide set of transport measures, including both transportation policy instruments and investments in infrastructure, such as new public transport pricing schemes, taxes and fares for motorized transport, new bus stops and lines, and new parking space.

In this paper, we propose a novel agent-based simulation model for supporting decision making in urban transport planning. The model, which we refer to as ASIMUT (Agent-based simulator for urban passenger transport), can be used to investigate how different transport measures affect the decisions of the travelers. It takes into account how factors like cost, time, convenience, and social norm influences the decisions on an individual level depending on the socio-economical features of the individual. Another innovative property of the simulator is that it makes use of online web services in order to generate travel options, rather than modeling the transport system explicitly.

B. Gaudou and J.S. Sichman (Eds.): MABS 2015, LNAI 9568, pp. 132–145, 2016.
DOI: 10.1007/978-3-319-31447-1_9

In the next section we review the related work and motivate the chosen agent-based approach. Section 3 presents ASIMUT. To make a first validation of the model, a simple case study of three scenarios is presented in Sect. 4, where we analyze the effects of changes to the public transport fares on commuter's travel choices in a region of Sweden. Some concluding remarks are provided in Sect. 5.

2 Related Work and Motivation

As the application of transport measures may have substantial impact on the travelers' behavior, it is very important to assess their impact before implementation, so that negative effects can be avoided and positive effects can be confirmed. One way of doing this is to perform experimental studies in the real world, but such studies are often very expensive and time-consuming. A common approach for assessing the effects of transport measures is to use computational models, which allows studying the transport system in a simulated environment. A recent review of policy impact assessment models concludes that conventional discrete choice models are the dominating method for travel behavior modeling [8]. These traditional models operate on highly aggregated data. Moreover, they are typically built to study transport in a particular country or a region, and they are often based on the so-called four-step modeling approach. The four steps are: trip generation, where the frequency of trips between zones is determined; trip distribution, where origins are matched with destinations; mode choice, where the proportion of trips between each origin and destination that use a particular transport mode is computed; and route assignment, where all trips are assigned to routes. However, four-step models have been criticized both for neglecting the interaction effects between the involved actors and for oversimplification, which often lead to significant biases in output, especially in settings where the interaction between policies and/or travelers is significant [17]. Furthermore, these models only take into account a limited number of the factors influencing travel behavior [8].

Agent-based simulation modeling is another approach that has been used for impact assessment of transport measures. It is often regarded as a bottom-up approach where each traveler is treated as an interacting, autonomous and independent entity. Thus, it differs from conventional top-down approaches that focus on overall aggregated analysis of the system's behavior [6, 18].

In the agent-based simulation model presented in this paper, the passengers are modeled as agents. We generate the different travel alternatives of an agent using existing web services of online travel planners. We consider both motorized and non-motorized modes of transportation and the combinations of them in generating travel alternatives. The model focuses on how to travel when the destination is already decided, i.e., corresponding to steps 3 and 4 of the traditional four-step models. More specifically, we focus on the mode choice, route choice and departure time choices of travelers, when source and destination data is available from the traveler agent, i.e., the traveler's home and work addresses. We believe that significant improvements to these steps can be made using a more detailed bottom-up approach, and that this can be used together with any approach to determine the travel demand.

The agent-based modeling approach provides a more dynamic approach with respect to the level of detail in modeling different parts. For instance, more interesting parts of the infrastructure can be modeled with a higher granularity. This makes it possible to study the effects of, e.g., building a new bike parking facility that is safe and efficient and close to a train station, or allowing the travelers to bring their bikes on the trains. Furthermore, by using an agent-based method it is possible to model what travel options different travelers actually are aware of, or consider, when deciding what option to choose. This makes it possible to study the effects of, e.g., travel awareness campaigns and the availability of advanced travel planning systems. Such interventions are difficult, or even impossible, to study using traditional models.

Furthermore, agent-based models are able to capture time-related aspects, such as the effects of synchronization and optimization of timetables [16]. There are many transport policy measures that concern time, e.g., time-differentiated congestion and parking fees. Such transport policies are difficult to study using traditional models, but they may have an important influence on travel choices.

We further argue that the use of an agent-based modeling approach, which captures the behaviors of travelers and their interactions between each other and with the environment, will facilitate capturing each individual's preferences and characteristics. This is critically important in order to determine the actual decisions of individual travelers. Thus, agent-based modeling seems very well suited to predict and analyze the effects of different transport measures, since it explicitly models the decisions of each individual and is able to compute the consequences of these decisions. It should be noted that agent-based modeling might require more information about travelers on an individual level than the traditional models, which to a large extent are based on population averages. However, modern consumer technology like smartphones, as well as ITS services like advanced ticketing and tracking systems based on "Internet of Things" technology (connected devices), enable efficient, large-scale, collection of individual travel data.

There are few studies that have applied an agent-based modeling approach in the context of transport policy analysis [8]. In most cases, the agent-based models have been very simple and do not realize the potential of the approach [3, 14]. These models are mostly developed to investigate the effects of a specific transport measure concerning a specific scenario. Furthermore, they do not include all relevant modes of transportation. The input variables, the model construction, and the collected output are very much chosen with a specific scenario in mind. Therefore, these models cannot investigate the effects of various kinds of transport measures in different scenario settings. This means that they are unable to be used as a decision support system to support transport policy making. An agent-based model that bears some resemblance with the one we propose was developed by Grimaldo et al. [7]. It takes into account cost, travel time and environmental in determining travel choice, but it does not regard convenience and makes no difference between individuals (age, income, etc.) except for car-ownership. Moreover, the transport system modeled is very simplistic, e.g., just one road and two travel options, either car or train. In particular, combined transport modes, such as walking, biking, car, bus, and train, are not at all considered.

There are also frameworks for implementing large-scale agent-based transport simulations, e.g. MATSim [4], but they focus on traffic flows and vehicles rather than travel option choices and travelers.

The majority of the traditional models are mode choice models [13], which aim to answer how many travelers will switch to another mode of transport in case of any change in transport system [2]. However, in addition to the choice of transport mode, there are also other important aspects of travel behavior, such as route choice and departure time choice [11]. In order to have a comprehensive and accurate impact assessment, we claim there is a need to investigate the impact on all aspects of travel.

3 ASIMUT

In the proposed model, each passenger is modeled as an agent. This enables us to include each individual's preferences and characteristics into the travel choice modeling. The decision-making process of travelers when choosing between the available travel alternatives is to some extent individual and not the same for all travelers. This means that there is no objectively optimal travel choice from point A to point B for all travelers in a given situation. Therefore, we assume that the "best" travel alternative can be different for different travelers. In ASIMUT, the choices between alternatives are based on four main factors: cost, time, convenience, and social norm. The perceived value (priority) of each of these factors is typically different for each traveler and depends on:

- The traveler's characteristics; refers to the attributes of each traveler and have an important influence on the choice of travel. Examples include socio-economic attributes and geographical location of home and workplace.
- The available travel options at the time of travel and their related cost, travel time, CO_2 emission, number of changes, and walking and cycling distance.
- Contextual factors, factors related to the context where the travel happens, e.g. the current and predicted weather.

Web-services are used in ASIMUT for data collection. We generate the travel alternatives for a traveler from point A to point B, using the web services provided by online travel planners. The use of online travel planners for generating travel alternatives is a novel approach which enables us to capture the most recent information about route alternatives and their relevant characteristics such as cost and travel time. Furthermore, it provides the model with real-time information that adapts automatically with updates, e.g., if the bus schedules change, this change will be automatically updated in ASIMUT. Due to recent developments in application of information systems for online trip planning, nowadays most travelers have access to online travel planners and are able to retrieve almost all the possible travel alternatives at the time of departure. Therefore, we believe integration of web services of online travel planners in ASIMUT makes the model represent the real traveling behavior and is highly consistent with the way travelers choose to travel in everyday life. We use the route alternatives' data gathered from web services as input in the decision-making model.

3.1 Passenger Behavior Modeling

For modeling the individual's travel decision-making we use the theory of planned behavior, which is an extension of the theory of reasoned action [1]. It assumes that humans are rational and they make systematic use of information available to them while they also consider the implications of their actions before they decide for a certain behavior. In ASIMUT, we consider cost, travel time, and convenience as the rational factors that affect the choice of travel. A rational agent aims to maximize the utility and hence minimize cost and travel time and maximize convenience.

However, travelers do not always act completely rational. Social norms and personal values may affect the choice of travel. The theory of planned behavior complements the theory of reasoned action by adding the concept of social norm [1]. Environmental awareness of the travelers is modeled as a social norm in ASIMUT. The theory of planned behavior has also the possibility to cover the behaviors that are not fully under an individual's volitional control. This is very important in travel decision-making where the choice of travel by each individual is not only influenced by her characteristics, attitudes, and subjective norms, but also on intervening environmental conditions, such as the weather which we have included as a contextual factor in ASIMUT.

As mentioned earlier, we use four main categories of factors when making travel choices: cost, time, convenience, and social norms. The significance of each of these factors is determined by each traveler's individual characteristics and contextual factors. In ASIMUT, the value of each of these factors is calculated based on traveler's characteristics and weather conditions. It has been argued that the factors influencing choice of travel can be valued differently for different travel purposes [7, 9]. We have included a weight for each of the factors (i.e., cost, time, convenience, CO_2 emission) in order to be able to change the significance of each factor for different travel purposes. These weights will also be used for calibration purposes. For the decision-making model, we use the weighted sum model [19].

The traveler characteristics that we include in ASIMUT are: age, income, work flexibility, environmental awareness i.e. eco-friendliness, work and home address, working start and end times, access to car, and access to bicycle at home and work. We use work and home address, working hours, access to car, and access to bicycle at home and work directly when generating the travel alternatives, while the other mentioned factors are used for choosing between different travel alternatives. In Table 1 we describe a model of how all these factors can potentially affect the choice of travel and how they interrelate. The main factors influencing travel behavior are listed as columns in Table 1, while the rows are referring to traveler's characteristics and contextual factors. We believe that the income level of the traveler can affect the traveler's perception of travel costs. Therefore, in the proposed decision making model, we use this concept to calculate the value of cost for each traveler; the higher income decreases the influence of the cost on the travel decision of the traveler [5, 13]. For calculating the value of time, we use the traveler's work flexibility factor. We assume that more flexible working hours decreases the value of travel time to some extent.

Johansson et al. show that travelers who are more environmentally conscious tend to take the travel options that have less negative effects on the environments, or more specifically, the travel options that generate least CO_2 emissions [12]. Therefore, in ASIMUT we assume that the amount of CO_2 emission can affect the individual's choice of transport, depending on the individual's level of eco-friendliness.

We assume that convenience is comprised of walking distance, cycling distance, and number of changes for a travel option. The number of changes is defined as the number of transfers between vehicles in order to complete a journey. It has a negative effect on the choice of a travel option; the more interchanges in a travel option, the less convenient it is perceived [10]. Moreover, the number of changes of a travel option makes it less attractive the older you are [15]. Furthermore, we assume that the interchange between vehicles is less convenient in case of bad weather conditions.

Heinen et al. [9] reviewed the factors influencing cycling and indicated that there is a relationship between age and cycling, although it is not universal. While most studies have concluded that the willingness to bike decline with age, there are also some other studies that have not found any significant relation between age and cycling. Weather has also a high influence on the distance the individuals are willing to cycle. High precipitation and low temperature have been found as the most significant weather conditions influencing cycling level. There appears to be no significant relation between the other factors (e.g., income) and cycling [9]. In ASIMUT, we assume that convenience is more important for older travelers. Moreover, bad weather conditions (e.g., rain, snow, or low temperature) decrease the convenience of travel options with long walking distance, cycling distance, and higher number of changes.

Table 1. Interrelationship between the factors influencing choice of travel

Factors		Travel option's attributes					
		Cost	Time	Environ. impact	Convenience		
		Travel costs	Travel time	CO_2 emission	No. of changes	Walking distance	Cycling distance
Traveler's characteristics	Age				*	*	*
	Income	*					
	Work flex.		*				
	Eco-friend			*			
Contextual factor	Weather				*	*	*

3.2 Decision-Making Model

We use a utility function in order to calculate a score for each travel option. The factors influencing travel behavior are the main components of the model. The values of these components are a function of the characteristics of the traveler (i.e., age, income, work flexibility, and eco-friendliness), and contextual factor (i.e. weather). It should be emphasized here that the calculated score actually represents the disutility of a travel option; therefore, an agent will always choose the travel option with the lowest score among the set of available options.

The components of the scoring function have different scales and unit of measurements, and some are quantitative (e.g., age and income), while the others are qualitative or categorical (e.g., weather and work flexibility). In order to avoid domination of larger values, make the components consistent, and neutralize the unit of measurement of the values, we chose to normalize the attributes of the travel options; corresponding to the columns in Table 1. These normalized attributes are referred as relative values in the Eq. (1), e.g., $rel_{oat}^{envImpact}$, which refers to the relative environmental impact of travel option o for agent a. The relative values are typically different for different agents, since these values are calculated with respect to the travel options available for a specific agent. Moreover, we have converted all the characteristics of the travelers and contextual factors to categorical data. These values are called as val_a^{xx} in the Eq. (1), where xx are the factors of the traveler a mentioned in the rows of Table 1 and val_t^{wth} is the value assigned to the weather conditions of trip t. As we discuss further below, all val_a^{xx} and val_t^{wth} are assigned values in the range [0,1].

As mentioned earlier, we chose to assign a weight to each factor, i.e., W_{cost}, W_{time}, W_{conv}, $W_{envImpact}$ refering to the weight of cost, time, convenience, and environmental impact, respectively. These weights are mainly used for calibration, but they can also be used in order to change the importance of each factor according to travel motive, e.g. traveling to work or travel for leisure. The score S_{oat} (i.e., disutility) for travel option o for agent a and trip t is calculated as:

$$\begin{aligned} S_{oat} = W_{cost} * rel_{oat}^{cost} * val_a^{income} + W_{time} * rel_{oat}^{time} * val_a^{workFlex} + W_{conv} * rel_{oat}^{conv} \\ * val_a^{age} + W_{conv} * rel_{oat}^{conv} * val_t^{wth} + W_{envImpact} * rel_{oat}^{envImpact} * val_a^{eco} \end{aligned} \quad (1)$$

As mentioned earlier, convenience is determined by the three factors of walking distance, cycling distance, and the number of changes of the travel option o for agent a in ASIMUT, and it is calculated as:

$$rel_{oat}^{conv} = rel_{oat}^{wlkDis} + rel_{oat}^{cycDis} + rel_{oat}^{noOfChange} \quad (2)$$

The relative time and cost are calculated by normalizing the cost and time of a travel option with respect to the other travel options of traveler a for trip t. In the below equations, O refers to the collection of all travel options of trip t for traveler a, i.e.,

$$\begin{aligned} rel_{oat}^{cost} &= \frac{Cost_{oat}}{\sum_{o\ O} Cost_{o\,at}}, rel_{oat}^{time} = \frac{Time_{oat}}{\sum_{o\ O} Time_{o\,at} Time}, \\ rel_{oat}^{envImpact} &= \frac{Co2Emission_{oat}}{\sum_{o\ O} Co2Emission_{o\,at}} \end{aligned} \quad (3)$$

The factors for convenience are also normalized, as shown below. For example, in order to calculate the relative environmental impact of a travel option o, the CO_2 emission of that travel option is divided by the sum over the CO_2 emissions of all the travel options o for trip t of the agent a:

$$rel_{oat}^{wlkDis} = \frac{WalkingDistance_{oat}}{\sum_{o\ O} WalkingDistance_{o\ at}}, rel_{oat}^{cycDis} = \frac{CyclingDistance_{oat}}{\sum_{o\ O} CyclingDistance_{o\ at}},$$
$$rel_{oat}^{noOfChange} = \frac{NoOfChanges_{oat}}{\sum_{o\ O} NoOfChanges_{o\ at}} \tag{4}$$

As part of the decision-making model, we translate the real values for the age, income, work flexibility, environmental awareness (i.e., eco-friendliness), and weather characteristics, into categories as shown in the Table 2 (in the value column). These translations are the values used in the disutility function, i.e., val_a^{xx} and val_t^{wth}, and they are all numbers between 0 and 1. As an illustrative example, for val_a^{age} we translate an income higher than 100000 SEK to $val_a^{age} = 0.1$, an income in the range [50000, 10000] to the $val_a^{age} = 0.3$, etc. It can be seen that val_a^{age} increases as the income level decreases, which means that the travel cost will be valued lower for the higher income level of the travelers. It should be noted that the values used in the scoring function are just preliminary estimations; they will be further analyzed and validated in future studies.

Table 2. The categorization of characteristics of travelers and contextual factor (val_a^{xx} *or* val_t^{wth})

Variable	Range	Value
Age	15–25	0.1
	25–35	0.3
	35–55	0.5
	55–70	0.7
	+70	0.9
Income (monthly)	+100000	0.1
	50000–100000	0.3
	25000–50000	0.5
	15000–25000	0.7
	<15000	0.9
Work flexibility	high	0.4
	average	0.5
	low	0.6
Eco-friendliness	not concerned	0.3
	medium engagement	0.5
	high engagement	0.7
Weather	Good (no rain or snow, and temp > 10°C)	0.2
	Average (no rain or snow and temp 0-10°C)	0.5
	bad (rain or snow, or temp < 0°C)	0.8

3.3 Generation of Travel Alternatives

For each trip of a traveler, ASIMUT generates a set of travel options, using web services of online travel planners. The attributes that are extracted from the web service, for each travel option include route specification, travel time, cost, CO_2 emission, and the number of changes. These attributes are later used as input data in the traveler decision-making model (see Sect. 3.2 for details).

Waking, cycling, and driving travel options refer to the options that use only one of walking, cycle, and car as the mode of transport all the distance from the origin to the destination. Public transport options refer to the travel options that use public transport together with some short walking to and from public transport stops. They might also include transferring between stops. The time and distance of these short walks are taken into account in the simulation. We further complete the set of travel options by adding additional options where we have replaced long walking distances from origin (A) to a station (A′), and from a station (B′) to destination (B) by cycling. Long walking is defined as walking distances (*d*) between 200 m and 6000 m. The different travel options from point A to point B are illustrated in Fig. 1.

We use the Google Maps direction API[1] in order to generate walking, cycling, and driving travel options. The cost for the driving option is calculated based on the travel distance and parking fees if the latter apply. To generate the public transport travel options, web services by the public transport providers in the area are needed. In our case, i.e., the most southern part of Sweden, the public transport travel options are provided by the Skånetrafiken Open API[2]. It provides cost, travel time, number of changes, CO_2 emission, and walking distance of each travel option from point A to point B in a specified time and date. We have also used an API called "Commute Greener"[3] in order to calculate the amount of CO_2 emission for car users. The output of the APIs is in XML[4] or JSON[5] schema format. These schemas are parsed in order to extract relevant information, e.g. travel alternatives, travel time, cost, and CO_2 emissions of each alternative.

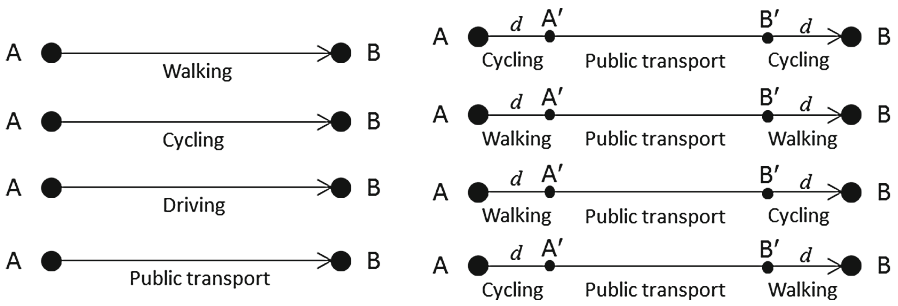

Fig. 1. All considered combinations of transport modes for generating travel options of a trip

[1] https://developers.google.com/maps/documentation/directions/.

[2] http://www.labs.skanetrafiken.se/.

[3] http://developers.commutegreenerinfo.com/.

[4] http://www.w3.org/XML/Schema.

[5] http://json-schema.org/.

When generating the travel alternatives from web services, the characteristics of the traveler are taken into account, i.e., in case the traveler has no access to bike at home, the travel options that include cycling from home will not be generated for that specific traveler, or if the traveler has no access to car, driving options will not be generated. Furthermore, the source and destination of travel options for a specific traveler, and the departure time of the travel are set according to the traveler's information i.e., work/home address and working hours.

Since it is not possible to obtain detailed weather forecast for more than 14 days ahead, we used historical weather data of the same day as the travel date from the last year provided by the Weather Underground service[6]. This service provides temperature, precipitation, and weather conditions (i.e., rainy or snowy) of the same day for the last year. The sequence of steps performed by the model is illustrated in Fig. 2.

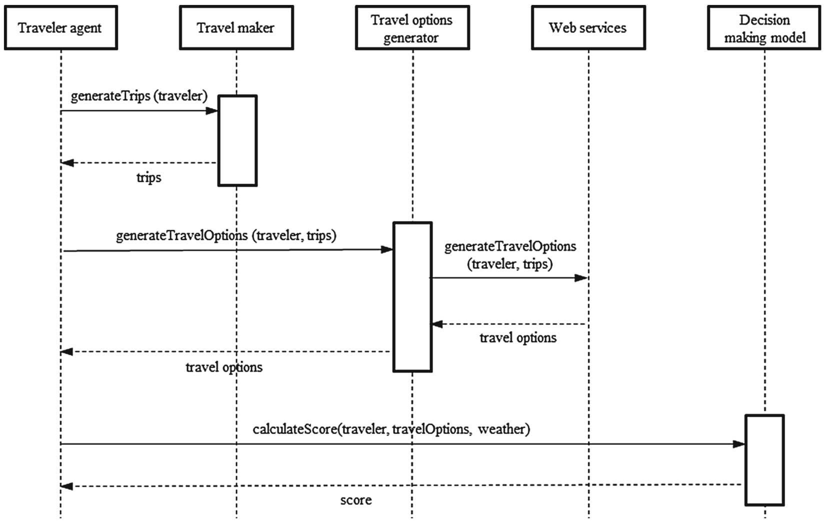

Fig. 2. Sequence diagram of ASIMUT.

4 Case Study

In this section, we present a small case study that is implemented within a prototype of ASIMUT. In this first basic experiment, we use a small sample population of 16 real travelers from the cities of Malmö and Lund in Sweden, who commute between the cities for work and study. This population sample provides the socio-demographic attributes of the travelers, including their work and home addresses.

For each traveler, we generate two trips for commuting to work and back to home respectively, using the traveler's home and work address and work schedule. Travel alternatives are generated for each trip using web services. A score is calculated for each travel option using our decision-making model.

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6 http://www.wunderground.com/.

We study three scenarios; in the first scenario, we simulate the current situation (CS), in the second scenario we examine the effects of reducing the public transport fare to half of the price (HP). The third scenario concerns doubling the public transport fare (DP). We investigate how these changes to the public transport fare are expected to affect the choice of travel and the modal share of the travelers using our implemented prototype. We run the simulation for ten randomly generated days with different weather conditions. The diagrams in Figs. 3 and 4 illustrate how changing the public transport fare is expected to affect the modal share, amount of CO_2 emission (estimated CO_2 footprint per traveler), and travel cost and time for the travelers' commuting during 10 random simulated days. It can be seen from the diagrams that reducing the public transport fare significantly affects the choice of travel and shifts the modal share from private vehicle use to public transport. The walking and cycling share decrease in

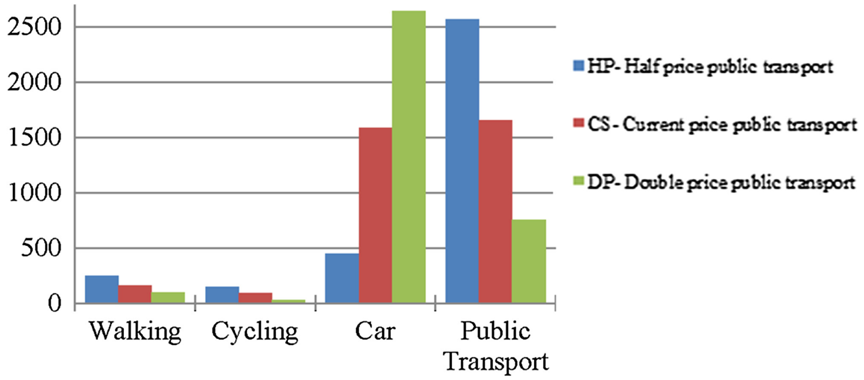

Fig. 3. Modal share (Km) for 10 random days.

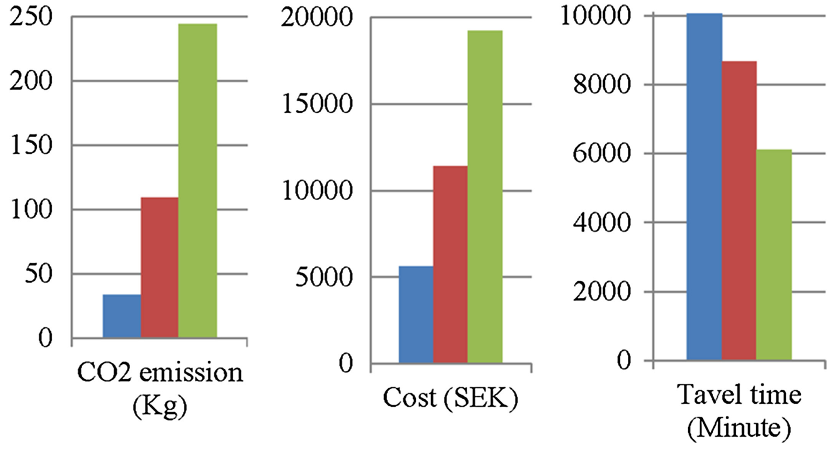

Fig. 4. CO_2 emission, cost and time of selected travel options for 10 random days. Blue = half price public transport, red = current price public transport, and green = double price public transport scenario (Color figure online).

the DP scenario, which we believe is mostly due to the small walking distances between public transport stations, or also due to the travelers who have combined cycling and public transport. When the travelers switch from public transport to private car, the mentioned walking and cycling links will also disappear. Therefore, we observe a decrease in walking and cycling share in the DP scenario. Furthermore, it can be seen from the Fig. 4 that the amount of CO_2 emission is expected to decrease when reducing public transport fare in HP scenario, which can be due to the shift from car use to public transport. Moreover, the selected travel option of the agents cost more when we increase the public transport fare in DP scenario, which can be both because of the increase in public transport fare and the shift to car that is a more expensive mode of transport.

5 Concluding Remarks

This paper has presented an innovative multi-agent based simulation model ASIMUT for modeling travel behavior of passengers. The aim is to support policy makers and urban transport planners in estimating the effects of new transport measures, e.g. policies and infrastructure investments. Some of the characteristics of ASIMUT are:

- It uses combinations of transport modes for generating travel alternatives.
- It uses web services of online travel planners to generate travel options.
- It investigates mode, route, and departure time choice of travelers.
- It considers a range of factors influencing the choice of travel in the travel behavior model, i.e., traveler characteristics, contextual data, and social norm.

Using online travel planners enabled us to access real-time network data that to a large extent corresponds to the data that the real travelers are able to access. It also helped reducing the effort and computation required for generating travel alternatives, calculating travel time, cost, and emissions within ASIMUT. It should also be noted that the use of web services as an input data source may have some potential drawbacks. Firstly, the web services might be temporarily down. Secondly, the performance of web services at a given time might be influenced by the load of the service at that time. Although these potential issues can affect the performance of ASIMUT, we did not notice any of these problems during the development and testing. In order to support the scalability of this approach, we currently cache travel options in order to minimize the number of requests. As a future extension of the approach, we will consider the possibility to run our own server.

We have also described the decision-making model and how the travelers choose between generated travel alternatives. We have included convenience factor in ASIMUT, which is a combination of walking distance, cycling distance and the number of changes in a travel alternative. The initial results from our case study show the feasibility of our approach in travel behavior modeling.

Future work consists of improving the decision-making model in different ways, such as including more factors (e.g. reliability), and investigating the best way to model the correlation between factors, e.g. how income influence the value of travel time. We will also validate the factors considered in the decision-making model and their influence on the travelers' decision-making. The convenience factor can be further developed to include more factors, such as availability of parking facilities. At this stage, social norms only concern environmental awareness, however, this will be further developed in future versions of ASIMUT. We will also investigate the possibility to consider factors like safety and health, for example avoiding walking through parks during night and choosing to walk or bike instead of car or public transport as a choice for healthier life style. The interaction between travelers will also be considered in the further work, e.g. in the form of car-pooling options. We have also planned to apply synthetic population methods in order to generate large populations of realistic agents. Moreover, we will further test ASIMUT through more complicated scenarios, where the effects of combinations of transport measures are investigated.

Future work also includes analyzing the performance of web services, focusing on how the approach scales with increasing number of simulated travelers. In addition, web services typically behave as black boxes, where the users have little (or no) insight in how the services actually operate. To be able to trust the output generated by a model that is based on externally provided web services, it is therefore critical to take special consideration to the output of the web services when validating the model. Future work also includes analyzing issues related to the use of services that cannot directly be validated.

Acknowledgements. We wish to thank K2– The Swedish National Knowledge Centre for Public Transport for partially funding this research, and the National ITS Postgraduate.

References

1. Ajzen, I.: The theory of planned behavior. Organ. Behav. Hum. Decis. Process. **50**(2), 179–211 (1991)
2. Alpizar, F., Carlsson, F.: Policy implications and analysis of the determinants of travel mode choice: an application of choice experiments to metropolitan Costa Rica. Environ. Dev. Econ. **8**(04), 603–619 (2003)
3. An, S., Cui, J.X., Li, L.Y.: Agent-based approach to model commuter behaviour's day-to-day dynamics under pre-trip information. IET Intel. Transport Syst. **5**(1), 70–79 (2011)
4. Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., Nagel, K., Axhausen, K.: MATSim-T: Architecture and simulation times. In: Multi-agent systems for traffic and transportation engineering, pp. 57–78 (2009)
5. De Witte, A., Hollevoet, J., Dobruszkes, F., Hubert, M., Macharis, C.: Linking modal choice to motility: a comprehensive review. Transp. Res. Part A: Policy Pract. **49**, 329–341 (2013)
6. Gilbert, N., Troitzsch, K.: Simulation for the social scientist. Open University Press (2005)
7. Grimaldo, F., Lozano, M., Barber, F., Guerra-Hernández, A.: Towards a model for urban mobility social simulation. Prog. AI **1**(2), 149–156 (2012)
8. Hajinasab, B., Davidsson, P., Persson, J.A.: A survey on the use of computational models for Ex ante analysis of urban transport policy instruments. Procedia Comput. Sci. **32**, 348–355 (2014)
9. Heinen, E., van Wee, B., Maat, K.: Commuting by bicycle: an overview of the literature. Transp. Rev. **30**(1), 59–96 (2010)

10. Hine, J., Scott, J.: Seamless, accessible travel: users' views of the public transport journey and interchange. Transp. Policy **7**(3), 217–226 (2000)
11. Horton, F.E.: Behavioral models in transportation planning. Transp. Eng. J. Am. Soc. Civ. Eng. **98**, 411–419 (1972)
12. Johansson, M.V., Heldt, T., Johansson, P.: The effects of attitudes and personality traits on mode choice. Transp. Res. Part A: Policy Pract. **40**(6), 507–525 (2006)
13. Lave, S.C.A.: A behavioral approach to modal split forecasting. Transp. Res. **3**(4), 463–480 (1969)
14. McDonnell, S., Zellner, M.: Exploring the effectiveness of bus rapid transit a prototype agent-based model of commuting behaviour. Transp. Policy **18**(6), 825–835 (2011)
15. Nitta, Y., Do, G.: Transportation mode-change model to special bus incorporating generalized time. In: 8th International Conference on Transport and Mobility for Elderly and Disabled People (1998)
16. Ramstedt, L.: Transport policy analysis using multi-agent-based simulation, Doctoral Dissertation Series No. 2008:09, Blekinge Institute of Technology, Sweden (2008)
17. Takama, T., Preston, J.: Forecasting the effects of road user charge by stochastic agent-based modelling. Transp. Res. Part A: Policy Pract. **42**, 738–749 (2008)
18. Teodorovic, D.: Transport modeling by multi-agent systems: a swarm intelligence approach. Transp. Planning Technol. **26**(4), 289–312 (2003)
19. Triantaphyllou, E.: Multi-criteria decision making methods a comparative study. Springer, New York (2000)
20. Walle, S.V., Steenberghen, T.: Space and time related determinants of public transport use in trip chains. Transp. Res. Part A: Policy Pract. **40**(2), 151–162 (2006)