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Agent-based congestion pricing and transport routing with heterogeneous values of travel time savings

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Abstract

An existing agent-based simulation framework and congestion pricing methodology is extended towards a consistent consideration of non-linear, user- and trip-specific values of travel time savings (VTTS). The heterogeneous VTTS are inherent to the model and result from each agent's individual time pressure. An innovative approach is presented which accounts for the non-linear, user- and trip-specific VTTS (i) when converting external delays into congestion tolls and (ii) when generating new transport routes. The innovative pricing and routing methodology is applied to a real-world case study of the Greater Berlin area, Germany. The proposed methodology performs better than assuming a constant value of travel time savings or randomizing the routing relevant costs. The improved consistency of setting congestion toll levels, identifying transport routes and evaluating travel plans is found to result in a higher system welfare.

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Keywords: Agent-based Simulation, Heterogeneous Values of Travel Time Saving (VTTS), Congestion Pricing, Routing, Tolling

1. Introduction

In this study, an existing agent-based simulation framework and congestion pricing methodology is extended towards a consistent consideration of heterogeneous VTTS (values of travel time savings). The applied congestion pricing methodology makes use of an iterative market mechanism: First, user-specific and dynamic tolls are computed based on the delay imposed on other travelers. Second, the transport demand is allowed change its travel behavior to avoid these toll payments. In this study, the transport users (agents) are enabled to generate new routes based on the generalized travel cost, taking into account both the travel time and the congestion tolls. Third, each agent's daily behavior, including the transport route, is evaluated to obtain the agent's affinity to repeat that behavior, i.e. to use the same transport route in the next iterations. Hence, the VTTS is required (i) to compute congestion tolls, (ii) to identify routes which minimize (generalized) costs and (iii) to evaluate transport routes.

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The approach uses the transport simulation framework MATSim.[1] The VTTS which is used for evaluation (iii) is inherent to the model and results from each agent's individual schedule delay costs and time pressure. However, the VTTS which is used for tolling (i) and routing (ii), normally is assumed to be constant and equal for all agents.

As an issue of increasing interest, heterogenous VTTS have been addressed in several studies. Empirical studies reveal that the VTTS depends on certain trip-specific attributes, such as the transport mode[6], trip distance[7] or traffic state[5]. Additionally the VTTS may vary with person-specific characteristics, such as the income[10].

Several studies address the importance of schedule delay costs. Based on Vickrey's bottleneck model[17], dynamic approaches allow for a consideration of the activity at the trip destination, to compute schedule delay costs, and to consider dynamic tolls. In several studies, the bottleneck model is extended to account for heterogenous transport users[18,3,15]. The level of heterogeneity is found to affect the increase in system welfare. For a larger heterogeneity in the user preferences, pricing will result in more diverse choices which reinforces the increase in system welfare[3,16].

In the present study, an innovative approach is presented which accounts for true VTTS when (i) converting external delays into congestion tolls (Sec. 3) and (ii) when generating new transport routes (Sec. 4). The advantage of an iterative simulation-based approach is that complex VTTS can be taken into account. In this study, the VTTS is considered to be non-linear, user- and trip-specific. Moreover, the VTTS is subject to destination-related constraints. As an illustrative example, the innovative pricing and routing methodology is applied to a real-world case study of the Greater Berlin Area, Germany.

2. Transport Simulation Framework MATSim

In MATSim, each transport user is simulated as an individual agent. The agents' initial behavior has to be provided in the form of travel plans describing the daily activity patterns (e.g. home-work-shopping-home), the activity end times and information about the trips between these activities. The initial travel behavior is then modified applying an evolutionary iterative approach. In each iteration, (1) the travel plans are executed (Traffic flow simulation), (2) scored (Evaluation) and (3) modified (Learning).

1. **Traffic Flow Simulation** All travel plans are simultaneously executed and the transport users interact in the simulated physical environment. Traffic congestion and vehicle movements are simulated applying a queue model[4]. Each road segment (link) is modeled as a *First In First Out* queue with certain attributes, i.e. a free speed travel time, a flow capacity c_{flow}, and a storage capacity (causing spill-back). The aggregation of individual vehicle movements to traffic flows is considered to be consistent with the fundamental diagram[1].
2. **Evaluation** For each agent, the executed plan is scored based on agent-specific predefined behavioral parameters and scoring functions. A plan's score is typically consists of two parts: (i) the generalized travel cost or trip-related disutility (e.g. travel time, toll payments) and (ii) the utility gained from performing activities. In the existing simulation framework, (ii), i.e. the utility person p gains from performing activity a, is computed as
$$V_{p,a} = \beta^{perf} \cdot t_a^{typ} \cdot \ln\left(t_{p,a}^{perf} \big/ t_{0,a}\right) , \tag{1}$$
where $t_{p,a}^{perf}$ is the time person p performs activity a, t_a^{typ} is an activity's "typical" duration, β^{perf} is the marginal utility of performing an activity at its typical duration, and $t_{0,a}$ is a scale parameter which is not relevant as long as activities cannot be dropped from the daily travel plans. Further activity-related constraints can easily be incorporated, for example activity opening and closing times[2].
3. **Learning** For the majority of agents, the plan to be executed in the next iteration is chosen based on a multinomial logit model. Some agents generate new travel plans by cloning an existing plan and changing parts of the cloned plan, for example the transport route (sequence of links between one activity location and another one).

A repetition of these steps enables the agents to improve and obtain plausible travel plans, and the simulation results stabilize[14]. Assuming that the set of each agent's travel plans represents a valid choice set, the system state is an approximation of the stochastic user equilibrium[11].

[1] Multi-Agent Transport Simulation, see www.matsim.org

3. Congestion pricing

Existing approach. The computation of external congestion costs builds on the queue model described in Sec. 2. Each time a transport user is delayed, i.e. cannot move from one link to the next one, the causing agent is identified and charged. The delay imposed on other travelers is converted into monetary units. Thereby, the affected agent p's cost of being delayed at activity a is composed of two parts:

$$c_{p,a} = c_{p,a}^{trip} + c_{p,a}^{perf} , \tag{2}$$

where $c_{p,a}^{trip}$ is the increase in generalized cost related to the trip to activity a, and $c_{p,a}^{perf}$ is the decrease in utility from having less time available to perform activity a. The trip related delay costs are

$$c_{p,a}^{trip} = d_{p,a} \cdot \left(-\beta^{travel} \middle/ \beta^{money}\right) , \tag{3}$$

where $d_{p,a}$ is the total delay of person p at activity a, β^{travel} is the normally negative marginal utility of traveling and β^{money} is the marginal utility of money. β^{travel} and β^{money} in this study are constant for all car users and trips.

For the conversion of activity related delays into monetary units, the existing approach[9,8] makes the approximation that users perform activities for their predefined typical durations ($t_{p,a}^{perf} = t_a^{typ}$), which means that the marginal utility is approximated as

$$\frac{\partial}{\partial t_{p,a}^{perf}} V_{p,a} \approx \left. \frac{\partial}{\partial t_{p,a}^{perf}} V_{p,a} \right|_{t_{p,a}^{perf} = t_a^{typ}} = \beta^{perf} \cdot t_a^{typ} \cdot \left. \frac{1}{t_{p,a}^{perf}} \right|_{t_{p,a}^{perf} = t_a^{typ}} = \beta^{perf} . \tag{4}$$

However, depending on the number and types of activities in a daily plan, transport users have more or less time available to perform their activities. Hence, they are differently pressed for time, thus being delayed in traffic affects different transport users differently. Furthermore, activities have certain constraints such as opening and closing times. If the activity is still closed, being delayed may for example result in zero activity delay cost. In the existing approach, all this is ignored, and the above leads to

$$c_{p,a}^{perf} \approx d_{p,a} \cdot \left(\beta^{perf} \middle/ \beta^{money}\right) . \tag{5}$$

In total, the marginal costs of being delayed are, for tolling purposes, assumed as

$$VTTS^{delay} = \partial c_{p,a} \middle/ \partial d_{p,a} \approx \left(-\beta^{travel} + \beta^{perf}\right) \middle/ \beta^{money} , \tag{6}$$

where $VTTS^{delay}$ is the value of travel time saving which is used to convert delays into congestion tolls. Consequently, congestion tolls payed by the causing agent may not correctly reflect the affected agent's true delay cost.

Extension 1: Non-linear and user-specific conversion of delays into tolls. In this extension, delays are now converted into monetary payments accounting for the affected agent's trip-specific VTTS making the tolls reflect true external congestion costs. Total activity delay costs are computed as

$$c_{p,a}^{perf} = \left[V_{p,a}\left(t_{p,a}^{perf} + d_{p,a}\right) - V_{p,a}\left(t_{p,a}^{perf}\right)\right] \middle/ \beta^{money} . \tag{7}$$

The costs for being delayed by one time unit are computed as $c_{p,a}^{perf} \big/ d_{p,a}$. The person and trip specific VTTS is thus approximated as

$$VTTS_{p,a}^{delay} \approx \partial c_{p,a}^{trip} \big/ \partial d_{p,a} + c_{p,a}^{perf} \big/ d_{p,a} = -\beta^{travel} \big/ \beta^{money} + \left[V_{q,a}\left(t_{q,a}^{perf} + d_{p,a}\right) - V_{q,a}\left(t_{p,a}^{perf}\right)\right] \Big/ \left(\beta^{money} \cdot d_{p,a}\right) . \tag{8}$$

The amount payed by each causing agent then is $m_{q,p,a} = d_{q,p,a} \cdot VTTS_{p,a}^{delay}$, where $m_{q,p,a}$ is the monetary toll payed by the causing agent q for delaying person p during the trip to activity a; and $d_{q,p,a}$ is the delay which the causing agent q imposes on person p during the trip to activity a.

4. Time- and cost-sensitive routing

Existing approach. The existing simulation framework generates new transport routes assuming a constant VTTS for all trips. The routing relevant costs are assumed as

$$g_{q,a} = VTTS^{travel} \cdot t_{q,a} + m_{q,a} = g_{q,a}^{trip} + g_{q,a}^{perf} , \tag{9}$$

where $g_{q,a}$ is the total routing relevant cost of person q traveling to activity a; $VTTS^{travel}$ is the VTTS which is used to convert travel time into travel cost; $t_{q,a}$ is the total travel time of person q traveling to activity a; $m_{q,a}$ is the total amount payed by person q during the trip to activity a; $g_{q,a}^{trip}$ is the generalized cost related to the trip to activity a; and $g_{q,a}^{perf}$ is the opportunity cost of time (that could have been spent performing activity a). The trip related travel costs and the opportunity cost of time are

$$g_{q,a}^{trip} = t_{q,a} \cdot \left(-\beta^{travel} \middle/ \beta^{money}\right) + m_{q,a} \qquad \text{and} \qquad g_{q,a}^{perf} \approx t_{q,a} \cdot \left(\beta^{perf} \middle/ \beta^{money}\right) , \tag{10}$$

where the same approximation as in Eq. (5) was made that activities are assessed at their typical durations. Hence, in the existing routing approach, the VTTS for all agents and car trips is assumed as

$$VTTS^{travel} = \partial g_{q,a} \big/ \partial t_{q,a} \approx \left(-\beta^{travel} + \beta^{perf}\right) \big/ \beta^{money}. \tag{11}$$

However, as described in Sec. 3, the utility gained from performing an activity depends on the transport users' individual time pressure. In Eq. 10, this utility is assumed to be equal to β^{perf}. Hence, the routing costs, and in particular the opportunity costs of time, neglect the non-linear, user- and trip-specific VTTS which is given by Eq. 1 (see Sec. 2, Evaluation). Thus, the existing routing approach may not correctly account for the agents' trip-specific weighting of travel time and monetary costs.

Extension 2: Non-linear and user-specific routing. In this extension, the opportunity costs of time are computed as

$$g_{q,a}^{perf} \approx t_{q,a} \cdot \left[V_{q,a}\left(t_{q,a}^{perf} + \epsilon\right) - V_{q,a}\left(t_{p,a}^{perf}\right)\right] \big/ \beta^{money}, \tag{12}$$

where $V_{q,a}(\cdot)$ is the utility person q gains from performing activity a (see Sec. 2, Evaluation, Eq. 1); and ϵ is one time unit. In this study, ϵ is set to 1 sec which implies that $t_{q,a}$ and $t_{q,a}^{perf}$ is given in sec. Hence, the opportunity costs of time are linearized accounting for the non-linearity in Eq. 1. The resulting user- and trip-specific VTTS is

$$VTTS_{q,a}^{travel} = \partial g_{q,a}^{trip} \big/ \partial t_{q,a} + \partial g_{q,a}^{perf} \big/ \partial t_{q,a} \approx \left[-\beta^{travel} + V_{q,a}\left(t_{q,a}^{perf} + \epsilon\right) - V_{q,a}\left(t_{p,a}^{perf}\right)\right] \big/ \beta^{money} , \tag{13}$$

where $VTTS_{q,a}^{travel}$ is the value of travel time savings of person q traveling to activity a.

5. Real world case study and simulation experiments

The proposed routing and congestion pricing approach is applied to the real-world MATSim model of the Berlin metropolitan area[13]. The road network contains all major and minor roads of the Greater Berlin area. The demand side is modeled as survey-based "population-representative" agents and "non-population representative" agents to include for example freight traffic. The transport demand was calibrated accounting for mode shares, travel times and travel distances. As initial plans the executed plans of the relaxed travel demand are taken from Neumann et al. (2014)[13]. The population size is reduced to a 10% sample.

The following simulation experiments are carried out: In experiment 0, the existing pricing and routing methodology is applied in which the VTTS is considered to be equal for all car trips and road users. Experiment 1 and 2 investigate both of the above described methodological extensions separately: Experiment 1 applies the extended pricing approach (extension 1) and the existing routing approach. Experiment 2 applies the extended routing approach (extension 2) and the existing pricing approach. Finally, simulation experiment 3 combines extension 1 and 2. The pricing experiments are compared with a simulation run without pricing which is considered as the base case. The adaptation of demand to supply is repeated for 100 iterations. During the first 80 iterations, choice sets are generated: In every iteration, 10% of the agents are rerouted based on link- and time-specific costs in the previous iteration. Thereby, the number of travel alternatives per agent is limited to 4 plans, thus poor plans are replaced by better plans. During the final 20 iterations, choice sets are fixed and plans are selected based on a multinomial logit model.

Table 1: Comparison of the pricing experiments with the base case (no pricing)

Changes in ...	Experiment 0	Experiment 1	Experiment 2	Experiment 3
travel time (car mode)	−13,800 hours	−14,422 hours	−15,563 hours	−17,012 hours
travel related user benefits (including toll payments)	−752,998 EUR	−1,179,869 EUR	−676,355 EUR	−1,033,819 EUR
toll revenues	+1,107,293 EUR	+1,559,639 EUR	+1,073,998 EUR	+1,484,971 EUR
system welfare	+354,295 EUR	+379,770 EUR	+397,643 EUR	+451,152 EUR

6. Results and discussion

Analysis of the model-inherent VTTS. In a first step, the base case is analyzed and the VTTS is calculated for each car trip non-linearly and for each user separately. The resulting distribution of the VTTS (see Fig. 1) reveals that for most trips the observed VTTS strongly differs from the VTTS which is assumed in the existing approach where non-linearities and user-specific differences are ignored. The median is 10 EUR/hour which corresponds to the VTTS assumed in the existing approach. For 9% of all car trips, the VTTS amounts to 4 EUR/hour which is the case if the opportunity cost of time is zero, e.g. if the activity at the destination is not open. However, for 30% of all car trips, the VTTS is larger than 16 EUR/hour.

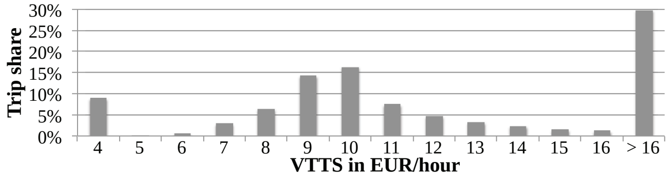

Fig. 1: Distribution of VTTS/hour (base case)

Improved pricing and routing. Next, extension 1 and 2 are used to compute congestion tolls to which transport users are enabled to react by adjusting their route choice decisions. Tab. 1 depicts the changes in welfare relevant parameters as a result of the pricing policy. In all pricing experiments, the travel time is reduced and the system welfare, defined as the sum of toll revenues and travel related user benefits, is higher compared to the base case situation. The travel related user benefits refer to the population wide utility converted to monetary units.

In experiment 1, congestion tolls that are payed by the causing agents better reflect the affected agents' true delay cost. Since transport users are allowed to react to these tolls, delays imposed on transport users with high VTTS are avoided and congestion costs decrease. A comparison of the different pricing approaches reveals that extension 1 (Experiment 1) improves the overall system welfare by 7% more compared to the existing approach (Experiment 0). Furthermore, in experiment 1, the toll revenues are higher compared to the existing pricing approach. This is explained by the overall higher level of the affected agents' VTTS. In turn, a higher VTTS results in a higher congestion toll to be charged from the causing agent.

In experiment 2, tolls are computed following the existing congestion pricing methodology. However, transport users are enabled to generate routes which take into account the user- and trip-specific VTTS. The improved routing approach (Extension 2) improves the overall system welfare by 12% more compared to the existing routing approach. The increase in welfare is explained by the agents' capability to identify better routes which do not only consider the trip related cost but also the expected gains from performing the activity at the destination.

In pricing experiment 3, extension 1 and 2 are combined. Congestion tolls are computed and transport users are routed accounting for the non-linear, user- and trip-specific VTTS. This pricing experiment results in the largest decrease in congestion and the highest welfare level. The welfare increases by 27% more compared to the existing approach. This is due to two effects. First, the tolls better reflect the delayed transport users' congestion cost. Second, the transport routes better reflect the agents' individual weighting of time and money.

Randomization. [12] have addressed the problem related to the router (Sec. 4) in a different way, by randomizing the VTTS before each run of the router, rather than computing an agent- and trip-specific approximation. Experiment 3 is thus repeated with the randomizing router instead of extension 2. First, the number of iterations is observed to have a crucial effect on the simulation outcome. For a total of 100 iterations, the randomizing routing approach results in a system welfare which is below the welfare level resulting from the extended routing approach without randomization (experiment 3). In contrast, for a total of 500 iterations, the system has more time to evolve. Using the randomizing router now results in a system welfare similar to the welfare level resulting from the extended routing approach without randomization (experiment 3). One can conclude that the randomizing router of [12] has a similar effect as extension 2 of this paper (Sec. 4), but extension 2 of this paper reaches similar results within a factor of five fewer iterations.

7. Conclusion

Overall, in this study, an innovative agent-based congestion pricing and routing approach was presented and successfully applied to a real-world case study. The study has shown that it is worth the effort to extend the routing and congestion pricing approach to account for heterogeneous VTTS which are inherent to the model and result from each agent's individual time pressure. Similar to the activity related travel cost, the proposed methodology may be applied to account for non-linear and user-specific trip related travel costs. The results of the case study reveal that the proposed methodology performs better than assuming a constant VTTS or randomizing the VTTS. The improved consistency of setting congestion toll levels, identifying transport routes and evaluating plans translates into a higher system welfare.

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