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Abstract

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Transportation Policy Evaluation using Minority Games and Agent-Based Simulation

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***Abstract*—Traffic congestion threats the vitality of cities and the welfare of citizens. Transportation systems are using various technologies to allow users to adapt and make different decisions towards transportation modes. Modification and improvement of these systems affect the commuters perspective and social welfare. In this study, the effect of road flow equilibrium on commuters utilities with different types of transportation modes will be discussed. A simple network with two modes of transportation will be illustrated and three different cost policies were considered to test the efficiency of reinforcement learning in commuters daily trip decision-making based on time and mode. The artificial society of agents is simulated to analyze the results.**

***Index Terms*—Artificial Transportation Systems, Agent-based Simulation, Minority Games, Policy Evaluation**

I. Introduction

Traffic congestion is one reason of negative externalities, such as air pollution, time losses, noise, and decreasing safety. As more people are attracted into cities, future traffic congestion levels are not expected to decrease but rather will increase, and extending road capacity would not solve congestion problems. Policy measures in transportation planning aim at improving the system as a whole. Changes to the system that result in an unequal distribution of the overall welfare gain are, however, hard to implement in democratically organized societies [1]. Different categories of policies can be considered in urban road transportation: negative incentives [2], positive incentives or rewards [3], [4], and sharing economy [5], [6]. Traditional transport planning tools are not able to provide welfare analysis. In order to bridge this gap, multi-agent micro-simulations can be used. Large-scale multi-agent traffic simulations are capable of simulating the complete day-plans of several millions of individuals (agents) [7]. A realistic visualization of an agent-based traffic model allows to yield visually realistic reconstructions of modern or historical road traffic. Furthermore, the development of a complex interactive environment can help scientists to open up new horizons in transport modeling by the interactive combination of a traffic simulation (to change traffic conditions or to yield emergence resulting from road interactions) and by enhanced visual analysis [8]. The main goal of this study is to develop a model, based on the concept of minority games and reinforcement learning, to achieve equilibrium flow through public and private transportation and to investigate the effect of cost in on the process of selecting transportation modes. Minority game is applied to consider rewards, positive policy, for the winner whereas learning is a tool to enhance the user's perception of utility based on such rewards. To illustrate, an artificial society of commuters is considered and instantiated on simple network with two transportation modes: public (PT) and private (PR).

The remaining parts of this paper are organized as follows. In Section II we discuss the conceptual framework, which consists of definitions of user utility, minority game, and reinforcement learning algorithms. Illustration scenarios of the network and commuters, as well as the preliminary setup are explained in Section III. Experiments and results are shown in Section IV, and the related work is revisited in Section V. Conclusions on the hypothesis and on results are drawn in Section VI.

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II. DESCRIPTION OF THE CONCEPTUAL FRAMEWORK

In this section, both theoretical and methodological aspects are described. Here, we combine a macroscopic representation of the transportation domain with a microscopic resolution of the agents decision-making processes.

A. Network Design

The network is formally represented as graph $G(V, L)$, in which V is the set of nodes such as Origin, Destination, and middle nodes, and L is the set of roads (edges or links) between nodes. Each link $l_k \in L$ has some properties such as mode, length, and capacity. In addition, a volume-delay function (eq. 1 is used to describe the congestion effects, that is, how the reaching capacity of flow in a link affects the time and speed of a journey, as represented by the equation below [9]:

$$t_k = t_0 k * [1 + \alpha(X_k/C_k)^{\beta}] \quad (1)$$

Where t_0k is the free flow travel time, X_k is the number of vehicles, and C_k represents the capacity of the link k. In this equation, α and β are controlling parameters.

B. Commuters Society

Commuters, agents of the artificial society, have some attributes regarding travel preferences. These attributes can have many interpretations, such as time (desired arrival time, desired travel time, mode of transportation, mode flexibility), cost (public transportation fare, waiting time cost, car cost if they have), socioeconomic features (income), and so forth. Agents learn from experience and make decisions as for their daily plan based on their daily expectations and previous experiences. The iteration module generates the demand of the transportation modes and desired times. Daily trips are scheduled for a given period of the day, to which a set of origins and destinations are defined with the respective desired departure and arrival times to and from each node.

An utility-based approach is considered to evaluate travel experience and help agents make decisions. Total utility of commuter j is computed as the sum of individual contributions as follow:

$$U^j_{total} = \sum_{i=1}^{n} U^j_{perf,i} + \sum_{i=1}^{n} U^j_{time,i} + \sum_{i=1}^{n} U^j_{cost,i} \qquad (2)$$

where U_{total} is the total utility for a given plan; n is the number of activities, which equals the number of trips (the first and the last activities are counted as one); $U_{pref,i}$ is the utility perceived for performing activity i; $U_{time,i}$ is the (negative) utility perceived as time, such as travel time and waiting time for activity i; and $U_{cost,i}$ is the (usually negative) utility perceived for traveling during trip i.

a) Performance Utility: To measure the utility of selecting activity i, each mode of transportation has different variables. For public mode, comfort level and bus capacity are considered, whereas for private, pollution and comfort level are the variables accounted for.

b) Time Utility: The measurement of the travel time quantifies the commuters perception of time based on various components like waiting and in-vehicle travelling. Waiting time indicates the service frequency of public transportation. In-vehicle travelling time is the effective time taken to travel from a given origin to a given destination.

c) Monetary Cost Utility: Monetary cost can be defined as fare cost of public transportation, cost of fuel, tolls (if those exist), car insurance, tax and car maintenance, for instance. This kind of cost will be measured based on the income of commuters.

C. Minority Games

A common assumption is that drivers choose the route between an origin-destination (OD) pair according to the principle of minimum experienced travel time [10]. As there are other drivers on the routes, the travel time between an OD pair depends on the choices of those other drivers who also aim to minimise their travel time. When all drivers succeed in choosing the optimal route that minimises their travel times, this is referred to as Equilibrium or User Equilibrium.

Challet and Zhangs Minority Game (MG) model [11] is one such approach in which coordination among the agents occurs through self-organisation with minimal information and without communication between agents. Route and mode choice can be seen as a problem of self-organisation, and thus iteration game agents can reach equilibrium. Therefore, the MG might be well suited for solving this problem.

The approach consists of a set of commuters, without the possibility of communication between agents who have to organise themselves while they are in a competition for a limited resource (road, bus-seat, etc.), and there is no solution deductible a priori. Here, every commuter has to choose a given transportation mode, using a predictor of the next attendance. It is given that the agents try to avoid congested situations; however, since there is no single predictor that can work for everybody at the same time, there is no deductively rational solution.

This kind of approach was originally developed as a model for financial markets, although it has been applied to different applications such as public transportation [12], route choice [13], road user charging scheme [14], among many others.

D. Reinforcement Learning

Reinforcement learning (RL) is a class of machine learning technique concerned with how agents ought to take actions in an environment so as to maximise cumulative reward. Roth and Erev [15] developed an algorithm to model how humans perform in competitive games against multiple strategic players. The algorithm specifies initial propensities q_0 for each of N actions and based on reward r_k for action a_k the propensities at time $t+1$ are defined as:

$$q_j(t+1) = (1-\phi)q_j(t) + E_j(\epsilon, N, k, t) \qquad (3)$$

$$E_j(\epsilon, N, k, t) = \begin{cases} r_k(t)(1-\epsilon) & \text{if } j = k \\ r_k(t)(\epsilon/N-1) & \text{otherwise} \end{cases} \qquad (4)$$

Where ϕ is a parameter that represents the recency of forgetting, whereas ”” is an exploration parameter. The probability of choosing action j at time t is:

$$P_j(t) = q_j(t) / \sum_{n=1}^{N} [q_n(t)] \qquad (5)$$

III. ILLUSTRATIVE SCENARIO

In the simulation phase, the perspective of the conceptual framework was considered in a simple scenario where commuters make decision over transportation mode and departure time during the morning high-demand peak hour. The simulation model was implemented in the NetLogo agent-based simulation environment [16].

A. Network and Commuters

In this study, two different links of two modes (PT or PR) encompass two middle nodes each. As shown in Figure 1 and for the sake of simplify, the upper link is for private and the other one is for public transportation where each road is composed of one-way links.

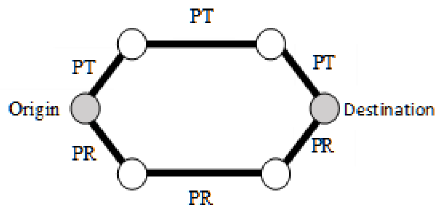

Fig. 1. A bi-modal transportation network

Commuters, as a type of agents, are defined by a number of state variables which are: i) desired departure and arrival times; ii) experienced travel time; iii) the uncertainty they experienced during the trip with a given transportation mode; iv) a set of preferences about the transportation mode; v) the perceived comfort as personal satisfaction for the mode choice; and vi) a daily income variable. While the agent experience its travel activities, the costs associated with the different transportation modes, the perceived satisfaction of travelling (expressed in terms of travel times and comfort) and rewards earned by winners will have a certain impact on its mode and time choices.

Commuters can choose between travelling by PT or PR modes based on the own-car value. The decision-making process of each agent is assumed to maximise the utility and flow equilibrium on roads. They perceive current traffic condition as well as previous experience and use this information in making other decisions.

With regard to the different utilities, the total utility of public and private modes can be measured as follow (we omit the index i indicating the activity):

$$U_{pr}^{total} = \sum_{j=1}^{n} U_{pr}^{j} \tag{6}$$

$$\begin{aligned} U_{pr}^{j} &= \alpha_{late}(t_{tt,exp}^{j} - t_{tt}^{j}) \\ &\quad - (\beta_{PR} cost_{PR}/income_{j}) \\ &\quad - \alpha_{pollution} t_{tt}^{j} pollution \\ &\quad + \alpha_{com_{PR}} t_{tt,exp}^{j}/t_{tt}^{j} \end{aligned} \tag{7}$$

$$U_{pt}^{total} = \sum_{j=1}^{n} U_{pt}^{j} \tag{8}$$

$$\begin{aligned} U_{pt}^{j} &= \alpha_{late}(t_{tt,exp}^{j} - t_{tt}^{j}) \\ &\quad - (\beta_{PT} cost_{PT}/income_{j}) \\ &\quad + \alpha_{com_{PT}} t_{wt,exp}^{j}/t_{wt}^{j} \\ &\quad + \alpha_{cap} t_{tt}^{j} capacity_{exp}^{j}/bus_{capacity} \end{aligned} \tag{9}$$

where t_{tt}^{j} and $t_{tt,exp}^{j}$ are total travel time and expected total travel time of agent j, $cost_{PR}$ is the monetary cost of private transportation (fuel, car maintenance, etc.), $cost_{PT}$ is the fare of public transportation, $income_j$ is the agents income per day, *pollution* is the amount of pollution produced by private vehicles, $capacity_{exp}^{j}$ and $bus_{capacity}$ are expected capacity of bus and total capacity of each bus respectively, $t_{wt,exp}^{j}$ is the expected waiting time and t_{wt}^{j} is the waiting time by agent j. α_{late}, β_{PT}, β_{PR}, $\alpha_{pollution}$, $\alpha_{com_{PR}}$, $\alpha_{com_{PT}}$, and α_{cap} are considered as marginal utilities or preferences for different components.

At the end of the journey each commuter memorises the experienced travel time, costs, crowding level (for PT mode users only), as well as emissions. These variables will be used to calculate the following days utility. After that each agent evaluates its own experience, comparing the expected utility to the effective utility. Based on the minority game concept, we considered the number of commuters on each road and type of transportation, and according to the Roth-Erev learning model, reward was assigned to winner who is in minority number and follows the criteria below:

- Their obtained utility $U_{effective}$ is greater than the utility prediction $U_{expected}$ as below:
$$U_{effective} > \alpha U_{expected}$$
where α is the marginal preference.
- The obtained utility of agent is higher than the mean utility in whole network :
$$U_{effective} > U_N$$
where $U_N = 1/N \sum_{j=1}^{N} U_{effective}^{j}$

Based on the reward, the effective utility they perceived in their daily trips, car-ownership and mode-flexibility, each commuter decides whether to opt for a new mode and time.

B. Cost Policy

In different research, the effect of cost was studied and different policies were proposed. In this paper, three different cost policies were defined, the cost of public transport is constant, and the cost of private transport will be changed as follows:

1) *Private cost is triple of public fare (Policy 1)*;
2) *Double of public fare is considered as private cost (Policy 2)*;
3) *The same cost for both mode of transportation (Policy 3)*;

Based on these policies, the simulation will be performed allowing for results to be collected and analysed.

C. Initial Setup

The capacity for all links of the network was considered 150 vehicles and max capacity for each bus was 70 passengers. A population consisting of 201 commuters was created, odd number to coordinate with minority game, and they iterated their daily trips in 60 days. They were characterised by the number of attributes such as departure and arrival times, mode, daily income, car-ownership and flexibility. Car-ownership is a Boolean variable and indicates whether the agent is a private or a public transportation user. Flexibility reflects the willingness of a private mode user to change its mode. See Table I for reference.

All plans of agents were performed in rush hours of the day from 6:30 am to 10:30 am, with a normal distribution to simulate peak times. It was observed a high demand in peak duration between 8- 9:30 am, on both roads. The range of income was 20 to 70 Euro per day. The routes between nodes Origin and Destination had both a length of 19 km.

The free-flow travel time from node Origin to Destination was approximately 25 minutes in the PR mode, whereas for the public transportation it was around 35 minutes plus the waiting time at the bus stop and walking time. The bus frequency service was 10 minutes before the rush hour and 5 minutes during the rush hour.

TABLE I
DEFAULT VALUE OF NETWORK AND LEARNING PARAMETERS

Variable	Value
Number of commuters	N=201
Capacity of links	L=150
Capacity of bus	B=70
Time	6:30am to 10:30am
Range of income	20 to 70 €per day
Simulation period	116 days
Recency (ϕ)	0.3
Exploration (ϵ)	0.6

IV. EXPERIMENTS AND RESULTS

We performed 60 iterations of the model, in which the Roth-Erev learning approach was used to establish the commuter equilibrium between both roads along the departure time interval. During simulation steps, we monitored agents expected and effective utilities, average travel times of public and private transportation, average total travel times, number of commuters on each mode and differences between averages of total travel time in public and private transportation.

Propensity of commuters to select public and private modes were set following a normally random distribution and updated based on recency and exploration learning parameters. Earned scores and two propensities were observed during all days.

Total times of daily trips for both mode of transportation selected by the agents were measured and the differences between these two times for all day long were calculated. In Figure 2, the result is shown for the simulation period. This fluctuation was related to different factors such as traffic on road, departure time and waiting time for public transportation on each day. However, on the final days, the difference time between public and private transportation was less than 10 minutes by reaching equilibrium flow on transportation modes which seemed to be stable.

Based on rewards and decision-making of departure time and transportation modes, commuters utilities were changed daily. Figure 3 represents daily changes in effective utilities

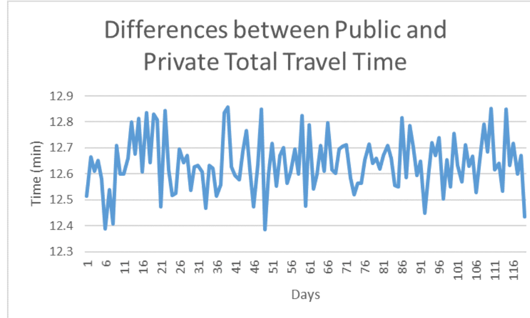

Fig. 2. Differences between Public and Private Total Travel Time

perceived by each of the commuters within the whole period. In this chart, it is shown that both public and private utilities were increased with day-to-day variations.

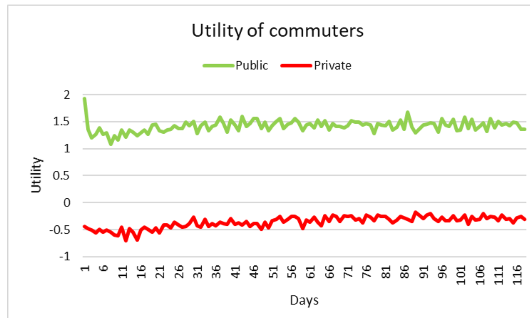

Fig. 3. Utility of commuters in both transportation

The number of commuters on different modes, effective utility, average time of public and private modes, and average total time which were observed on the last day along with values for some parameters are described in Table II. The values there rendered show that the average total travel times of each mode were roughly similar to the average total travel time of both modes, as well as that effective utilities of commuters had a bit difference from the ones they had expected (all margins were consider as 0.1 except $\alpha_{com_{PR}}$ = 0.65)

TABLE II
DEFAULT VALUE OF RUN TIME PARAMETERS

Variable	**Value**
No. of commuters on PT	106
No. of commuters on PT	95
Average total time on PT	34.7 min
Average total time on PT	22.26 min
Average total time of both mode	28.82 min
Average effective utility on PT	1.35
Average effective utility on PR	-0.38
Average expected utility on PR	-0.74
Cost of PT	3 Euros per Day
Cost of PR	8 Euros per Day

To compare the effect of cost on commuter's mode decision, three different categories of cost were defined, whose impact on the system performance was simulated and analysed. The cost categories are shown in Table III.

TABLE III
COST CATEGORY

Type	Cost Value of PT (Euro/Day)	Cost Value of PR (Euro/Day)
Cat. 1	3	8
Cat. 2	3	6
Cat. 3	3	3

Figure 4 shows that cost of transportation can change the number of commuters on different modes, as it is expected, and the same costs of public and private transportation result the closer number of commuters on each road. Increasing the cost of private transportation also increases the number of commuters on public transportation.

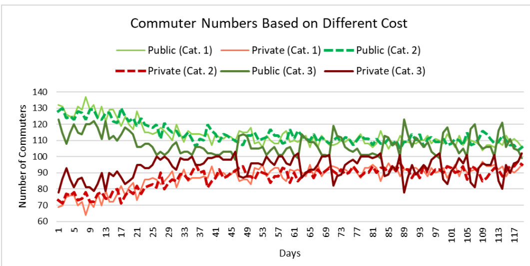

Fig. 4. Number of Commuters with different Category of Cost

Total time of both modes in each category was monitored and depicted in Figure 5. The highest difference in cost resulted in lower total time differences. However, in consequence of the same price of public and private transportation, total travel time in both modes is better than a smoother cost difference.

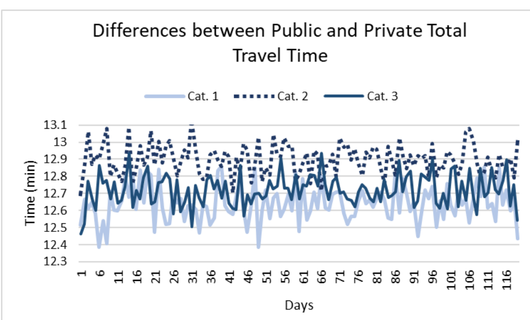

Fig. 5. Differences between Public and Private Total Travel Time in different Category

Through decreasing cost of private transportation, the utility of commuters will increase, even though the utilities of commuters on public transportation was approximately the same. The fluctuation of utilities is shown in Figure 6.

V. RELATED WORK

Kokkinogenis et al. discussed on a social-oriented modelling and simulation framework for Artificial Transportation Systems, which accounts for different social dimensions of the system in the assessment and application of policy procedures. They illustrated how a social agent-based model can be a useful tool to test the appropriateness and efficiency of transportation policies [17]. Nallur et al. introduced the mechanism of algorithm diversity for nudging system to reach distributive justice in a decentralised manner. They use minority game as an exemplar of an artificial transportation network and their result showed how algorithm diversity leads to a fair reward distribution [18]. Klein et al. developed a multi-agent simulation model for analysing daily evolution of traffic on roads, in which the behaviour of agents was reinforced by their previous experiences. They considered various network designs, information recommendations, and incentive mechanisms, and evaluated their models based on efficiency, stability, and equity criteria. Their results suggest that punishments or rewards were useful incentives [5]. In [19] is detailed an agent-based demand model following the beliefs-desires-intentions (BDI) architecture, emphasising on decision-making processes such as departure time, route selection, and itinerary deviation. The model was then implemented and tested elsewhere [20].

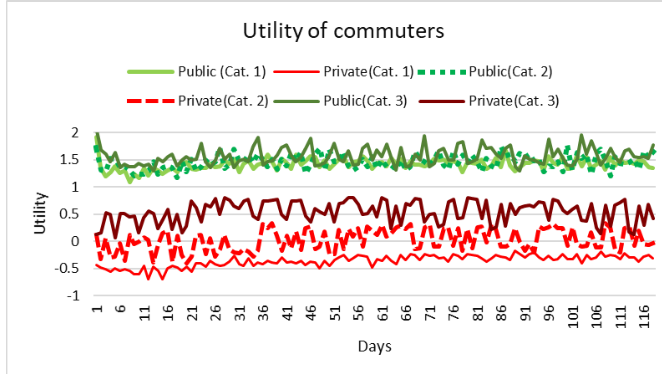

Fig. 6. Utility with different Category of Price

The authors in [21] underline the potential of agent-based models based on their bottom-up approach with signicant degree of disaggregation, intelligence, autonomy, and ability to capture interactions among individuals. Travel demand emerges from the interactions of agents in the transportation system. The work in [22] combine the four-step model with an agent-based framework to model such a demand in multi-modal transportation networks. In [23], an agent-based model is used to analyse price competition, capacity choice, and willingness to pay for different services on congested networks. Grether and colleagues [1] show how multi-agent simulation can be used in road pricing policy evaluation adding an individual income attribute to each agent so that personalised utilities are considered. In [24], a toll-based policy for air pollution reduction is evaluated, and the long-term user reactions are discussed. [25] proposes an agent-based model that considers individual characteristics and collective group behaviours in the evaluation of bus service performance from the perspective of passengers. In [26], authors describe an articial urban transit system as an instance of artificial transportation systems (ATS) for public transport. Authors present their model as a set of interactions of different types of agents for simulating transport operations and planning. A similar approach for modelling ATS is proposed in [27]. The A qualitative evaluation of several traffic simulation frameworks is presented in [28], with respect to their ability to model various aspects of modern ATS.

VI. Conclusions

In this paper, we have proposed the framework for evaluating the effect of reinforcement learning and minority games on the equilibrium of traffic flow on road networks. We suggested to apply agent-based modelling and simulation as a platform to implement our framework. To illustrate such an approach, a simple network consisting of two different modes of transport (PT and PR) was considered, and a population of commuters with memory of previous travel experiences were generated. They performed their daily plan in morning high-demand hours and their activities iterated for sixty days. Their experiences, expected and effective utilities, expected and effective travel times and rewards were observed and analysed.

Regarding the results, commuters learned to predict total travel time in both modes, and their exceptions were similar to obtained total travel time on each mode. By balancing the number of commuters on each type of transportation, they gained higher utilities rather than on the first days. From the illustrative example, the hypothesis of the study, which was to use reinforcement learning and minority game to reach equilibrium flow, was reached and it is concluded that equilibrium flow can follow higher utilities and more precise time prediction of daily trips.

As for future work, we will consider a realistic large-scale network and demand, different types of incentives and roads with a wider combination of transportation modes so as to better study and analyse commuter behaviour, as well as the performance of the transportation system as a whole. With such improvements, we are confident that our framework can be proper and accurate to enhance commuters experience and also improve the performance of the road transportation system.

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