


Activity rescheduling within a multi-agent transport simulation framework (MATSim)

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1 ABSTRACT

2 People's desire or the need to perform certain activities during the day drives their activity-
3 scheduling decisions. However, these decisions are dependent on the state of the transportation
4 system, its supply and demand. The need for the tools able to deal with the kind of adaptations
5 to the daily plans that come with these decisions, is ever growing. The introduction of new
6 modes and services and the fast approaching era of autonomous vehicles, among other things,
7 has increased the need for suitable tools to look at the induced/suppressed demand effects on the
8 activity schedules.

9 The work in this paper presents a methodology for the adaptation of the activity schedules
10 inside of the multi-agent transport simulation (MATSim), based on the changes of supply in the
11 system. The first results show that the proposed methods are able to adapt people's schedules
12 when they are faced with shorter or longer travel times and this with only 10% in the computation
13 time. However, further development is needed in order to more realistically represent human
14 behavior, which is discussed at the end of this paper.

1 INTRODUCTION

2 People's desire or the need to perform certain activities during the day drives their activity-
3 scheduling decisions. However, these decisions are dependent on the state of the transportation
4 system, its supply and demand.

5 Changes in the transportation system, policy or infrastructure often lead to the change in
6 the people's daily decisions. This change in the demand depends on, among other factors,
7 socio-demographics, income, household structure, priorities etc.. These changes can be short-
8 term, like changing the departure time or a route, or long-term, like changing the home or work
9 location. On the activity-schedule side, short-term adaptations can be of various degree and
10 dimension. Spatial changes include the change of the location of secondary (flexible) activities
11 like shopping or leisure, while the temporal dimension includes the change of the departure time
12 or length of activities. Changes of a higher complexity include chaining, removing, adding or
13 changing the order of the activities in a daily schedule.

14 Modeling these changes inside the daily plan has become more important in recent years with
15 the constant improvements in the transportation systems (i.e. new bridges, tunnels, increase in
16 the highway capacity) and introduction of new transportation modes: like bikesharing, carsharing
17 or ridesharing. Moreover, new concepts like Mobility as a Service or a fast approaching era
18 of autonomous vehicles requires the suitable tools to investigate their induced (or suppressed)
19 demand effects on the daily plans of the population.

20 Accurate prediction of these changes to the activity schedule is a non-trivial problem, because
21 of the various dimensions and the amount of information involved in making the decisions.
22 Moreover, the methodology used needs to be able to produce the solutions within a reasonable
23 time.

24 To this end, the work presented in the remainder of this paper will propose a methodology
25 for activity-scheduling adaptations inside of the multi-agent transport simulation (MATSim)
26 framework.

27 BACKGROUND

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

35 One of the biggest challenges in activity scheduling is the complexity of finding the optimal
36 solution (2, 3). In order to find the best solution, one needs to take into account many different
37 aspects that influence the person's choice of his daily activity pattern. Household structure, set
38 of known places, personal needs, time constraints, transportation options available, coordination
39 are just some of many dimensions that need to be considered. However, no person is aware of
40 the whole search space in front of him, but is aware of a limited number of alternatives (in a way
41 of an activity calendar and a mental map (4)) which needs to be taken into the account when
42 trying to solve this complex problem.

43 In order to model activity scheduling, in the last two decades several activity-based frame-

1 works were proposed (SCHEDULER (5), ALBATROSS (6), TASHA (7), CEMDAP (8),
2 ADAPTS (9) among others). SCHEDULER was one of the pioneers in activity-based models
3 that are not based on the utility-maximization process, but belong to computational process
4 models (CPM) also known as rule-based approaches. ALBATROSS, TASHA and ADAPTS also
5 belong to CPM strand of work in activity-scheduling literature. ALBATROSS is a rule-based
6 activity scheduling framework that decides which activities are performed, where, with whom,
7 for how long, which transportation modes are used, depending on the household spatial-temporal
8 constraints. Both TASHA and ADAPTS incorporate the modeling of the planning horizon and
9 the main difference between the two being that they use different models in order to predict the
10 activity schedules and while ADAPTS uses econometric models, TASHA uses rule-based ones.
11 CEMDAP uses econometric models in order to generate complete daily activity-travel patterns
12 for every member of each household in the study area. Furthermore, Vovsha et al. (10) describe
13 an activity based approach in order to model the population inside of the Ohio region. They
14 base their models on the fact that intra-household interactions have a great effect on the daily
15 activity scheduling. All these approaches, however, are mainly focused on the development on
16 the demand side and lack the high level of detail required on the supply side.

17 Agent-based frameworks that model individuals decisions on both demand and supply levels
18 have also been developed in the past. TRANSIMS (11) is one of the first agent-based models. It
19 combines activity planning with a microsimulator. One of disadvantages of this framework is
20 that the agents are only allowed to change their route during the simulation. FEATHERS (12)
21 was developed as an extension of ALBATROSS and incorporates activity re-scheduling, learning
22 process and rerouting. Some of the recent additions to the literature on agent-based transportation
23 simulation are SimMobility (14), SimTRAVEL (15) and a multi-state supernetwork approach
24 (16). SimMobility goes a step further and besides using short-term and mid-term planning also
25 has a long-term planning module where the time step is in range of days to months to years and
26 agents decisions also include house and work location choice and car ownership. SimTRAVEL
27 besides pairing activity-based model with dynamic traffic assignment also includes a land use
28 component like a SimMobility, however does not implement a microscopic traffic simulator
29 like SimMobility. Work by Liu et al. (16) presents a supernetwork approach which is able to
30 deal with multi-dimensional choice features simultaneously. A multi-agent transport simulation
31 (MATSim (13)) framework also belongs to this strand of literature. In theory only the demand
32 components that do not really change should be provided to MATSim (like population and work
33 and residential location) however, MATSim is still not ready to endogenously model complete
34 travel demand.

35 It is the purpose of the work presented here to provide the backbone for the extension of
36 MATSim in order to be able to deal with the activity re-scheduling within its framework.

37 **Previous research on activity-scheduling in MATSim**

38 Some of the previous efforts to extend MATSim framework in order to capture full activity-
39 scheduling can be found in the works of Charypar and Nagel (17) and Feil (3). Charypar and
40 Nagel (17) used a Genetic Algorithm in order to compose optimal daily schedules under utility-
41 maximization. However, given that genetic algorithms are very inefficient, Feil (3) proposes an
42 approach using a Tabu Search Algorithm which even though it reduces a computation time, still
43 creates a substantial increase in running time. Both these approaches tend to create optimized
44 activity schedules from scratch and while Charypar and Nagel (17) use a default CharyparNagel
45 utility function (13), Feil (3) proposes using an S-shaped utility function based on Joh (18).
46 However, both approaches experienced problems in replicating behaviorally plausible reality.

1 Therefore, the need for an alternative approach.

2 Modeling the multi-activity scheduling for flexible activities was proposed by Ordóñez Medina (19). Using the skeleton already filled with primary activities like education and work, the
3 author then continues with filling the rest of the schedule with secondary activities using the
4 commonly available data like travel surveys, without prioritizing or fixing scheduling dimensions
5 and creating personalized solutions. In order to optimize the daily schedule the author makes
6 use of the already mentioned CharyparNagel scoring function.
7

8 **Recent studies on re-scheduling in the Swiss context**

9 Recent studies on short-time adaptations to daily schedules in Switzerland have shown that
10 people are very reluctant to change their daily activity patterns when faced with changes in the
11 transportation system (20, 21). Weis and Axhausen (20) show that almost 90% of the surveyed
12 people decide not to change the number of activities in their daily schedule when the travel times
13 change in the range [-30min , +90min]. In the Post-Car World (21) project similar behavior
14 is observed when respondents were asked to state if and how they will change their full daily
15 schedule when transportation costs increase up to 4 times. Therefore, one can assume that
16 changes are not dramatic, but rather small. This should be taken into consideration in the efforts
17 to reduce the search space that individuals are facing.

18 **Travel time budgets**

19 Metz (22) reports that what emerges from different studies is that the travel time budget per
20 person per day is somewhere between 1.0 - 1.1 hours. Moreover, he states that if there was any
21 trend over time, it is more upwards than downwards. Looking at the Swiss travel diaries across
22 the span of two decades we observe similar numbers and trends. In Switzerland, between 1994
23 and 2010 the travel time budget grew from 1.1 to 1.2 hours (23). Therefore, it is noticeable
24 that the potential of saving travel time due to transportation changes is not substantial. This
25 only supports the previous findings that travel time changes do not have a dramatic effect on
26 re-scheduling activities in Switzerland.

27 **METHODOLOGY**

28 The work presented in this paper has been carried out using an agent-based transport simulation
29 tool, called MATSim. The software, through the agent paradigm (24) simulates daily life of
30 individuals. Each agent in MATSim has a daily plan of trips and activities, such as going to work,
31 school, leisure or shopping. The initial daily plans of agents are provided in the initial demand
32 together with supply models, e.g. street network and building facilities. The plans of all agents
33 are executed by a micro-simulation, resulting in traffic flow along network links, which can cause
34 traffic congestion. The execution of these plans is then scored and assigned a utility. Traveling
35 between the activities reduces the agent's utility score while working (earning money) and other
36 activities increase the utility. The goal of each agent is to maximize the utility of its daily plan
37 by re-planning its day, which is based on a co-evolutionary algorithm (see e.g., (25)). The daily
38 plans are evaluated, and 'bad' daily plans (plans with low performance, respectively low utility)
39 are deleted, which corresponds to survival of the fittest in co-evolutionary algorithms. Thereafter,
40 new plans are generated based on the previous set of plans. The re-planning algorithm, in
41 the current state, has several degrees of freedom, such as changing routes, departure time,
42 travel mode or secondary location choice of agents. The execution of all plans, its scoring and
43 re-planning is called an iteration. The simulation is an iterative process, which approaches a

1 point of rest corresponding to a user equilibrium, called relaxed demand. More details about the
2 conceptual framework and the optimization process of the MATSim toolkit can be found in (13).

3 Re-planning within MATSim

4 The current re-planning strategies allow us to investigate changes in the daily schedules of the
5 agents on temporal and spatial dimensions (as previously mentioned these are mode, route,
6 departure time and secondary activities location choice). However, the sequence of the activities
7 in the daily agenda is kept unchanged. In the current work the re-planning algorithm is extended
8 in order to handle the adaptations to the activity chains of the agents including adding or
9 removing an activity and swapping two activities in the current plan.

10 MATSim utility function

11 The scoring of the agent's plan is performed based on the utility function:

$$12 \quad U_{plan} = \sum_{i=1}^m (U_{act,i} + U_{travel,i}) \quad (1)$$

13 where m is the number of activities that agent has in his daily plan. In general, performing
14 activities increases the score (positive utility), while traveling decreases it (negative utility). The
15 utility of an activity is defined as:

$$16 \quad U_{act,i} = U_{dur,i} + U_{wait,i} + U_{late.ar,i} + U_{early.dp,i} + U_{short.dur,i} \quad (2)$$

17 $U_{dur,i}$ is the utility of performing the activity, where the opening times of activity locations
18 are taken into account. $U_{wait,i}$ is the disutility for waiting (i.e. for the store to be opened) and
19 $U_{late.ar,i}$ and $U_{early.dp,i}$ represent the disutility for being late and early respectively. $U_{short.dur,i}$ is
20 the penalty for performing the activity too short.

21 Here we will focus on the utility of performing the activity, as it is central and most important
22 part of activity scoring. The current scoring function in MATSim has logarithmic form (Equation
23 3):

$$24 \quad U_{dur,i} = \beta_{dur} \cdot t_{typ,q} \cdot \ln(t_{dur,q}/t_{0,q}) \quad (3)$$

25 where $t_{typ,q}$ is the typical duration of the activity (the amount in seconds that the person
26 wishes to perform the activity), $t_{dur,q}$ is the actual performed duration and $t_{0,q}$ is the zero utility
27 duration (the utility at this duration is equal to 0) and is defined as follows:

$$28 \quad t_{0,q} = t_{typ,q} \cdot \exp\left(-\frac{const}{t_{typ,q}}\right) \quad (4)$$

29 This implies that the score of each activity at the point of typical duration will generate
30 the same score ($const \cdot \beta_{dur}$). This can be problematic because the marginal utility of short
31 activities is greater than the one for longer activities, causing the longer activities to be dropped
32 first. Since longer activities are usually work and home, this is behaviorally unrealistic.

33 The alternative approach is to use the zero utility duration as in Equation 5.

$$34 \quad \tilde{t}_{0,q} = t_{typ,q} \cdot \exp(-const) . \quad (5)$$

1 which will make score of performing the activity proportional to its duration.

2 However, since both of these approaches use logarithmic form one can observe that the
3 utility function will favor short activities compared to longer ones. Therefore, in the case of
4 flexible number of activities, the schedules will tend to be filled with many short activities which
5 will divert from the realistic travel behavior of people.

6 Activity re-scheduling in the MATSim framework

7 The methodology for activity re-scheduling used in this work relies on using the presented
8 CharyparNagel activity scoring function and on the previous empirical work on adaptations of
9 daily schedules in the Swiss context.

10 Agent's daily schedule in MATSim

11 Agent's daily schedules in MATSim consist of the sequence of activities connected by trips.
12 Each agent starts and finishes his day at his home location. Each activity has an end time when
13 the agent departs on his way to the next activity in his daily plan. One example of a daily
schedule can be seen in Figure 1.

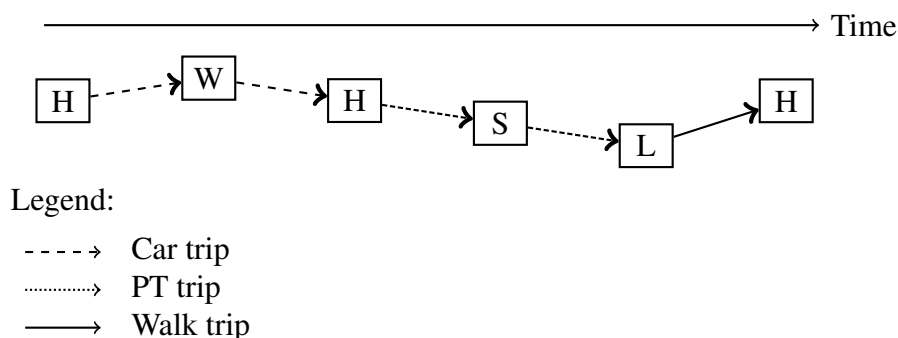


FIGURE 1 Activity chain in MATSim.

14 Here additional information is provided to each agent which consists of a set of activities
15 that the agent wishes to perform during the day. For each activity in this set the agent has a
16 typical duration, which is then used at the end of each iteration in order to calculate the score of
17 the executed plan, as was previously explained.

18 During the re-planning phase an agent (if he was chosen for re-planning) can choose to add
19 or remove an activity or swap two activities in his daily plan. The complete algorithm used for
20 re-scheduling can be seen in Figure 2.

22 Insert activity operation

23 Adding an activity to the current plan is performed following certain rules:

- 24 • An activity cannot be inserted at the start or the end of the plan. This is obvious, because
25 we want agents starting and ending their day at the home location. Moreover, adding
26 home activity at one of these positions does not make sense, since then the agent will have
27 two consecutive home activities.
- 28 • An activity is inserted only if the previous and the next activity in the new plan are not of
29 the same type as an activity to be inserted.

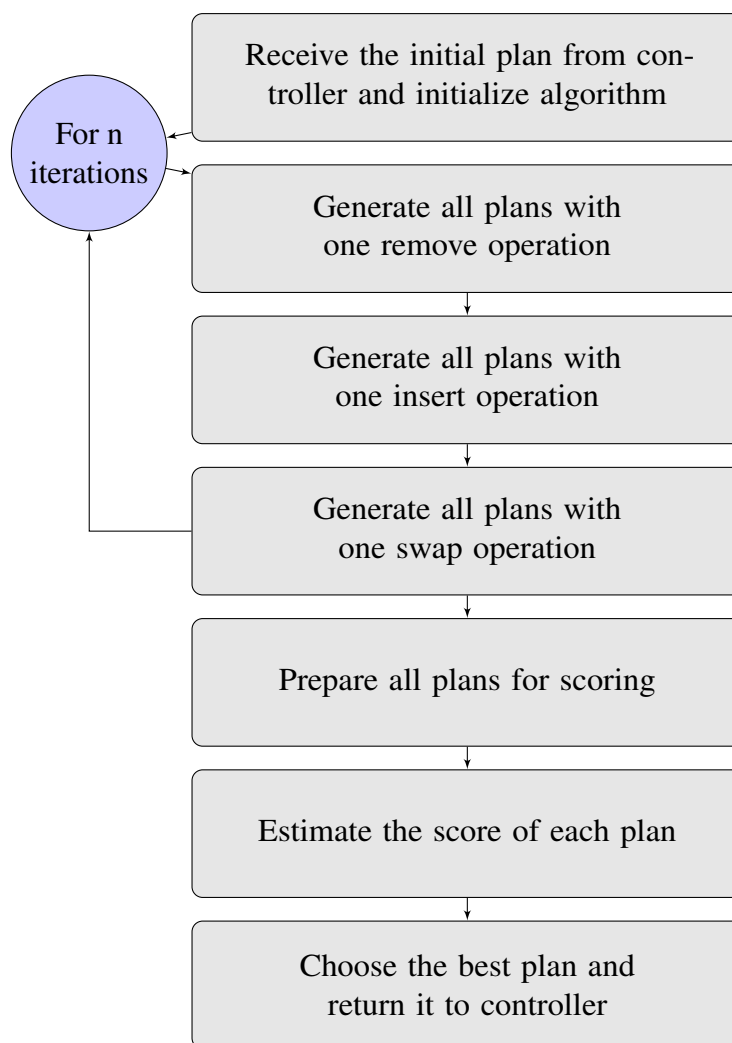


FIGURE 2 Re-scheduling algorithm.

- 1 • The duration of the inserted activity is set to a minimum duration (predefined and config-
- 2 urable). This duration depends on the activity type and is no longer than 1h. This value
- 3 can then be changed in the later course of the simulation during the re-planning phase.
- 4 • The location of the inserted activity is approximated to a location in the middle between
- 5 the previous and the next activity. Later this location is adapted using the destination
- 6 choice re-planning strategy.

7 Figure 3 shows an example of allowed and illegal insert operations.

8 **Remove activity operation**

9 Removing an activity from a schedule uses the following rules:

- 10 • First and the last activities cannot be removed.
- 11 • Duration of the removed activity is added to the previous activity.
- 12 • If the action of removing an activity leads to a plan that contains two identical consecutive
- 13 activities, then these activities are merged into one and the trip that was connecting them
- 14 is removed.

15 Figure 3 shows an example of allowed and illegal remove operations.

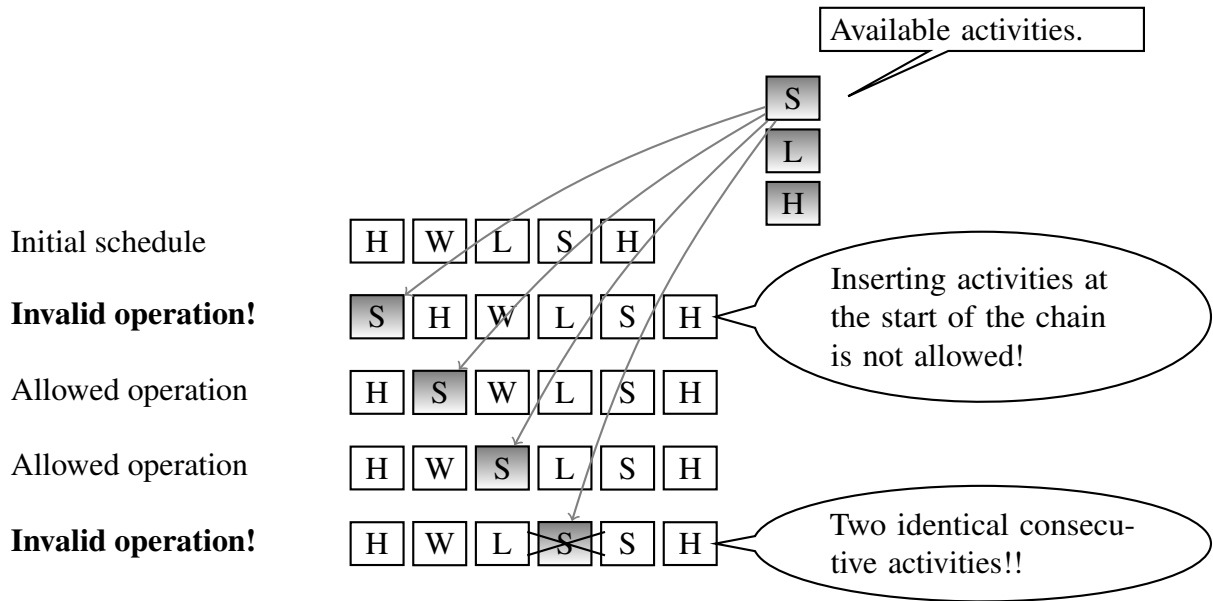


FIGURE 3 Illustration of the Insert operation - with (S)hopping activity

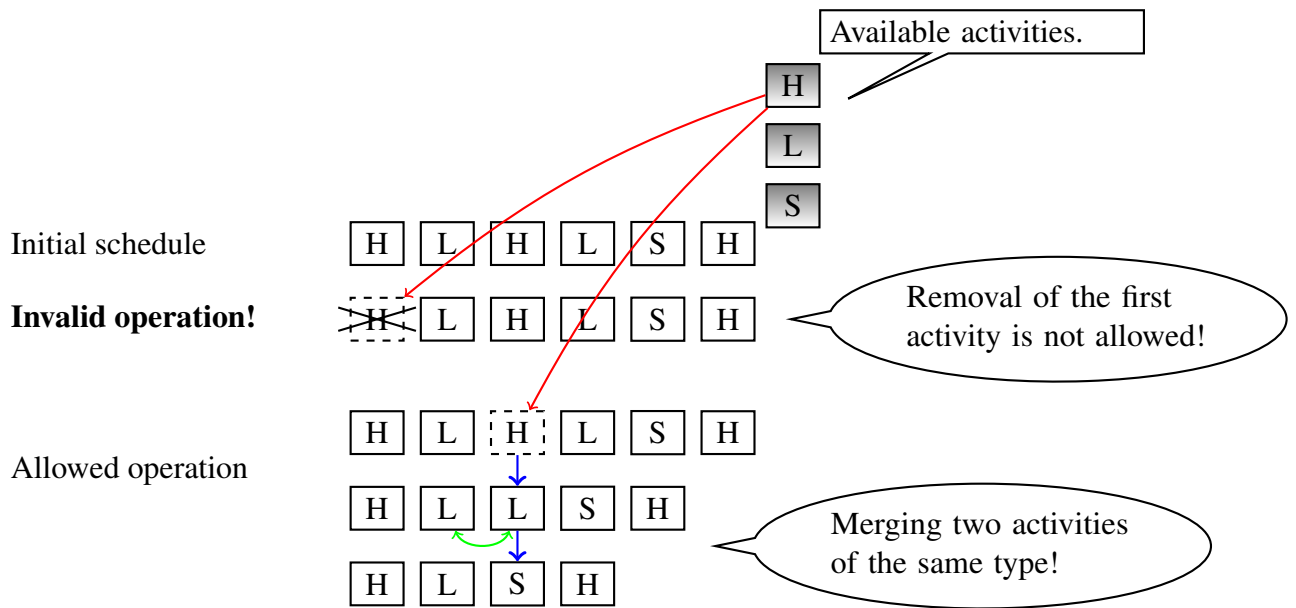


FIGURE 4 Illustration of the Remove operation

1 Swapping activities operation

2 Rules for swapping two activities within a daily schedule are as follows:

- 3 • First and the last activities cannot be swapped.
- 4 • Activities of the same type are not swapped.
- 5 • The swap that will lead to having consecutive activities of the same type is not performed.
- 6 • The duration of the swapped activities is preserved and end times of the affected activities
- 7 (if any) is corrected.

1 Figure 5 shows an example of allowed and Figure 6 shows illegal swap operations.

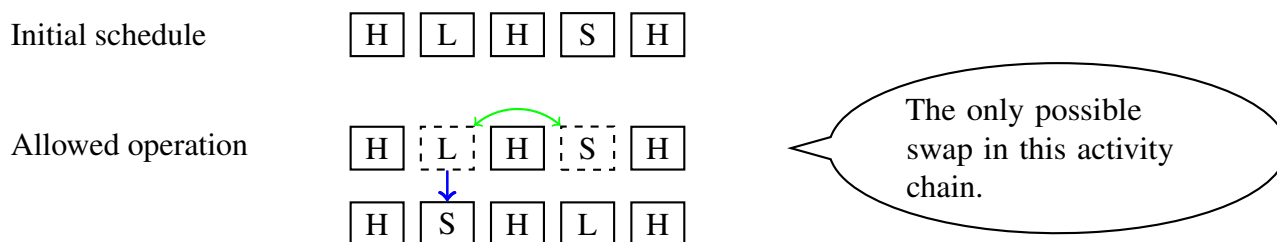


FIGURE 5 Illustration of the Swap operation

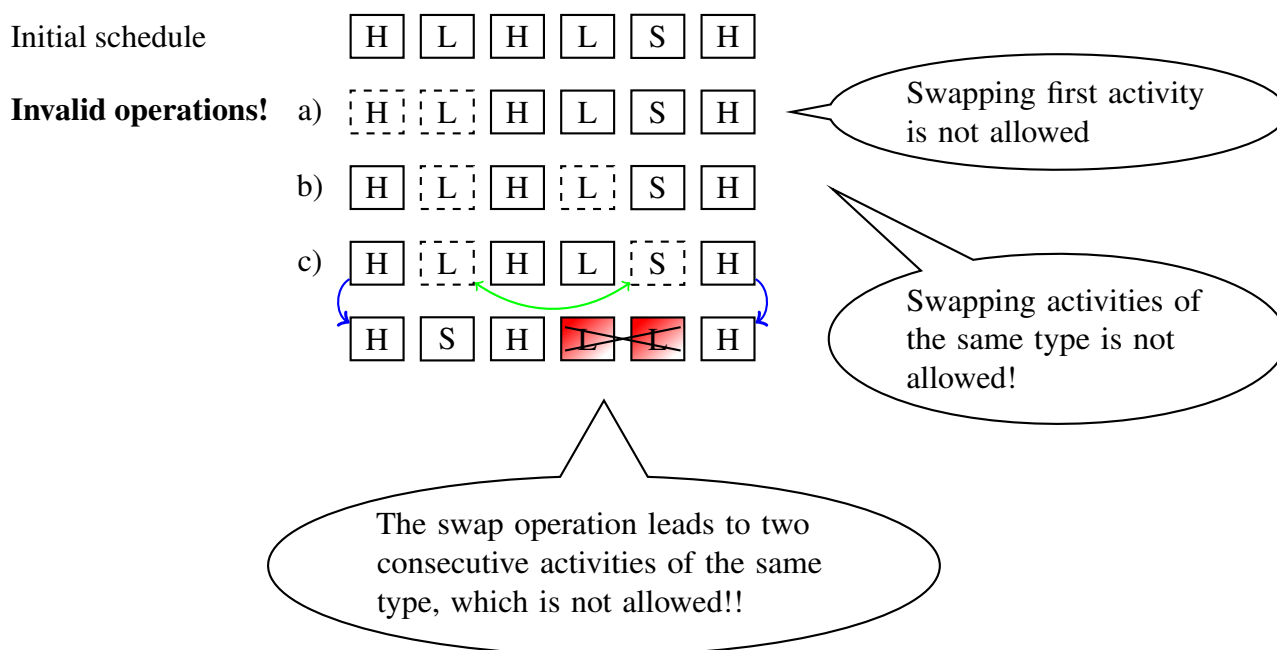


FIGURE 6 Illustration of the Swap operation - not allowed swaps example

2 After performing any of the three operations described above, the travel times of all the trips
3 inside of the plan are recalculated and end times of the activities are adapted.

4 Search space

5 As explained previously the search space in order to find the "best" plan for every agent is
6 enormous. Therefore, we reduce the search space to something that we call a "Known search
7 space". During the re-planning phase, only a number of agents try to adapt and improve the
8 utility of their schedule using the above strategies. In this phase, the current plan is modified in
9 the following way:

- 10 • All possible plans obtained by one removal operation are generated and stored.
- 11 • All possible plans obtained by one insertion operation are generated and stored.
- 12 • All possible plans obtained by one swap operation are generated and stored

13 Here number of iterations was set to 1 in the algorithm ($n = 1$ in Figure 2) This new set of
14 modified plans can contain zero, one or more different plans. This set is usually quite small.

1 One example of the set of possible solutions can be seen in Figure 7.

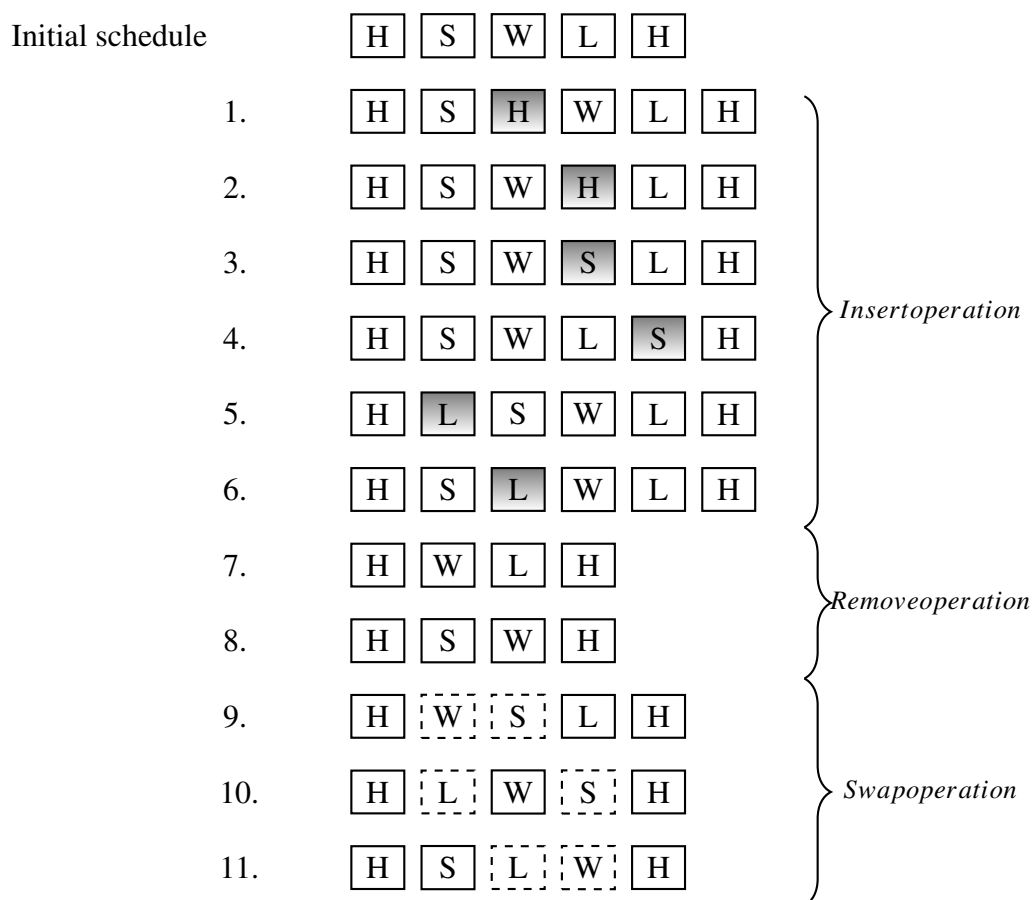


FIGURE 7 Illustration of the possible solutions given an initial chain.

2 These plans are then scored and the plan with the highest utility is compared to the utility of
 3 the original plan. If the new plan has a higher utility it is kept, otherwise the agent keeps his
 4 original plan.

5 RESULTS

6 In order to avoid the problem that logarithmic scoring function favors the generation of many
 7 short activities, we slightly modified the activity scoring function. If there are more than one
 8 activities of the same type, their durations are summed up and they are scored as one activity.

9 We have tested the proposed methodology on a Zurich scenario with 0.1% population in
 10 order to save computation time. Since the work presented here was not intended as a case study
 11 but more as a proof of concept it was considered as a suitable simplification. Each agent during
 12 the iterative process was allowed to change his route, mode, departure time and the location of
 13 the secondary activities along with the re-scheduling. We have tested both approaches to scoring
 14 performance of the activities described previously using the CharyparNagel activity scoring
 15 function:

- 16 • Approach I - each activity at typical duration produces the same score.
- 17 • Approach II - the score of performing an activity is proportional to the duration.

18 Moreover for each approach we simulated four scenarios:

- 1 • Base Scenario - the agents are not allowed to re-schedule.
- 2 • With Adaptation - the agents can re-schedule.
- 3 • With Adaptation with speed reduction - the agents can re-schedule and we impose a speed
- 4 reduction of 30 % on the network.
- 5 • With Adaptation with speed increase - the agents can re-schedule and we impose a speed
- 6 increase of 30 % on the network.

7 In Table 1 one can see how different approaches behave. It is very important to notice that
 8 with the speed reduction and the decrease of accessibility people tend to have on average less
 9 activities then in the original situation, while the increase of the speeds generates the opposite
 10 effect. Both approaches with activities re-scheduling strategies increase the scores of the agents
 11 which is expected because they are profiting from higher degree of freedom in choosing their
 12 daily plan. Moreover, the number of different chains and the average number of activities are
 13 reduced. This is a side-effect of the current description of activities. For instance, each shopping
 14 activity is considered the same, so MATSim assumes that it is better to merge these activities
 15 and save time on traveling, even though in reality this is most probably unrealistic. This can be
 16 avoided by providing different names to different shopping activities, thus making sure that they
 17 are not merged into one.

TABLE 1 The simulation results for different scenarios.

Scenario	Avg. No. of Activities	Avg. Score	No. of different Chains
Base Scenario - Approach I:	4.67	274	377
Base Scenario - App. I w/ speed red:	4.67	270	377
Base Scenario - App. I w/ speed inc:	4.67	278	377
With Adaptation - Approach I:	3.98	279	238
With Adaptation - App. I w/ speed red:	3.94	271	229
With Adaptation - App. I w/ speed inc:	4.01	282	251
Base Scenario - Approach II:	4.67	256	377
Base Scenario - App. II w/ speed red:	4.67	252	377
Base Scenario - App. II w/ speed inc:	4.67	261	377
With Adaptation - Approach II:	3.39	260	126
With Adaptation - App. II w/ speed red:	3.33	255	120
With Adaptation - App. II w/ speed inc:	3.47	263	147

18 We also compared how each agent behaves in each scenario (Table 2). Here it is clear that
 19 the biggest improvement of score comes from reducing the length of the chains by combining
 20 the activities of the same type into one activity.

TABLE 2 The comparison of the length of activity chains and average score between different scenarios.

Scenarios	Longer	Shorter	Same	Longer - Score	Shorter - Score	Same -Score
Base I vs Resch. I:	553	13	1,057	-11.8	1.0	-1.0
Base sp. red. I vs Resch. sp. red. I:	576	17	1,030	-15.0	-0.6	-1.5
Base sp. inc. I vs Resch. sp. inc. I:	522	26	1,075	-20.7	-14.2	-8.7
Base II vs Resch. II:	845	6	772	-7.8	-0.6	-0.1
Base sp. red. II vs Resch. sp. red. II:	883	4	736	-12.3	4.6	- 0.1
Base sp. inc. II vs Resch. sp. inc. II:	820	5	798	-16.2	-6.6	-6.8

1 Figure 8 presents the progress of scores for all the agents during the simulation. It is
 2 important to notice that the scores are reaching a plateau where the equilibrium state is reached.
 3 Therefore, the newly introduced re-scheduling strategies do not have any noticeable negative
 4 effects on the co-evolutionary process.

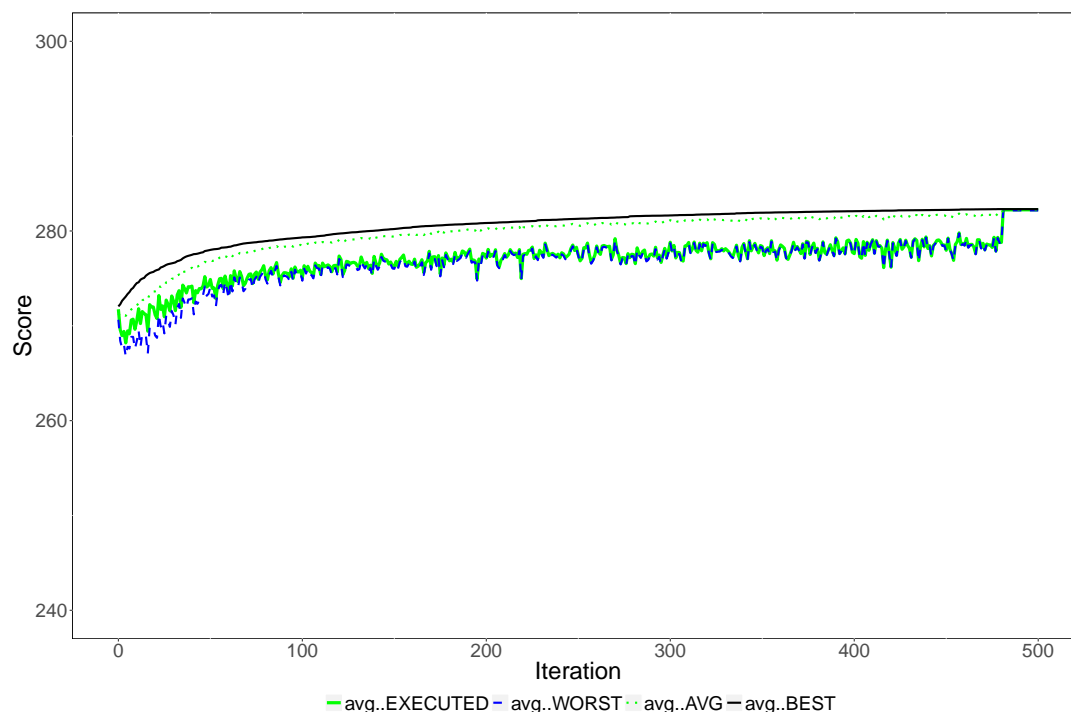


FIGURE 8 Scores of the agents during the simulation.

5 The computation time was 1-2 seconds longer in the re-planning phase when using the
 6 activity re-scheduling strategies. This is a 25-30% increase in the computation time of this phase
 7 of the simulation. Looking at the computation time of one whole iteration (re-planning, execution
 8 and scoring), activity re-scheduling created an overhead of around 10% in the simulations that
 9 we conducted so far, which is drastically shorter than the costs of the Feil (3) approach.

10 DISCUSSION

11 Even though the presented methodology is able to re-schedule activities and the first experiments
 12 with changing the travel times on the network produces an expected shift in amplitude and the
 13 sign of the number of daily activities, additional improvements are needed and will be the focus
 14 of the on-going work within the Post-Car World project.

15 Population sample

16 Here we used 0.1% Zurich population sample in order to test the proposed algorithm. However,
 17 larger population samples are needed in order to have a clearer picture of what is happening in
 18 the study area. Moreover, in order to observe the effects of different policies bigger samples are
 19 necessary.

1 **Simulation variance**

2 Even though we had more than one run for each of the simulations and they all showed the same
3 effect of activity re-scheduling strategies, much higher number is necessary to show for certain
4 the reliability of the simulation outcomes. This paired with larger population samples will bring
5 a more precise output of the simulation.

6 **Activities - scoring and scheduling**

7 Activity scoring function in the current form has some drawbacks that need to be repeated here.
8 Because of the logarithmic form it favors activities with short duration. This can be avoided,
9 as we explained earlier by summing up all the activities of the same type and scoring them as
10 one activity. However, this leads to a different problem, where a person benefits from merging
11 his shopping or leisure activities into one single shopping or leisure activity thus saving on
12 travel time. This, however is not realistic behavior. The solution might be naming each of the
13 activities with a different name (like shopping1, shopping2, etc.). This however, leads to a higher
14 complexity of maintaining all the necessary information.

15 Moreover, when under time pressure an agent will try to proportionally reduce each of his
16 activities. This however might not be realistic, because one would try to stay at work for 8h and
17 reduce the duration somewhere else. Therefore, additional constraints need to be added and
18 adjusted for the individuals.

19 Sometimes the order of activities inside of the schedule is important to the agent. For
20 example, one might want to do his grocery shopping after and not before going to work. So far
21 this is not included in the model and agents can freely swap activities, therefore some unwanted
22 behavior might emerge. In the future work, we will include preferences for the order of the
23 activities in order to more realistically represent the true behavior.

24 Additional problem with the current method of scoring the same type of the activities together
25 is the duration of each individual activity. Performing two shopping activities each with the
26 duration of 2h or performing one for 1h55min and the other 5min would generate exactly the
27 same score. This, however can also be avoided by having for each activity in the daily schedule
28 specific parameters for scoring (like name, desired duration, priority, etc.).

29 Taking all this in mind, we go back to Axhausen and Gärling (*1*) and the research problem
30 of how to assign utilities to different activities. This will be one of the most important areas of
31 research in our future work, because this will influence how the agents inside of the simulation
32 will re-schedule their activities under different circumstances. Thereafter, it will bring us closer
33 to the realistic behavior of people.

34 **Computation time**

35 As mentioned previously the overhead in the computation time caused by activity re-scheduling
36 strategies is around 10%. This results, however, should be taken with caution, because of the
37 sample size. Larger population samples, will also give more confidence to this results.

38 **CONCLUSION**

39 The purpose of this study was to provide the backbone for the full implementation of the
40 activity re-scheduling inside of the multi-agent transport simulation (MATSim) framework. The
41 methodology presented was tested on a small sample in the Zurich area. The results show

1 that the average number of activities per day per person changes in the right direction with the
2 increase/decrease of the travel times in the network. Moreover, the computation time overhead
3 is substantially lower than the previous approaches.

4 The drawbacks of the current utility function are presented and some solution were already
5 tested. However, as stated in the previous section, there are still some aspects that are in the
6 urgent need of development.

7 Our future work as a part of the Post-Car World project is the further development of the
8 activity re-scheduling in MATSim along with finding and testing the alternative approaches to
9 the activity scoring inside of the MATSim framework.

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