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Alternative approach to scoring in MATSim and how it affects activity rescheduling

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Alternative approach to scoring in MATSim and how it affects activity rescheduling

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ABSTRACT

Improvements of or technological advancements in the transportation systems have always influenced the demand for traveling and activity scheduling of people. Disruptive inventions like the invention of wheel or locomotive have brought substantial changes. Autonomous vehicles are promising to do the same. Consequently, there is a need for suitable tools to model these changes.

In this paper we present improvements of a previously developed methodology for activity rescheduling in a multi-agent transport simulation (MATSim). In order to address some of the limitations of the previous approach an alternative approach to score the activities performed by agents during the day is proposed. The results show that the proposed alternative activity scoring function is able to ensure that agents perform their activities with the desired duration. It performs on the same if not better level than the current scoring function. Moreover, it provides higher level of flexibility which is needed in order to more realistically simulate activity adding or dropping. The rescheduling algorithm with the proposed activity scoring function reacts and adapts the activity schedules of agents with the right magnitude and sign.
INTRODUCTION

The constant improvements or changes in the transportation systems influence the people’s activity-scheduling decisions. Historically speaking these changes happened through the whole history of mankind: domestication of animals, invention of wheel and boat, building road networks, invention of locomotive and cars. As a more modern example one can take the possible disruptive effects of the introduction of large-scale autonomous fleets in the existing transportation systems and its potentially substantial influence on the demand and people’s daily activity chains. Modeling these changes inside the daily plan has become important in recent years since we live in a fast developing era with new transportation systems appearing within short periods of time, like bikesharing, carsharing or ridesharing. Moreover, new concepts like Mobility as a Service or a fast approaching era of autonomous vehicles (which might have disruptive effects) requires tools able to investigate their induced (or suppressed) demand effects on the daily plans of the population.

Activity schedules of people can be affected in many ways: chain structure (size, order of activities), departure time from activities, transportation mode used to reach activities, location of secondary activities in the short-term and location of primary activities (like home and work) in the the long-term planning. Some of the decisions to adapt the activity chain can be also spontaneous because of unplanned shortage or excess time.

Accurate prediction of these changes to the activity schedule is a non-trivial problem, because of the various dimensions and the amount of information involved in the decision making. Moreover, the methodology used needs to be able to produce the solutions in tractable time.

The work presented in this paper focuses on improving the previously introduced methodology for activity-scheduling adaptations (1) in the multi-agent transport simulation (MATSim, 2). We propose a new activity scoring function in order to answer these limitations.

The remainder of the paper is organized as follows. Firstly, background on the activity-scheduling and activity scoring in MATSim is presented. Secondly, current scoring in MATSim is explained in detail and the proposed scoring function is presented. Thirdly, comparison between the current and proposed scoring function is outlined and lastly, discussion and concluding remarks are given.

BACKGROUND

One of the first literature reviews of activity-based modeling approaches was conducted in 1992 (3). The authors also describe some of the research problems that were urgently in need of further investigation at that time: "...one such important and unresolved problem concerns how utilities are assigned to activities. ". They also mention that empirical evidence needs to be sought and how utilities or priorities change over time needs to be investigated. Moreover, they point out that changes in the activity-scheduling are some of the key aspects of changes in travel behavior which are brought on by transport policies.

One of the biggest challenges in activity scheduling is the complexity of finding the optimal solution (4, 5). In order to find the best solution, one needs to take into account many different aspects that influence the person’s choice of his daily activity pattern. Household structure, set of known places, personal needs, time and money constraints, transportation options available, coordination are just some of many dimensions that need to be considered. However, no person is aware of the whole search space in front of him, but is aware of a limited number of alternatives
(in a way of an activity calendar and a mental map (6)) which needs to be taken into the account when trying to solve this complex problem.

Some of the most prominent approaches to model activity-scheduling are, but not limited to: SCHEDULER (7), ALBATROSS (8), TASHA (9), CEMDAP (10), ADAPTS (11), ABM-DTA (12). Also works done by (13), (14), (15) belong to this part of literature. Some of the agent based models dealing with activity scheduling are ORIENT/RV (16), TRANSIMS (17), MobiTOPP (18, 19), SimMobility (20), SimTRAVEL (21). These activity- and agent-based models have been used in numerous studies and have proven realiable to observe and forecast demand from different perspectives. The multi-agent transport simulation (MATSim (2)) framework used in this work belongs to strand of literature that model individuals decisions on both demand and supply levels (like ORIENT/RV, TRANSIMS, SimMobility and SimTRAVEL). In theory only the demand components that do not really change should be provided to MATSim (like population and work and residential location). However, MATSim is not ready to endogenously model complete travel demand.

In an earlier paper by Balac and Axhausen (1) the authors propose a methodology for activity-rescheduling in MATSim and point out some of the limitations. One of the most important limitations is the logarithmic form of the current activity scoring function in MATSim, which has several disadvantages when activity-rescheduling is concerned. Previously, some work has already been done to overcome this limitation as described by Feil (5). He adopted an S-shaped function developed previously by Joh (22). However, the estimation of the function proved cumbersome and the activity chains were not freely chosen (2). Therefore, we propose an alternative - an approximation to the S-shaped function as it is described in the remainder of this paper.

**SCORING IN MATSIM**

A MATSim simulation is an iterative process, where agents compete for the transportation infrastructure. At the end of each iteration each agent gets a quantitative score for the executed plan based on a utility function. The current utility function as presented in (23) is of the following form:

\[ U_{\text{plan}} = \sum_{i=1}^{m} (U_{\text{act},i} + U_{\text{travel},i}) \]  

where \( m \) is the number of activities an agent has in his daily plan. In general, performing activities increases the score (positive utility), while traveling decreases it (negative utility).

Equation (2) presents the utility of traveling (negative):

\[ U_{\text{travel},i} = \alpha_{\text{mode}} + \beta_{\text{it},\text{mode}} \cdot TT + \beta_{\text{cost},\text{mode}} \cdot \beta_{\text{money}} \cdot \text{Cost}_d \cdot \text{Dist} \]  

where \( \alpha_{\text{mode}} \) is a constant, \( \beta_{\text{it},\text{mode}} \) is the marginal utility of traveling, \( \beta_{\text{cost},\text{mode}} \) is the marginal utility of cost for the specific mode and \( \beta_{\text{money}} \) is the marginal utility of money.

The utility of activity is defined as:

\[ U_{\text{act},i} = U_{\text{dur},i} + U_{\text{wait},i} + U_{\text{late},ar,i} + U_{\text{early},dp,i} + U_{\text{short},dur,i} \]  

\( U_{\text{dur},i} \) is the central part of the activity scoring and represents the utility of performing the activity,
where the opening times of activity locations are taken into account. A logarithmic form is used to calculate the utility of performing:

\[
U_{\text{dur},i} = \beta_{\text{per f},i} \cdot t_{\text{pref},i} \cdot \ln\left(\frac{t_{\text{per f},i}}{t_{\text{z},i}}\right)
\]  

(4)

where \(t_{\text{pref},i}\) is the preferred duration of the activity (which is obtained from a travel survey), \(t_{\text{z},i}\) is the duration of the activity at zero utility. In order to generate the same amount of utility for all activities at the preferred duration, it looks as follows:

\[
t_{\text{z},i} = t_{\text{pref},i} \cdot \exp(-10h)
\]  

(5)

The definition of the zero utility duration ensures that all activities have the same marginal utility at the preferred duration. This makes certain that if all activities are performed for their preferred duration an agent is not better of by prolonging one at the expenses of shortening another activity, resulting in a stable point. \(t_{\text{pref},i}\) is actual performed duration and \(\beta_{\text{per f},i}\) is the marginal utility of activity \(i\) at the preferred duration. These preferred durations are sampled from empirical distributions that are extracted from the survey data.

\(U_{\text{wait},i}\) is the utility (negative) for waiting (i.e. waiting for a store to be open) and \(U_{\text{late,ar},i}\) the utility (negative) of being late for an activity which is supposed to start not later than a certain time (for example going to school) and \(U_{\text{early,dp},i}\) represent leaving early from an activity which is supposed to last at least until a certain time (i.e. leaving the workplace before the shift is over). \(U_{\text{short,dur},i}\) is the penalty for performing the activity shorter than what is supposed to be a reasonable time for a certain activity (i.e. less than 8 hours of work). All of these utilities are linear functions.

Even though the current logarithmic utility function has proven to be reliable in the numerous studies conducted using MATSim, it has some limitations. Because of its logarithmic form an activity with duration slightly larger than \(t_{\text{z},i}\) gains substantial amount of utility. This becomes a problem when agents are allowed to add additional activities. Therefore, they start adding many short activities. As already described in (5) in the case of shortage of time the agents will first remove the longest activities because they produce least amount of utility per time unit. This means that home or work activities will be dropped first which is not realistic. Additionally, when facing shortage of time, the agents will proportionally decrease all their activities with longest activities decreased the most. The same applies in case of excess time. Consider an agent with 3 activities during the day, home, work and shopping, with duration of 14h, 9h and 1h respectively. If the agent has to spend 1h on traveling, it would need to shorten some of activities. Therefore, home activity will be shortened the most, closely followed by work. While shortening home activity makes sense, shortening work is unrealistic.

As suggested in (2) and tested in (1) an alternative approach can be used in order to avoid the limitation that many short activities dominate one longer activity (when total duration is the same). This approach assumes that the utility generated by an activity is proportional to its duration. This is achieved by setting zero utility duration to the following value:

\[
t_{\text{z},i} = t_{\text{pref},i} \cdot \exp(-10h)
\]  

(6)

However, this approach has a limitation that short activities are dominated by longer ones. Therefore they will be dropped-out first in time shortage situations which is not always realistic.
In order to avoid these limitations, Feil (5) proposed to use an S-shaped scoring function as developed by Joh (22). Figure 1 presents the proposed function for different kind of activities (the values are illustrative). It starts horizontally at zero and bends upward with a positive second derivative and then changes curvature with the negative second derivative at longer durations. The proposed function is represented by the following equation:

\[ U_{dur,ij} = U_j^{\text{min}} + \frac{U_j^{\text{max}} - U_j^{\text{min}}}{1 + \gamma_j \exp(\beta_j(\alpha_j - \text{duration}_{ij}))^{1/\gamma_j}} \]  

(7)

where \( U_j^{\text{min}} \) is the time-independent minimum utility of performing activity \( j \), and \( U_j^{\text{max}} \) is the time-independent maximum utility of performing activity \( j \). \( \text{duration}_{ij} \) is the duration for which agent \( i \) performs activity \( j \). \( \alpha_j, \beta_j \) and \( \gamma_j \) are the parameters that define the shape of the curve.

Feil empirically estimated the parameters of the S-shaped function using an enhanced Multinomial Logit (MNL) model. However, the estimated utility function did not satisfactorily reproduce reality and further adjustments were needed. After a manual calibration process, Feil showed that an S-shaped function can match certain census and traffic data, with the largest differences being the frequency of activity chains. Nevertheless, the estimation of the utility function parameters was difficult which was accounted to the non-linearities of the S-shaped function. Therefore, there is still a need for an alternative.

**PROPOSED SCORING FUNCTION**

As discussed in the previous section, an alternative approach for activity scoring is needed in MATSim or other models employing logarithmic utility functions of activity durations. In order to answer the limitations of the current activity scoring function, and avoid the difficulties of estimating the parameters for the utility function as proposed by Feil (5) and Joh (22), we propose a piece-wise linear function for agent \( i \) and activity \( j \) for scoring the performance of
activities (which is an approximation of an S-shaped function):

\[
U_{\text{acttype},i j} = \begin{cases} 
    U_{\text{max}}^{i j} \cdot (t_{\text{dur},i j} - t_{\text{z},i j}), & \text{when } t_{\text{dur},i j} < t_{\text{pref},i j} \\
    U_{i j}^{\text{max}} + \alpha_{i j} \cdot (t_{\text{dur},i j} - t_{\text{pref},i j}), & \text{when } t_{\text{pref},i j} < t_{\text{dur},i j}
\end{cases}
\]  

(8)

where \( U_{i j}^{\text{max}} = \beta_{\text{dur}} \cdot \text{const} \) is the utility the agent \( i \) gets for performing the activity \( j \) at the preferred duration \( t_{\text{pref},i j} \). The utility of performing starts negative, rather than being equal to 0, for durations less than the zero utility duration \( t_{\text{z},i j} \) in order to avoid agents shortening the activities below \( t_{\text{z},i j} \) in order to avoid agents shortening the activities. \( t_{\text{z},i j} \) defines the importance of performing the activity close to the preferred duration, while \( U_{i j}^{\text{max}} \) defines the importance of the activity in comparison to others in the activity chain. When the duration is above the preferred duration the utility gain is controlled by the parameter \( \alpha_{i j} \).

Total marginal utility of travel time savings is in this case:

\[
m\text{UTTS} = -\beta_{\text{travel}} + \frac{U_{i j}^{\text{max}}}{(t_{\text{pref},i j} - t_{\text{z},i j})}
\]

which corresponds to the \( \beta \) parameter (marginal penalty for traveling) as defined in (24).

When looking at the utility function estimated by Feil (5) (Figure 1), one can observe that they very much resemble piece-wise linear functions. Therefore, the approximation is reasonable. The proposed function eliminates the drawback of logarithmic forms, namely that shorter activities would be favored over the longer ones. The drawback of this approach is that it assumes somewhat ideal activities, where utility of an activity is linearly rising with time.

**DEFAULT VS PROPOSED UTILITY FUNCTION**

In order to test the suitability of the proposed utility function we used a scenario featuring the city of Sioux Falls, South Dakota, which is widely used as a benchmark in transportation research. The MATSim scenario for Sioux Falls was first developed by Chakirov and Fourie (25) and recently improved by Hörl (26). This scenario distinguishes between three types of activities: home, work and leisure. Activity chains of the agents contain only one tour, either home-work-home or home-leisure-home. All agents that have an activity chain home - work - home want to perform work for 9 hours and to stay at home for 14 hours. On the other hand, agents that have chains home - leisure - home, want to stay at home for 22 hours and perform their leisure activity for 1 hour. The preferred durations do not sum up to 24 hours, since the agents need to travel between their activities. However, the average traveling time per day per agent is approximately 16 min in this scenario, thus leaving additional time for performing activities, which makes it suitable to observe when an activity will be added to the daily plan. Starting time of work and leisure activities is flexible and only constrained by the opening times of the facilities. These chains are unrealistic, but provide a controlled environment where we can easily observe the differences between different utility functions. Each simulations was run for 1000 iterations with a full sample size (100%) and each allowed the following choices to agents’: mode, route and departure time.

The approach where all the activities at the preferred duration produce the same score is used in the remainder of this paper. Moreover, zero utility durations for the piece-wise linear function are set to the same values as in the logarithmic activity scoring function. Additionally, \( U_{i j}^{\text{max}} \) for the piece-wise linear function is set to the value equal to the utility of the logarithmic function in Equation 4 when the duration of the activity is equal to the preferred duration. This
was done in order to have a consistent comparison between the two functions.

In Figure 2, the progress of the average scores of the agents is presented. As can be seen, the average best scores do not improve substantially for both simulations after 200 iterations. Thus, both simulations reach an equilibrium state through the iterative process. The absolute scores differ between the simulations, because the two scoring approaches are substantially different and therefore cannot be compared in absolute terms. The average score of the executed plans has a jump after 950 iterations, because the agents are not allowed to replan anymore in order to allow them to choose a plan from a stable set of plans. The plan that is executed in each iteration until the 1000th iteration is chosen based on an MNL model favoring the plans with higher scores, causing the average scores of executed plans to increase reaching close to the average scores of the best plans. The results of the two simulations can be compared since both reach an equilibrium.

FIGURE 2  Scores progression for both default and proposed scoring functions.

To better see how these two scoring functions represent what agents want to do during the day, a comparison between the performed and preferred duration of activities is shown in Figure 3. More precisely, a histogram of the ratio of performed duration and preferred duration is presented. A value of 0.5 means that the corresponding activity was performed just half as long as the preferred duration. A value of 2.0 implies that the corresponding activity was performed twice as long as the preferred duration. Consequently, a ratio of 1.0 (the performed duration equals the preferred duration) is the target value in the simulation. The histogram of the ratios is shown for the two non-home activities within the scenario, i.e. work and leisure activities. The results are similar for both activity types. Both scoring approaches induce a ratio distribution that is close to a normal distribution around 1.0. The deviation is smaller for leisure activities since leisure activities are shorter than work activities, i.e. an absolute duration deviation of 10 minutes is small on a relative scale for work activities, but rather large for leisure activities. Nevertheless, the proposed scoring function outperforms the default scoring function. One can see that for both activity types the deviation is much higher using the default scoring approach. Consequently, the proposed scoring approach yields activity durations that are much closer to the preferred durations. Therefore, the daily plans of the simulation using the proposed scoring are much closer to the initial daily plans. Thus, all results of the simulations with the proposed scoring (e.g. traffic assignment) are more trustworthy assuming a real world example.
In (1) a proposed rescheduling algorithm was tested on the city of Zurich. In all simulations the population was scaled down to 0.1% for computational reasons. Default MATSim activity scoring function was used with two approaches to activity scoring (uniform and relative) as explained previously in the paper. Moreover, in order to avoid that many short activities are generated using the proposed algorithm, the durations of activities of the same type were summed up and scored as one activity. This, however, was not realistic for the following reasons: agents were shortening their activity chains in order to avoid travel (which brings negative utility) and were tending to have one activity per type and when it happened that the agent had more than one activity of the same type the durations of these activities were arbitrary. Therefore, we propose to have each of the activities performed by the agent scored separately, each with its own preferred duration.

In the current study the rescheduling algorithm was slightly adapted (Figure 4 shows how the algorithm is executed).

FIGURE 3 Ratio of performed and preferred durations for both scoring functions
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For n iterations

Receive the initial plan from controller and initialize algorithm

Generate all plans with one remove operation

Generate all plans with one insert operation

Generate all plans with one swap operation

Prepare all plans for scoring

Estimate the score of each plan

Choose the best plan and return it to controller

FIGURE 4 Re-scheduling algorithm.

To avoid redundancy the full description of the algorithm is skipped since it is in detail described in detail in (1). The adaptations to the algorithm made in the current study are the following: 1) Previously if the algorithm encountered two consecutive activities of the same type next to each other they were merged into one. However, since we now completely distinguish activities of the same type, this is no longer the case and 2) The duration of the inserted activity, when the algorithm is generating all plans with one insert operation, is calculated as a uniformly random distributed value between zero utility duration (explained in Scoring in MATSim section) and a preferred duration; this ensures that the score of the activity will be positive and that it will not last longer than desired.

Table 1 shows simulation results using uniform logarithmic and piece-wise linear scoring respectively. Using the piece-wise linear function we have varied the maximum utility that can be gained by performing shopping activity and here we distinguish 3 cases: I) shopping activity at the preferred duration generates the same utility as other activities, II) shopping activity at the preferred duration generates 30% utility as other activities, III) shopping activity at the preferred duration generates 10% utility as other activities and IV) shopping activity at the preferred duration generates 10% utility as other activities and in order to highlight the importance of executing this activity the zero utility duration is set to 90% of the preferred duration. In reality the activities that were not preformed in the course of the day, but under different circumstances might have been included in the schedule probably generate less utility than other activities. Therefore, with the reduced maximum utility of shopping activities we are closer to the real situation. These differences in the maximum utility gained from different activities can also be seen in the work by Feil (5) where the author estimated utility function parameters using an S-shaped function. Consequently, our assumptions are plausible. Results in Table 1 show that agents react to the change in maximum utility gained by doing a shopping activity by deciding not to perform it. Though very simplistic, the reaction of the agents shows that the algorithm is able to adapt the schedules in the right direction. Average shopping times are decreasing from scenario I to III. The reason is that the slope of the activity scoring function for shopping is
decreasing. The slope \( k \) is calculated using the following equation:

\[
k_{\text{type}} = \frac{U_{\text{max, type}}}{(t_{\text{pref, type}} - t_{z, \text{type}})}
\]  

(9)

In scenario I the slope of the activity scoring function for shopping is larger than for home and work activities and equal to the one for leisure activities. In scenario II the slope of the shopping scoring function is still larger than for home and work activities, but smaller than for leisure activities. In Scenario III the slope of shopping activity scoring function falls below all other slopes. In Scenario IV with moving the zero utility duration close to the typical duration once again the slope for shopping activity scoring is higher than the slopes for home and work activities and approximately equal to the slope of scoring function for leisure activities.

The logarithmic function could also be used to adapt the utility gained at the preferred duration. However, in order to keep a stable point at the preferred duration zero utility duration has to be adapted as well. If 10h in the equation 5 is replaced with a constant \( c \), the utility of performing an activity (Equation 4) at the preferred duration can be controlled with \( c \) as can be seen in Equations 10 and 11.

\[
t_{z,i} = t_{\text{pref},i} \cdot \exp\left(-\frac{c}{t_{\text{pref},i}}\right)
\]

(10)

\[
U_{\text{dur, }i_{\text{pref},i} = t_{\text{pref},i}} = \ldots = c \cdot \beta_{\text{pref},i}
\]

(11)

This reduces the degrees of freedom, since by changing the utility at the preferred duration the zero utility duration needs to be adapted as well as we have used in the scenario IV with the piece-wise linear function. In scenario IV one can observe that the number of added shopping activities is substantially lower than in scenario III. The reason is that most of the agents do not have enough free time during the day in order to accommodate the shopping activity with such a high slope and low maximum utility. This is exactly what one expects in reality when observing induced/suppressed demand effects.

**TABLE 1** The simulation results for different scenarios. Scenario I - \( U_{\text{max, shop}} \) the same for each activity. Scenario II - \( U_{\text{max, shop}} \) is 70% lower. Scenario III - \( U_{\text{max, shop}} \) is 90% lower and Scenario IV - \( U_{\text{max, shop}} \) is 90% lower and \( t_{z, \text{shop}} \) is increased

<table>
<thead>
<tr>
<th></th>
<th>Avg. No. of Activities</th>
<th>Avg. Score</th>
<th>Avg. Shopping Time[min]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Base scenario:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logarithmic</td>
<td>3.0</td>
<td>456</td>
<td>na</td>
</tr>
<tr>
<td>Piece-wise linear</td>
<td>3.0</td>
<td>470</td>
<td>na</td>
</tr>
<tr>
<td><strong>With Adaptation:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logarithmic</td>
<td>3.98</td>
<td>675</td>
<td>59</td>
</tr>
<tr>
<td>Piece-wise linear - I</td>
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<td>662</td>
<td>65</td>
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<tr>
<td>Piece-wise linear - II</td>
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<td>45</td>
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<tr>
<td>Piece-wise linear - IV</td>
<td>3.22</td>
<td>457</td>
<td>63</td>
</tr>
</tbody>
</table>

The inflexibility of the logarithmic function arises from the fact that zero utility duration is controlling the maximum utility, therefore it is not possible to independently set these two important parameters.
DISCUSSION

Estimation of the parameters

The proposed utility function used in this paper was not personalized and the parameters used were not estimated. This of course limits the predictive power of the function. In order to have a powerful tool to accurately forecast the effects of changes or proposed policies in the transportation system on the behavior of people, one needs to provide a personalized and properly estimated utility function. Feil (5) attempted the estimation of the parameters for the S-shaped utility function using an enhanced MNL model, but encountered several problems. One of the issues was the larger number of parameters needed to be estimated. Authors hope that the proposed approximation of the S-shaped function will prove easier to estimate as it only has 3 parameters. The estimation of the parameters could follow a similar procedure as in (5) where an actual activity chain of a person can be considered as a chosen alternative and other activity chains as unchosen alternatives. This and other possible methods will be investigated as part of the future work.

Scoring in MATSim

Utility function in MATSim provide a quantitative measure to the executed plan. It provides a way to compare different plans and to chose among them according to a proposed strategy. The utility function used in MATSim was proposed more then a decade ago and since then it was used in numerous studies as it has shown certain reliability and no better alternative way was found. However, some of the limitations of the existing scoring functions was presented here, where the most important limitation is its unsuitability for activity adding or dropping.

The activity scheduling in general is a highly complex process. Different aspects affect the daily plan of individuals as previously explained. Therefore, the approach presented here can only serve as an approximation of the actual rescheduling behavior. However, it can still serve as a guidance for the transport planners. In order to better grasp the influence of different policies on the activity chains of people one might need the help of activity-based models paired with MATSim framework. One of these attempt have already been made where TASHA an activity based model is paired with MATSim (27) in order to model emissions. The authors show that the new modeling framework is a promising tool that can provide better understanding of how the system can affect the behavior of people. In our future work we will explore if this kind of framework can be beneficial for activity rescheduling.

Computation Time

In (1) the authors report that for 0.1% Zurich scenario (about 1,600 agents) there was an approximately 10% overhead when using the rescheduling algorithm. In this paper, Sioux Falls scenario with approximately 60 times more agents was used and no overhead was observed. This happened for several reasons. First, the algorithm was optimized in order to reduce the computation time and remove redundant computations, and the activity chains in Sioux Falls scenario are simpler, leading to less cases of adding or removing activities.

CONCLUSION

The main goal of this paper was to present and test the performance of an alternative activity scoring function in MATSim which can be used to observe induced/suppressed demand effects. The results show that the proposed piece-wise linear function is represents the behavior of people
on the same if not better level than the logarithmic form. Piece-wise linear functions avoid several limitations of the logarithmic form. They avoid that even small performance duration leads to high utility scores. They better represent the behavior of people in case of shortage or access time by prioritizing different activities which is controlled by the slope of the function.

Logarithmic form, on the one hand, assumes decreasing marginal utility per unit of time, while on the other hand piece-wise form assumes uniform marginal gains per unit of time. Consequently, they both assume similar behavior for all activities which is a limitation. Nevertheless, piece-wise linear functions provide higher degree of freedom than a logarithmic form which is important to more accurately value different activities and their priorities. This is specifically important when agents are allowed to reschedule their activities during the day based on policy measures. The results show that with the piece-wise linear function agents are able to value their activities and prioritize them better and therefore more realistically adapt their schedules.

Future work will have two directions as explained in the previous section. One will be focused on further improving the proposed methodology in this paper by estimating the parameters for the piece-wise linear function in order to realistically represent the behavior of people. The second will focus on investigating whether the integration of activity-based model with MATSim is feasible and whether it can provide more behaviorally realistic results for activity rescheduling.

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