Long-Term-C-TAP Simulation
Generating long distance travel demand for a full year

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ABSTRACT

To date, travel demand generation for microscopic traffic simulation has focused mostly on reproducing daily life. This stands in contrast to the significant part of traffic caused by journeys related to activities not usually undertaken in daily life. The paper investigates the possibilities of extending an existing approach (continuous target-based planning) to cover some of these exceptional activities.

A microscopic continuous target-based model applies the idea of agents which try to satisfy individual, behavioral targets by execution of corresponding activities. The decisions on the executed activities are based on heuristic functions. Simulations using this model usually produce data for a few weeks and thus take only daily life into account.

This paper shows how to modify this approach in order to generate travel demand for a full year. The main proposed modification is a new model for the activity planning module. This leads to an enormous reduction in the number of calibration parameters in comparison to similar models. Additionally, validation results show that the simulation is able to produce reasonable travel demand patterns including the impact of weekdays as well as seasonal effects.


INTRODUCTION

Microscopic travel demand simulations simulate the (traveling) behavior of virtual agents individually. One of the well known approaches is the one proposed by Balmer (1): agents choose a daily schedule for their behavior and execute it. The execution results are reported and the agents can re-plan their schedule based on the results of all agents. This procedure is iterated until a stochastic user equilibrium with consistent travel demand is reached (2). Due to high computational complexity and memory issues (all current schedules have to be maintained) a reasonable simulated period is a single day. This is not sufficient for the task of long distance travel demand generation, because long distance traffic is a significant part of today's traffic and short term simulations are not capturing this part.

In case of long distance travel demand it is necessary to simulate a long period of travel behavior, because long distance trips are usually rare and take more time than short distance trips. We use and adapt the Continuous Target-based Activity Planning (C-TAP) simulation which is proposed by Märki (3). It was shown that this approach is able to reproduce individual behavior of six weeks (4). We modify this model in order to simulate long distance trips over an even longer period. The main goal of the simulation is the generation of travel demand data for a whole year. A secondary goal is the minimization of the number of parameters used for the calibration of the model. The measures taken for the parameter minimization are described at several points within this paper.

The remainder of this paper is structured as follows. First, we present the C-TAP model and the adjustments needed for the long term simulation. After that, we focus on the activity planning model as this is the main addition for the long term simulation. This is followed by simulation results, where the model is validated and some considerations on runtime behavior are presented. We conclude the paper with a consideration on limitations of the current simulation.

RELATED WORK

Agent based simulations have a long tradition in analysis and explanation of social behavior. Schelling (5) is often referred to be the first developer of an agent based simulation. Microsimulations were also used to estimate travel demand (6) or to generate an activity-based travel forecast (e.g. Bhat et al. (7) or Miller (8)). Nowadays agent based simulations make a notable contribution to the field of transportation research (e.g. Balmer (1)).

The target-based approach is related to the need based theory which was introduced by Arentze and Timmermans (9). They developed also a model for activity generation with the assumption of utilities described as dynamic function of needs (10). Märki proposes to use targets instead of needs as an explanation of human behavior (11). He validated his model in (4) for short distance travel generation using a six-week continuous travel diary provided by Löchl et al. (12).

Long distance trips have been also the focus of recent literature. The travel behavior have been analyzed several times, e.g. for the UK and the Netherlands Limtanakool et al. (13). Some statistical long distance travel demand models have been developed (e.g. Erhardt et al. (14)) as well as used for traffic forecast (e.g. Beser and Algers (15)). Recently, different surveys were also analysed to derive an outlook on the future of long distance travel demand (Frick and Grimm (16)).

Finally, the usage of a continuous target-based model for a long term simulation was introduced recently by Janzen et al. (17).
CONTINUOUS TARGET-BASED MODEL

We introduce a microscopic travel demand model, which is used to generate long term and long
distance travel demand. The core of microscopic models is built with agents representing virtual
people. In contrast to iteration-based models (like the one used by Balmer (1)) a continuous
planning model does not iterate to a steady state, but generates continuously an activity schedule
without a systematic replanning. One of the main advantages is the capability of the simulation
to generate arbitrarily long activity plans in linear runtime. Thus, it is a better basis for the
generation of long term, long distance travel demand. Finally, we choose an event-driven
simulation, because it is known to be more flexible and more effective than a time-driven
simulation.

The simulation presented in this section was introduced by Märki et al. (11) and further
developed by Märki et al. (18) and Märki et al. (19). We explain in this section the main ideas
of C-TAP, i.e. the behavioral targets, the activities and their interaction within the simulation
algorithm. Additionally, we present all modifications of the default model, which are necessary
for a long term simulation, as well as further developments of the algorithm. The main modifica-
tion is the adaptation of the activity planning process and is presented in the end of this section.
The modified model is called Long-Term-C-TAP within this work.

Behavioral Targets

The core idea of C-TAP is the usage of behavioral targets, which represent the motivation of the
agents to perform an activity. Examples of long distance and long term motivations are holidays,
e.g. an agent might have the motivation to go on holidays for two weeks twice a year.

There are several options to define targets. In the following we present the types of targets
proposed by Märki:

- percentage-of-time target: indicates how much relative time within an observation window
  an agent would like to spend on a specific activity (e.g. the motivation to spend a specific
  amount of time on holidays within one year).
- frequency target: indicates how often an agent would like to execute a specific activity
  within an observation window (e.g. the motivation to go a specific number of times on
  holidays within a year).
- duration target: indicates how much time an agent would like to spend for a single
  execution of a specific activity (e.g. the motivation to spend a specific amount of time on
  each holiday trip).

Note that the first two target types include the definition of an observation window. But in
case of the simulation presented here it is not necessary to include additional parameters to the
 calibration of the simulation, because it is sufficient if the observation window just equals the
simulated time, i.e. one year. Regarding our goal of parameter minimization we need just one
numerical parameter for each agent and each activity.

Obviously, the definition of all three targets for a single activity has redundancy as just any
two of the three target types are necessary to fully describe the motivation of the agents for a
single activity.
Activities and State Values

The targets described above can be satisfied by the execution of a corresponding activity. The decision on the executed activities is based on state values. For each target we define a state value, which is necessary to measure the satisfaction. We need to introduce two types of state values:

- for targets with observation windows: the state value is the result of a convolution of the activity execution pattern with an exponential kernel, which is restricted to the length of the observation window. So it increases during the execution of the relevant activity, respectively decreases during non-execution.
- for duration targets: the state value is defined as the activity duration.

The level of satisfaction now is measured by the quadratic difference of state value and target value. This measurement is called discomfort and its influence within the model is described in detail in section Activity Planning. As the goal of C-TAP is the generation of travel demand an activity definition should also include one or more locations and travel times, where the activity can be executed.

Core Algorithm

The core algorithm of the C-TAP simulation has a simple structure and is shown in algorithm 1.

```
Algorithm 1 Core C-TAP Algorithm (Pseudo Code)
1: while simulation end not reached do
2:   for all agent with no activity do
3:     state ← UpdateAgentState(agent)
4:     nextActivity ← MakeDecision(agent, state)
5:     agent.execute(nextActivity)
6:   end for
7:   nextTimeStep = minimum(all execution endpoints)
8:   proceed to nextTimeStep
9: end while
```

The main procedure is a continuous, event-driven iteration over discrete points of time. This iterative process is implemented by the outer while-loop including the incremental computation of the consecutive time points in lines 7 and 8. Whenever an agent finishes the execution of an activity, the function MakeDecision (line 4) computes the next activity based on its current state, which has to be updated before (line 3). After that, the activity is executed until the computed execution end. Activity execution also includes traveling to the location of the activity. Recording these trips we have obtained the travel demand. The simulation stops after a predefined stopping condition is reached. This condition is usually a time period, which has to be simulated. In case of long term simulations a time period of one year is reasonable.

Considering this algorithm there is one important task remaining, namely the implementation of the MakeDecision function, which describes the activity planning. This challenge is the main topic of section Activity Planning.
Modifications for Long-Term-C-TAP

Our object is the generation of long distance travel demand. So we are not interested in every short trip, but just in those trips with long distances. We propose to use aggregated activities, e.g. we introduce a single activity representing daily life, which includes all short daily journeys like traveling to work, shopping, etc. In comparison to (3) this is a higher abstraction level of activities.

The C-TAP simulation is mainly used to generate travel demand for a few weeks, e.g. in (4) six weeks were simulated in order to reproduce a travel diary. We are interested in larger scales and run the simulation for a full year. You can find the results of these simulations in section Results.

ACTIVITY PLANNING

As mentioned before the main challenge of the continuous agent-based simulations is the modeling of activity decisions. The core of the decision process is the discomfort value

\[
D(t) = \sum_{k=1}^{n} (f_{\text{target}}^k(t) - f_{\text{state}}^k(t))^2 \ast w,
\]

where \(n\) is the number of targets and \(w\) a bandwidth normalization factor. The function \(f_{\text{target}}^k(t)\) describes the target value at a given point of time \(t\), while \(f_{\text{state}}^k(t)\) describes the state value at \(t\). This section describes how the discomfort is used in the activity planning of the C-TAP model and also presents in detail the influence in the Long-Term-C-TAP.

C-TAP Decision Model

First, we present the main idea of the C-TAP decision model due to Märki et al. (11). The discomfort function is used to define the discomfort reduction \(DR\) of an activity execution:

\[
DR(t_{es}, t_{ee}) = D(t_{es}) - D(t_{ee}),
\]

where \(t_{es}\) is the execution starting time and \(t_{ee}\) the execution end time. The discomfort reduction itself is the main factor of an heuristic function, which measures the attractiveness of each activity. The activity with the best heuristic function value is then executed next.

Long-Term-C-TAP Decision Model

We use another approach for the decision model, because in case of aggregated, long term activities as explained in subsection Modifications for Long-Term-C-TAP we need a longer planning horizon. In other words we want the agents in the simulation to plan more than one activity in advance. This is reasonable, because long distance journeys are usually planned in advance. Additionally, the number of the decision computations decreases and therefore also the runtime is reduced substantially. There is no need of a look-ahead function (as in (3)) , too. This fact reduces again the number of neccessary calibration parameters enormously.

For the time being we propose a decision model, which provides decisions for the next two activities. This includes of course also the decisions about the duration of these two activities. We will not focus on the discomfort reduction of the considered activity execution as described above, but on the overall discomfort \(D(t)\). Thus, our goal is the minimization of \(D(t)\). In contrast
to the C-TAP model, the future value of $f_{state}^{k}$ is not anymore dependent on the execution time of a single activity, but on the execution times of two activities. Additionally, the state value of the non executed activities decreases, which also includes the traveling time between the activities. We use two auxiliary functions $g_{1}$ and $g_{2}$ to compute the state values after the execution of two activities. Assuming that $t_{s}$ is the current simulation time and the two activities, which are considered to be executed are $a$ and $b$, the future state value $f_{state}^{k}$ can be computed by:

$$g_{1}^{k}(t_{s}, t_{1}) = \begin{cases} INC^{k}(f_{state}^{k}(t_{s}), t_{1}) & \text{if } k = a \\ DEC^{k}(f_{state}^{k}(t_{s}), t_{1}) & \text{otherwise} \end{cases}$$

$$g_{2}^{k}(t_{s}, t_{1}, t_{2}) = DEC(g_{1}^{k}(t_{s}, t_{1}), t_{2})$$

$$f_{state}^{k}(t_{s}, t_{1}, t_{2}) = \begin{cases} INC^{k}(g_{1}^{k}(t_{s}, t_{1}, t_{2}), t_{2}) & \text{if } k = b \\ DEC^{k}(g_{2}^{k}(t_{s}, t_{1}, t_{2}), t_{2}) & \text{otherwise} \end{cases}$$

As above, $k$ is the enumerating id of the targets belonging to a agent. Furthermore, $t_{1}$ and $t_{2}$ are the considered execution times and $t_{s}$ is the (constant) travel time between the two activities. All durations $t_{1}$, $t_{2}$, and $t_{s}$ as well as the point of time $t_{s}$ are expected to be non-negative. $DEC(s, u)$ is the state value resulting after decreasing due to non-execution of the associated activity over the time $u$ with the starting value $s$. $INC(s, u)$ is the respective state value after increasing. Note again that this definition holds for all targets with observation windows. The discomfort of duration targets is of course only dependent on a single execution time.

You can find an illustration of the state value function in figure 1. The state value corresponding to the activity, which is considered to be executed first, increases during the first execution period $t_{1}$ and decreases during travel time and the second activity execution period $t_{2}$ (figure 1.a)). The state value of the second target/activity increases during $t_{2}$ and decreases otherwise (figure 1.b)). Finally, all other state values decrease during the whole considered period (figure 1.c)). Though, the value we focus on is not the absolute state value but the discomfort which is the quadratic difference of the state value and the target. Possible (static) target values are plotted in the graph as green dotted lines. The sum of all quadratic differences at the end of the second activity execution is the overall discomfort we want to minimize and can be identified in the figure as the sum of $d_{1}^{2}$, $d_{2}^{2}$ and $d_{i}^{2}$ for all not executed activities $i$.

As the starting time $t_{s}$ is fixed and the traveling time between two activities $t_{s}$ is assumed to be constant the state value computation after two activities is dependent on two values ($t_{1}$ and $t_{2}$). Also the projected discomfort after the executions depends on these two values. During the activity planning process we computate the optimal, discomfort minimizing execution times for any available combination of the current activity and a possible next one. This leads to $n$ two-dimensional minimization problems, which are non-linear. In our case the number of available activities $n$ is small, because we use aggregated activities. We solve the minimization problem for every activity-pair using a version of a discrete grid method (20).

The procedure during the simulation is the following. After solving all minimization problems we choose the execution time pair, which leads to the lowest discomfort. Then we assign the first activity to the agent and let him execute this for the computed duration. After the execution we do the next decision computation step. The agent might now also choose not to undertake the activity, which was proposed initially by the last decision. He might even choose to keep doing its current activity for some time.
RESULTS

Calibration of the Model

The data used for the calibration of our simulation is taken from an existing long term survey about long distance journeys from the INVERMO project (see Chlond et al. (21)). The survey is divided into four subsurveys covering one year. For simplicity we assume that the interviewed persons reported their journeys continuously for one year, although this was not the case. It is reasonable because the time periods of the subsurveys are a disjoint set covering of a full year, i.e. every season of the year is reported in one of the subsurveys. We focus on all journeys which have all necessary details reported.

Just 2367 of the 6593 reported trips have accurately reported travel times. Most of the other trips have just the traveling days reported. We use the conditional mean imputation (as proposed by Little and Rubin (22), sec. 4.2) to fill in the missing values. For each missing value of traveling time we look in the survey for all traveling times with the same travel purpose, the same travel mode and a similar travel distance and use the mean of these values for the imputation. Finally, we extract 1944 persons, who reported in total 6444 long distance journeys.

Keeping in mind the goal of minimizing the number of parameters for our simulation we calibrate the simulation as follows. We aggregate the journeys for every person based on travel purpose. This results in 3456 combinations of persons with travel purposes (there are 9 different purposes reported, which are: holidays, shopping, private trip, business trip, non-daily commuting, study trip, care, visit and miscellaneous). Due to big differences in trip durations within the same travel purpose we subdivide the purposes, if the duration differs by a factor of at least 2. The subdivision leads to an increase of person-purpose combinations to 5235.

We use these combinations to create for any person a virtual agent with two targets for every traveling purpose reported by this person. The first target is a static percentage-of-time target which is set to the respective relative time the agent spent on this purpose. The second target is a duration target defined by the average duration spent by the agent on this purpose (excluding traveling time). Additionally, we create a percentage-of-time target for the daily-life activity. This number of parameters is still big (up to 19 parameters per agent for the 19 targets), but it
is a reduction in comparison to the work of Märki (3). Finally, we simulate one year of long distance traveling with the described parameters.

Validation

We validate the quality of the presented Long-Term-C-TAP simulation, i.e. we check, if the simulation is able to reproduce the traveling behavior of the interviewed people. We measure the quality by extracting two variables from the survey and compare them to the corresponding values from the simulation output. The first is the number of trips within one year grouped by agent and traveling purpose, e.g. does the virtual agent go on holidays as often as the person he is simulating. The other is the average trip duration, which is again grouped by agent and traveling purpose.

Table 1 shows the differences of simulated and sampled trips grouped together by trip duration. You can see that the number of trips is reproduced well: more than two third are reproduced perfectly and in more than 92% of the cases the difference of simulated and sampled trips is less than one. Though, you can see that there are still some trip frequencies not reproduced well. Especially the short trips (trip duration less than 4 hours) are sometimes executed more often in the simulation than they were executed in the underlying data set. But these trips have just a small share on the overall travel demand. So the overall travel demand is not much distorted by these outliers.

**TABLE 1 Difference of the sampled trips and simulated trips grouped by trip duration**

<table>
<thead>
<tr>
<th>sampled trips - simulated trips</th>
<th>0h-4h</th>
<th>4h - 4d</th>
<th>4d - 14d</th>
<th>14d - 30d</th>
<th>30d+</th>
</tr>
</thead>
<tbody>
<tr>
<td>-10</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-9</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-8</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-7</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-5</td>
<td>103</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-4</td>
<td>239</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-3</td>
<td>11</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-2</td>
<td>30</td>
<td>22</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>-1</td>
<td>8</td>
<td>918</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>46</td>
<td>2431</td>
<td>955</td>
<td>77</td>
<td>6</td>
</tr>
<tr>
<td>1</td>
<td>101</td>
<td>101</td>
<td>138</td>
<td>39</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

In case of the average trip duration we can find similar results. In figure 2: the difference values (in hours) are plotted in a boxplot, where we dropped the outliers. The median is very close to zero here. We can also see again that the difference is in most cases is low. Considering the range of the trip length error, you notice that the simulated trip durations are basically less than 24 minutes shorter and less than 36 minutes longer than the sampled trip duration. As many of the sampled trip durations are higher than 24 hours this results are reasonable.
Travel Patterns

The presented Long-Term-C-TAP simulation is a travel demand simulation for a full year. Thus, it is not sufficient to properly simulate the trip frequencies and trip durations within a year, but it is also important to simulate the travel behavior of specific weekdays or seasons. We show now that the simulation can generate also this travel demand by adding a small additional amount of information. For simplification we aggregate the reported trip purposes to three purposes, namely holidays, work related trips and private trips.

First, we focus on the weekly trip distribution. We generate additional penalties for specific weekday-purpose combinations. These penalties are considered during the activity planning and force agents to prefer specific weekdays for specific trips. The penalties are based on information from the survey and can be summarized as follows:

- Holidays: no special handling as there is no preference for a specific weekday found.
- Private trips: a big penalty added for trips on Mondays, Tuesdays, Wednesdays and Thursdays and a smaller penalty for trips on Fridays
- Work-related trips: a big penalty added for trips on the weekend and a smaller penalty for trips on Fridays

These few additional parameters are sufficient to simulate the weekday travel demand as you can see in figure 3: Here you can find for each weekday two stacked bars. The left bar indicates for each purpose the share of out-of-house days on this specific weekday within the simulation, while the right bar indicates the same information extracted from the INVERMO survey. The dark part of the bar represents holiday trips, the gray one represents private trips and the bright...
one represents the work related trips. The weekly out-of-house patterns of the simulation are similar to the patterns of the survey. One can surely improve the similarity further by adding more information than we proposed here, but perfect reproduction is not the final goal of this simulation. The goal is still a simulation which fits the real world well and is kept simple, though.

More important than weekly patterns are seasonal dependencies of the trips. We analyze the seasonal effects by a comparison of the share of out-of-house days grouped by calendar week and aggregated purpose. Again we analyzed the survey data set and extracted the peaks and the valleys of the shares within one year. Similar to the weekday handling the valleys are simulated by an added penalty to the trip executions on these seasons. Additionally, the peaks are reproduced by a reduction of discomfort on specific weeks for specific trips. In detail these adjustments are the following:

- Holidays: a penalty added on trips of the calendar weeks 11, 12, 13, 19, 25, 47 and a discomfort reduction added to trips on calendar weeks 15, 51, 52.
- Private trips: a penalty added on trips in the third quarter of the year and a discomfort reduction added for trips on the 52nd calendar week.
- Work-related trips: a penalty added on trips in the third quarter of the year and a discomfort reduction added for trips on the 51st and 52nd calendar week.

In figure 4 you can find a comparison of the share of trips by purpose for each calendar week. The stacks within all bars are defined as in the figure of weekday patterns. You can find in figure 4(a) the share of 52 calendar weeks found in the INVERMO survey, while figure 4(b) presents the share of the simulated trips for a full year. Comparing the two barplots you will notice that the main seasonal effects are matching, although not all details are reproduced perfectly.
Additionally, there is the question if the used information is displaying the real world or if there should be another source added.

**Runtime**

Additionally to the validation results we also present our runtimes. Analysis has shown that most of the runtime during the (Long-Term-)C-TAP simulations is spent for the computation of the decision process. As this is the main modification of our model in comparison to the default model, differences in runtime were expected. We do not focus on the runtime differences of the both simulations, but we show by runtime analysis that the main advantage of the modification is the reduction of parameters.

We used the same data set and created the same targets as above for the runtime evaluation and simulated 100 days with the C-TAP simulation as well as with the Long-Term-C-TAP simulation described in this work. Both simulations were running on the same machine with 4 CPU’s of 2.9 GHz and 8 GB RAM. Both simulations use parallelization (4 processes) for the decision computation.

**TABLE 2  Runtime Results**

<table>
<thead>
<tr>
<th></th>
<th>Overall Runtime [h:min:s]</th>
<th>Optimization Steps</th>
</tr>
</thead>
<tbody>
<tr>
<td>C-TAP</td>
<td>19:05:31</td>
<td>7451489</td>
</tr>
<tr>
<td>Long-Term-C-TAP</td>
<td>00:01:14</td>
<td>19764</td>
</tr>
</tbody>
</table>

The results presented in table 2 show that the decision model of the Long-Term-C-TAP induces a much smaller runtime than the default C-TAP model. The reason for the tremendous gap is also shown in the table, namely the number of decision computations. The presented C-TAP model without further adjustments tends to produce activities with small durations, even though the activity might last for a long time. In that case agents decide again and again to continue their current activity. This process generates a lot of decision steps. Although the decision computation of the Long-Term-C-TAP might be slower, it generates usually long-duration decisions.

The difference in runtime might look huge, but we have to point out again that we did not use the full model proposed by Märki (3). Some core ideas like effectiveness functions and dynamic targets are missing in our simulation runs. So the runtimes are not fully comparable. Still they give a hint how to overcome the big amount of calibration parameters needed by the full C-TAP simulation and still produce suitable travel demand in reasonable runtime. This is an enormous improvement towards a simulation which is not fully driven by its input.

**CONCLUSION**

This paper presents the idea to use a continuous target-based activity planing model to simulate long distance travel demand within a full year. We adapted an approach initially used for shorter term simulations and presented a modification of the core module, the decision module. The validation of the model has shown that the simulation performs well for the majority of the data set. The impact of weekdays as well as basic seasonal effects could be reproduced by the simulations with simple adjustments. We have also shown that the number of calibration
FIGURE 4  Share of out-of-house days for 52 consecutive weeks of a year grouped by trip purpose
parameters can be reduced dramatically without a big loss of the simulation performance.

The presented simulation is still facing a number of limitations. For example, neither a location choice nor a mode choice is implemented so far. Despite these existing obstacles the proposed simulation is suitable to be a base of future long distance and long term traffic flow simulations.

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