Modelling Individual Preferences to Study and Predict Effects of Traffic Policies

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Abstract. Traffic can be viewed as a complex adaptive system in which systemic patterns arise as emergent phenomena. Global behaviour is a result of behavioural patterns of a large set of individual travellers. However, available traffic simulation models lack of concepts to comprehensibly capture preferences and personal objectives as determining factors of individual decisions. This limits predictive power of such simulation models when used to estimate the consequences of new traffic policies. Effects on individuals must not be ignored as these are the basic cause of how the system changes under interventions. In this paper, we present a simulation framework in which the self-interested individual and its decision-making is placed at the center of attention. We use semantic reasoning techniques to model individual decision-making on the basis of personal preferences that determine traffic relevant behaviour. As this initially makes the simulations more complex and opaque the simulation framework also comprises tools to inspect rule evaluation providing a necessary element of explainability. As proof of concept we discuss an example scenario and demonstrate how this type of modelling could help in evaluating the effects of new traffic policies on individual as well as global system behaviour.

Keywords: Traffic Simulation · Agent Modelling · Policy Assessment.

1 Introduction and Motivation

Infrastructure and mobility have a strong influence on societal progress and economic growth and can become obstacles in the process of developing an economy [5]. However, change and extension of infrastructure are extremely costly and may take long time periods before showing the desired effects. Moreover, infrastructure extension often requires massive interventions with strong ecological effects and environmental impact that is counterproductive to the good intentions. This may lead to open resistance and public opposition (e.g. [20]) slowing down infrastructure projects thus further prolonging the time before measures get effective. Beyond that, actual outcomes of measures are difficult to predict, e.g. it is well known that an extension of streets with excessive traffic often does not lead to an improved flow of vehicles but may attract more individuals than before, deteriorating the situation even more (see [15]). Therefore, innovative ideas for new mobility services (e.g. car/ride-sharing) that achieve more efficient and sustainable use of available resources can have a high leverage effect on mobility and the environment. Problems, such as frequent traffic jams and perpetual lack of parking space, are obvious indicators of a system in overload mode that requires a fundamental change in the concepts of everyday mobility. Private companies and public institutions are already working intensely on alternative strategies that exploit contemporary technological innovation [12], but need more elaborate tools for working out new mobility strategies. Before designing new mobility services cause and effect of the current traffic situation must be scrutinised in order to develop services that are accepted by the public and can eventually provide relief. Measures in complex public systems are threatened by rebound effects [4], e.g. car sharing services at first sight encourage people to abandon their private vehicles thus freeing up space in urban areas. However, if they apply to the wrong audiences effects end up worsening the inner-city traffic. It has been observed that car sharing services were accepted as an alternative to *public transport*, which in consequence has increased the number of people travelling in individual vehicles [13].

Computer-based simulations can be applied to analyse measures in complex traffic systems and to foresee such effects in advance. State of the art research has been investigating traffic as an emergent phenomenon, rather than a problem that can be modelled from a global perspective where system behaviour is modelled based on aggregated and abstract parameters (see [18] for a discussion). Emergent traffic models assume that global system behaviour results from the interactions between the personal behaviours and preferences of a large set of individuals [7]. Therefore, the application of agent models is particularly suitable for the simulation of traffic. However, available models have focused on simulating traffic as the primary subject, thus not prioritising individuals pursuing personal objectives, such as travelling to work or going to shop for grocery. In order to achieve these objectives, movement of individuals to a different location should merely be regarded as a necessary means. Consequently, road traffic itself should not be considered the sole focus when modelling traffic scenarios as individual traveller objectives are just as relevant. These objectives strongly depend on individual preferences. Hence, it is important to include these individual preferences in the process of modelling. At the same time, analysis of individual-based simulation models is difficult, because the results are based on many reciprocally influencing variables. A detailed modelling of individuals adds complexity, and therefore requires a methodical approach that achieves a higher degree of transparency through explainability.

In this paper, we create a simulation model that focuses on the individual in order to examine how new policies on mobility affect both individual and global system behaviour. For this purpose, we make use of semantic reasoning mechanisms which helps to improve analysis of individual-based simulation results. The following section provides an overview of related work and presents capabilities and scope of available modelling options. Following this, in Section 3 we reflect on modelling aspects that are relevant to modelling individuals and their self-interested decision behaviour. In Section 4, we describe modelling procedures and implement an example simulation using AGADE Traffic simulator. We then perform experimentation for a demonstration scenario and discuss results using the analysis instruments of our simulator. Finally, in Section 6 conclusions are drawn and possible options for future work are indicated.

2 Related Work

Multi-agent systems have become established tools for traffic simulation and there is a variety of simulators that range from general purpose platforms to systems specifically designed for specific traffic scenarios. In [18], we have studied and discussed a broad range of available simulation tools. However for this work, we will focus on three applications with functionality appropriate for modelling individual traffic participants.

1. *ITSUMO* is an open-source agent-based microscopic simulator that has been applied for the simulation of route choice scenarios. However, primary focus of the application is on traffic control [21, 2]. In ITSUMO, travel demand is modelled using global origin-destination matrices. Traffic actors such as drivers and traffic lights are modelled as autonomous software agents. Regarding the aspects of agent modelling, the ITSUMO approach is fairly detailed. ITSUMO distinguishes between prejourney planning and the en route (re)planning. En route replanning refers to route changes that occur during the journey. Route selection is based on established routing algorithms. The application supports both centralised and decentralised routing.
2. *MATISSE* is a large-scale agent-based simulation platform for Intelligent Transportation Systems (ITS) [25, 17]. The application focuses on the simulation of scenarios related to traffic safety. Agents are used for the representation of both vehicles as well as intersection controllers. MATISSE provides options for modelling inter-vehicle communication as well as communication with intersection controllers. Similar to the ITSUMO approach, MATISSE also supports centralised and decentralised routing for both, prejourney and en route (re)planning. However, MATISSE goes one step further in modelling the individual by including a parameter that imitates a virtual level of distraction for driver agents which causes unpredicted driving behaviour.
3. *SimMobility* is an agent-based multi-scale simulation platform that has been used to simulate the effects of different fleet sizes for on-demand autonomous mobility [1, 16]. It uses an activity-based approach to generate travel demand. Agents are used to represent all sorts of entities and communication in the system such as travellers, vehicles, phones, traffic lights, etc. SimMobility also supports prejourney and en route (re)planning. This not only refers to route choices but also to scheduling of activities that ultimately causes travel demand. Going one step further, SimMobility includes a mechanism that enables day-to-day agent learning. Key figures of the previous day are calculated to update agent knowledge for new decisions.

The applications covered demonstrate current features implemented in available traffic simulators. In the following section, we discuss the gaps and limitations as well as unused potential in the modelling of individuals.

3 Gaps and Limitations in the Modelling of Individuals

Modelling of individual traveller behaviour must consider several aspects (see Figure 1) and usually starts with the choice of travel destination which is closely related to modelling of travel demand. For this purpose, different options of *demand modelling* have been addressed in related work. Models that make use of activity based demand generation allow a more detailed modelling of the individuals in comparison to global origin-destination matrices (see [26, 24]). Agents make a series of decisions depending on the modelled scenario. *Cost-based decision-making* is an evident criterion for decisions. However, available models have mostly been limited to obvious metrics such as travel time or distance. In order to assess the effects of traffic policies on the individual, further aspects such as *individual preferences* related to traffic as well as the simulated domain are required to be included in the modelling. Simulation models also differ in the timing of decision-making. Models that consider both prejourney and en route decisions let travellers spontaneously deviate from their initial travel plans based on situational conditions. Continuous access to real-time information via smartphones has led to *dynamic decision behaviour*. However, only a few approaches even include simple en route replanning of the travel route. SimMobility is the only approach that has gone one step further and includes replanning of the personal activity schedule. Other types of decisions such as spontaneously changing modes in the event of a sudden weather change have not been considered. This is why more work on modelling this type of spontaneous decision behaviour is required. The final modelling aspect refers to agent capabilities to individually *learn* from past experiences. To date, there has been almost no implementation of this in available traffic models. SimMobility is the only exception that has shown any concepts towards individual agent learning in traffic simulation.

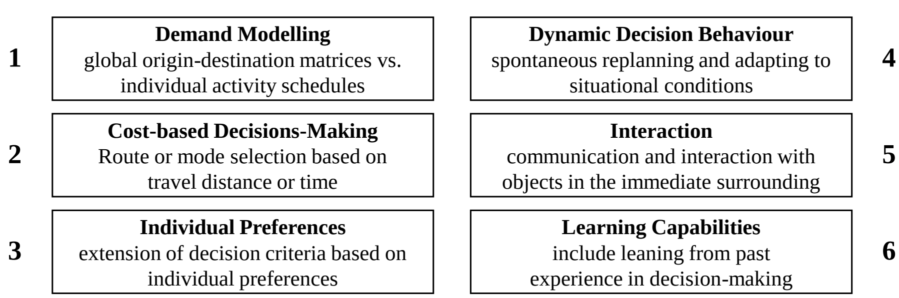

Fig. 1. Aspects of modelling individuals in traffic simulations.

In this work we focus on modelling individual preferences using semantic reasoning techniques to improve explainability of the effects of traffic policies on both the individual and global system behaviour.

4 Modelling Individuals with AGADE Traffic

AGADE Traffic is an agent-based traffic simulator that integrates a rule-based component for modelling knowledge and individual preferences. In particular, ontologies are used to express agent knowledge in a formalised machine readable form [10]. Using rules enables the application of reasoning algorithms to infer additional agent knowledge from explicitly formulated facts. In our own previous work, we have demonstrated effectiveness and efficiency of this approach for application in agent simulation [8]. Agents can be equipped with personal ontologies that contain knowledge on domains relevant for the simulated scenario. The following scenario simulates mobility of individuals that is associated with their grocery shopping. Agents are assigned a randomly generated list of food items selected from a set of products available in the supermarkets of the simulation. This set is categorised (e.g. fruit, vegetable, grains) and probability distributions over the categories can be defined and assigned to different agent types. Agents aim at purchasing items in their lists in the course of which they have to make decisions, e.g. choosing a supermarket together with a mode of travel. Available modes of travel are using private vehicles, cycling or walking. As of now we have simplified the scenario by excluding public transport due to current state of implementation. Moreover, modelled supermarkets not only differ in product supply, but also in which products they stock, price tendency, product quality, and sustainability. In consequence, individuals may purchase the items on their assigned shopping list from more than one supermarket, which causes additional travelling to other target locations.

An agent a has a set of attributes A. A is the disjoint union of descriptive attributes $\mathit{\Delta}$ and preference attributes $P = T \cup \mathit{\Phi}$ with traffic related preferences T and food related preferences $\mathit{\Phi}$. While ranges of attributes in $\mathit{\Delta}$ all are nominally scaled, attributes in P take values from a *Likert scale* of 1 to 5 (1=“not important“ and 5=“very important“). Selection of attributes relevant for modelling is based on behavioural surveys on mobility [6] and grocery shopping [3] (see Table 1). Agents are given values for attributes of $\mathit{\Delta}$, whereas attributes of P are derived using provided survey data. For this purpose, we modelled rules in the ontology with which for each preference a probability distribution over the Likert scale is derived. For this, descriptive attributes $\delta \in \mathit{\Delta}$ are used as input for the rules which output probabilities for each value on the Likert scale. For each agent a and each of its preferences τ let $p(\tau, \delta, l)$ be the probability that l will be assigned to τ for agent a depending on the values of attributes δ. As agent preference is influenced by all its attributes $\delta \in \mathit{\Delta}$ the values are aggregated over $\mathit{\Delta}$ into the weighted sum $p(\tau, l) = \sum_{\delta \in \mathit{\Delta}} \lambda_\delta \cdot p(\tau, \delta, l)$ with $\sum_{\delta \in \mathit{\Delta}} \lambda_\delta = 1$. In this sum we weigh all attributes as of equal importance: $\lambda_\delta = \frac{1}{|\mathit{\Delta}|}$.

Table 1. Attributes and preferences assigned at initialisation of an agent.

$\boldsymbol{\Delta}$	**T**	$\boldsymbol{\Phi}$
Age	Flexibility	Price Tendency
Education	Time	Product Quality
Gender	Reliability	Eco-Friendliness
Occupation	Privacy	Fair Trade
Marital Status	Safety	
	Monetary Costs	
	Environmental Impact	
	Convenience	

An example will illustrate this: Assume that Δ contains the two attributes *age* and *occupation* and P consists of a single preference $\tau =$*Environmental Impact*. Let a_1 with $\Delta_{a_1} = \{$*18-25, student*$\}$ and a_2 with $\Delta_{a_2} = \{$*46-55, factory worker*$\}$ be agents. Given their difference in descriptive attributes Δ, a_1 and a_2 probably differ in their personal preference on τ. Survey data for *age* =*18-25* indicates that higher values for agent a_1 have higher probabilities (see Table 2). For the second descriptive attribute *occupation* again probabilities for Likert scale values are concluded from the empirical distribution of data in the survey. The weighted sum of the values for *age* and *occupation* yields $p(\textit{Environmental Impact}, l)$ for each Likert scale value. Roulette wheel selection is used, based on the aggregated probabilities $p(\tau, l)$, to determine the value l which is then assigned to preference τ. Computation of the $p(\tau, \delta, l)$ uses rules in the ontology. By logging rule evaluation a detailed protocol of firing and non firing rules can be obtained. This log transparently explains how preferences of an individual were determined. This concludes initialisation of agent a.

During the simulation, agents undergo two phases. The first phase is referred to as *prejourney* planning. Preference values serve as input to utility functions which are used in the planning process for the *selection of supermarkets* as well as the *choice of travel mode*. A characteristic of this scenario is that decisions are mutually interdependent and have to happen simultaneously e.g. distant supermarkets can only be reached by car while choosing to walk will likely determine a nearby market. Thus, decision making is multi-criteria and not only based on traffic related aspects but also on individual preferences relevant for the selection and purchasing of food items. In order to purchase all items on its shopping list an agent has to visit supermarkets following its personal preferences. Therefore,

Table 2. Example inference of preference probabilities for agent a_1.

Probabilites/Likert Values l	**1**	**2**	**3**	**4**	**5**
$p(\textit{Environmental Impact}, \textit{age}, l)$	0.05	0.1	0.15	0.3	0.4
$p(\textit{Environmental Impact}, \textit{occupation}, l)$	0.1	0.1	0.2	0.3	0.3
p(*Environmental Impact*,l)	**0.075**	**0.1**	**0.175**	**0.3**	**0.35**

preferences as well as the degree to which these are satisfied is quantified in compound utility functions. The agent successively constructs a shopping journey consisting of legs from supermarket to supermarket (and from home to the first supermarket and back home from the last) with appropriate traffic modes. Supermarkets and traffic mode are chosen to maximise the utility of the agent. We first define a utility that reflects all traffic related preferences of an agent a. For a given attribute $\tau \in T$ (T the set of traffic related attributes) and a traffic mode $m \in M$ (M the set of available traffic modes), let $u(\tau, m)$ be the given utility of mode m with regard to a specific mode attribute τ and a_τ the preference value of τ for agent a. Spontaneous modal change en route accounts for extra effort and therefore involves costs which we model with a function $c : M \times M \rightarrow \mathbb{R}$ with $c(m, m')$ the associated cost for changing from mode m to mode m' with $c(m, m') = 0$ for $m = m'$. Note that we add an artificial mode m_{null} to represent the start of the food shopping journey and that $c(m_{null}, m) = 0$ for all $m \in M$. Based on this, the total traffic utility U_{TT} of traffic mode m for agent a is defined. Note that the value of this function also depends on the traffic mode m_c of the last leg.

$$U_{TT}(a, m, m_c) = \sum_{\tau \in T} u(\tau, m) \cdot a_\tau - c(m_c, m) \tag{1}$$

Supermarkets $s \in S$ (S the set of supermarkets) are assigned utilities $u(\phi, s)$ that rate their products with regard to $\phi \in \Phi$ (Φ the set of food related attributes) (see Table 1). Furthermore, a_ϕ is the value for preference ϕ of agent a. Based on this a shopping utility $U_\Phi(a, s)$ is determined:

$$U_\Phi(a, s) = \sum_{\phi \in \Phi} u(\phi, s) \cdot a_\phi \tag{2}$$

Besides personal utility we assess supermarkets by the degree to which the products they stock cover the items on the shopping list of an agent and by its vicinity to the current whereabouts of an agent. If the agent a has r_a open items on its list q_s of which are available in supermarket s the quotient $\frac{r_a}{q_s}$ quantifies the product coverage of s for a. Furthermore, for each agent a a randomly generated value e_a models aversion of a towards additional trips to other supermarkets based on probabilities provided by [22]. The *euclidean distance* $d(a, s)$ from the current position of a to the supermarket s is used as an estimate for the travel distance to s. For each agent values for U_{TT}, U_Φ and $d(a, s)$ are normalised with *min-max normalisation* so that they lie in [0,1]. As decisions on mode of travel and selection of supermarket are interdependent, we aggregate the traffic and food related utilities into a single utility function with which an agent determines which supermarket to go to next and how. Therefore, the leg $r = (m, s)$ to the next supermarket s is an element in $M \times S$ (with M travel modes and supermarkets S) that has a utility:

$$U(a, r, m_c) = (1 - d(a, s)) + U_{TT}(a, m, m_c) + U_\Phi(a, s) + \frac{r_a}{q_s} * e_a. \tag{3}$$

Algorithm 1 shows how an agent successively selects supermarkets and determines rides that are concatenated into a journey. We assume that the overall supply of all supermarkets covers all items on shopping lists and that items are abundantly available. Furthermore, no additional optimisation with respect to order is performed as we try to simulate natural behaviour of individuals. This concludes planning phase for agent a.

Algorithm 1: Algorithm to determine agent journey.

Input: agent a, location origin, set of supermarkets S, list of shopping items I_a
journey=emptylist;
while I_a *is not empty* **do**
  $r = (m, s) = \underset{r \in M \times S}{\text{argmax}}\, U(a, r)$;
  journey=journey+r;
  I_a=I_a\supply(s);
end
Result: journey

The following phase refers to agents travelling *en route*. As decisions about travel mode and target supermarkets primarily depend on preferences, which currently do not change en route, agent decisions from prejourney planning remain the same. However, agents are able to spontaneously change routes depending on present traffic load. Routing was implemented using the A* algorithm based on shortest time. Let W be a route with $w \in W$ being a continuous section of route W with same speed limit $v(w)$. Travel speed of an agent is defined $v(w, m) = min\{v(w), v(m)\}$ for $v(m)$ the maximum speed of travel mode m. Furthermore, $d(w)$ defines distance to be covered on w and $n(w)$ an indicator for present traffic load. Thus, overall travel time T is computed:

$$T(W, m) = \sum_{w \in W} \frac{d(w)}{v(w, m)} + n(w) \tag{4}$$

5 Proof-of-Concept

As an example, we look at a scenario situated in the German city of Wetzlar. According to data from the German census of 2011 [23], Wetzlar has circa 50,000 inhabitants distributed over 20 residential areas. For performance reasons, we assume that one person shops for one household and 20% of the household shop during the simulated time interval. We therefore created a population of 2130 agents which is distributed over the 20 residential areas, replicating the empirical distribution of residents. Google maps search produced 29 supermarkets. Furthermore, a consumer study [9] defines the most significant social groups in the German demographic from which we derived 12 agent types (see [19]). Agents in our population are assigned to one of these agent types respecting the distribution of these social groups in the areas under investigation. Agent types define values for the descriptive properties required for rule evaluations on preferences. Details of simulation data as well as source code of the simulation are available at GitHub.[3] Note that our current implementation uses stochastic elements only while computing preference values, thus keeping the subsequent decision processes deterministic. This simplifies analysis and proof of concept making comparison of simulations easier.

We performed two simulation runs with identical agent populations. In the second run the value for the traffic preference *Environmental Impact* changed, ceteris paribus, for 35% of the agents, meaning that 756 agents were affected, 42 of which changed their preference value from 1 to 5, 200 from 2 to 5, and 514 from 3 to 5. This models a change of attitude of 35% of the inhabitants to traffic and its environmental consequences. In the real-world, this experiment could be used to answer the research question "*How does awareness on environmentally friendly transportation affect traffic behaviour?*".

We now analyse effects that result from this change of attitude on the decisions *selection of supermarkets* and *mode choice*. Using the analysis instruments of our simulator on data that is logged during the simulations, calculated metrics and visualisations show that in total 300 agents, i.e. circa 40% of agents affected by change of attitude, have changed from their original mode of travel. Table 3 compares modal choices of both simulation runs. The number of agents travelling by car has decreased while the percentage of pedestrians and cyclist has increased as 33 agents have changed from travelling by car to cycling, 266 from car to walking, and a single agent from cycling to walking. We assume that policy makers prefer agents to choose green transportation modes such as *walking* or *cycling* to avoid emission of exhaust fumes. In the simulation, this is mirrored through key performance indicators on aggregated travelled distances. Environmental impact is measured by the indicators *global travel distance* which is the sum of the overall distances travelled by the set of all agents, and *combustion distance* that only considers modes of travel that produce exhaust gases (see Table 4). Hence, results indicate a favourable shift in modal choices. At this stage, policy makers need to evaluate whether implementation of this type of policy is worth the effort, considering that changes in modal choice in total affected circa 14% of the entire population.

In addition to this, 36 agents (4.8% of agents affected by change of attitude and 1.6% of the entire population) have changed their journey because of their selec-

Table 3. Comparison of Modal Choices.

Modal Choice	**Simulation 1**	**Simulation 2**	**Difference**
Car	77.18%	63.15%	-14.03%
Bike	1.69%	3.19%	+1.5%
Walking	21.13%	33.66%	+12.53%

[3] see https://github.com/kite-cloud/agade-traffic

Table 4. Evaluation Indicators.

KPI	Simulation 1	Simulation 2	Difference
Global Travel Distance [km]	9752.14	8771.92	-10.1%
Combustion Distance [km]	9009.25	7520.85	-16.5%
Avg. Traveller Satisfaction (Normalised)	0.882525	0.881825	-0.079%

tion of supermarkets. We assume policy makers to prefer agents to visit markets in their immediate neighborhood as this reduces overall traffic load. However, individual preferences may lead to selection of markets that are farther away. For example, some agents prefer to travel if products are more affordable at the target store than in their direct vicinity. Results show that 20 of these agents have in fact travelled a shorter distance but also that for the remainder travel distance has actually increased. Even though the number of agents reducing their travel distance is relatively equal to the number of agents that travelled longer distances, *global travel distance* as well as *global combustion distance* show a significant drop in the second simulation. This implies that agents reducing their travel distance have caused more impact and thus larger changes in comparison to changes caused by agents with increasing travel distance. Consequently, this is an improvement of global system behaviour with respect to the amount of traffic and pollution. In most simulation models assessment of policies ends with findings on global system behaviour due to the limited information about the individual. However, the detailed modelling of individuals enables further interpretation of results. For assessing interventions in a system by (individual) utility, we necessarily have to take a utilitarian perspective on utility [11]. Experienced utility has been associated with happiness measures [14]. We are aware that this relation between utility and happiness is debatable, but so far there is no consensus on this matter (see [11] for a discussion). Hence, we use experienced utility as an indicator for satisfaction of individuals. *Average traveller satisfaction* (see Table 4) has changed only to a minimal extent as a result of changes in surrounding social conditions. Negative effects on individuals are thus barely noticeable. Based on this, results have shown how change of attitude affects travel behaviour in this example scenario.

6 Conclusion and Future Work

As urban mobility is in constant transformation, there is a need for computer-based simulation tools to study and predict effects of new policies. However, available simulation models lack of concepts for capturing preferences and personal objectives of individuals. This makes evaluation of traffic policies difficult, as lack of information about individual behaviour limits analysis of its effects on global system behaviour. Especially, as it is well known that opposing impact of individuals can lead to counterproductive global effects. In this paper, we created a simulation model that focuses on modelling individual preferences. We demonstrated that modelling individual preferences using semantic technology can help achieve more transparent and meaningful agent decisions that are accessible to the user and increase explainability of simulation results. For future work, we will extend our models of personal preferences and utility to apply instruments of game theory and mechanism design. This will allow creation of richer simulation models for investigating effects of interventions into traffic systems as well as new mobility services on individual traffic.

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