Long Term Simulation of a Continuous Target-Based Model

Maxim Janzen

IVT, ETH Zürich

10th July 2014

Outline

Motivation

Current State:
Microscopic traffic flow simulations focus on daily life behavior.

But:
There is a significant part of traffic volume caused by long term activities.

Our goal:
Cover the long term acitivities.

Continuous Target-Based Model

Core ideas:

- microscopic travel demand model,
- agents represent virtual people,
- make decisions continuously / without any replanning,
- our goal: long term / long distance travel demands.

Continuous **T**arget-based **A**ctivity **P**lanning (C-TAP) simulation (Ph.D. thesis by F. Märki (2014)).

C-TAP: Targets

Behavioral Targets:
Describe the motivation of agents to perform an activity.

Possible targets are:

- percentage of time target
- frequency target
- duration target

C-TAP: Targets

Behavioral Targets:
Describe the motivation of agents to perform an activity.

Possible targets are:

- percentage of time target
- frequency target
- duration target

Note: definitions of the first two target types include observation windows.

C-TAP: Activities and State Values

For each target there is a corresponding activity and possibly a state value.

Acitivities:
Activities are executed by the agents in order to satisfy their motivations / targets.

State Values:
Targets with observation windows include state values for the agents.
They increase during the execution of the relevant activity, respectively decrease during non-execution.

C-TAP: Core Algorithm

Algorithm 1 Core C-TAP Algorithm

while simulation end not reached **do**
  for all *agent* with no activity **do**
    $state \leftarrow UpdateAgentState(agent)$
    $nextActivity \leftarrow MakeDecision(agent, state)$
    $agent.execute(nextActivity)$
  end for
  $nextTimeStep = minimum(\text{ }all\ execution\ endpoints)$
  proceed to nextTimeStep
end while

Main Question: Implementation of *MakeDecision*.

C-TAP Decision Model

Core: Optimization of the discomfort value:

$$D(t) = \sum_{k=1}^{n} (f^k_{target}(t) - f^k_{state}(t))^2 \tag{1}$$

n: the number of targets,
$f^k_{target}(t)$: target value function,
$f^k_{state}(t)$: state value function.

C-TAP Decision Model

Core: Optimization of the discomfort value:

$$D(t) = \sum_{k=1}^{n} (f^k_{target}(t) - f^k_{state}(t))^2 \qquad (1)$$

n: the number of targets,
$f^k_{target}(t)$: target value function,
$f^k_{state}(t)$: state value function.

C-TAP model use mainly the discomfort reduction:

$$DR(t_{es}, t_{ee}) = D(t_{es}) - D(t_{ee}), \qquad (2)$$

t_{es} is the execution starting time t_{ee} the execution end time.

C-TAP Decision Model

The decision procedure is subdivided into several steps.

1. maximize the product of $DR(t_{es}, t_{ee}) \cdot LA(t_{ee})$ for every available activity. More precisely, the idea is to find the t_{ee} maximizing the product.
2. multiply with execution time ratio $\frac{t_{ee}-t_{es}}{t_{ee}-t_{ts}}$, where t_{ts} is the starting time of the travel.
3. multiply with an optional random term $(1+\epsilon)$.

C-TAP Decision Model

The decision procedure is subdivided into several steps.

1. maximize the product of $DR(t_{es}, t_{ee}) \cdot LA(t_{ee})$ for every available activity. More precisely, the idea is to find the t_{ee} maximizing the product.
2. multiply with execution time ratio $\frac{t_{ee}-t_{es}}{t_{ee}-t_{ts}}$, where t_{ts} is the starting time of the travel.
3. multiply with an optional random term $(1+\epsilon)$.
4. results in a heuristic function:

$$HF(t_{ts}, t_{es}, t_{ee}) = DR(t_{es}, t_{ee}) \cdot LA(t_{ee}) \cdot \frac{t_{ee} - t_{es}}{t_{ee} - t_{ts}} \cdot (1+\epsilon). \tag{3}$$

The agent will now execute the activity, which yields the highest HF-value.

Long-Term-C-TAP Decision Model

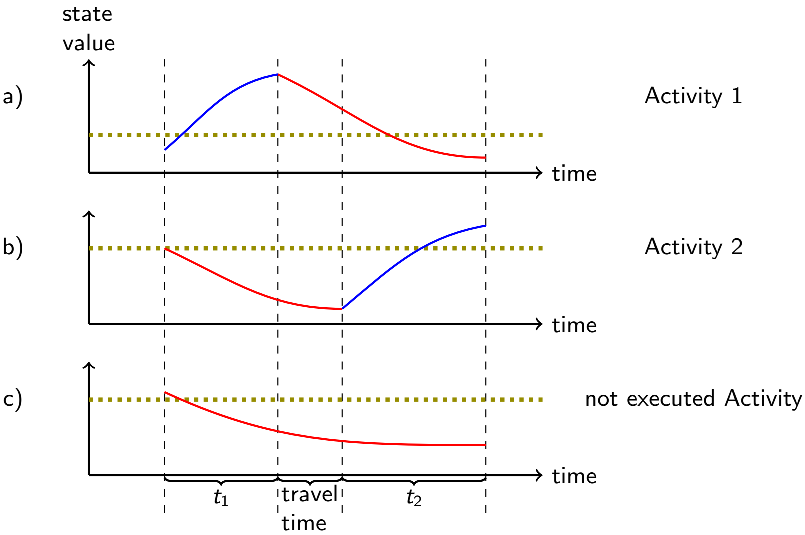
Default Model:

- heuristic function based on discomfort reduction.
- consider one activity

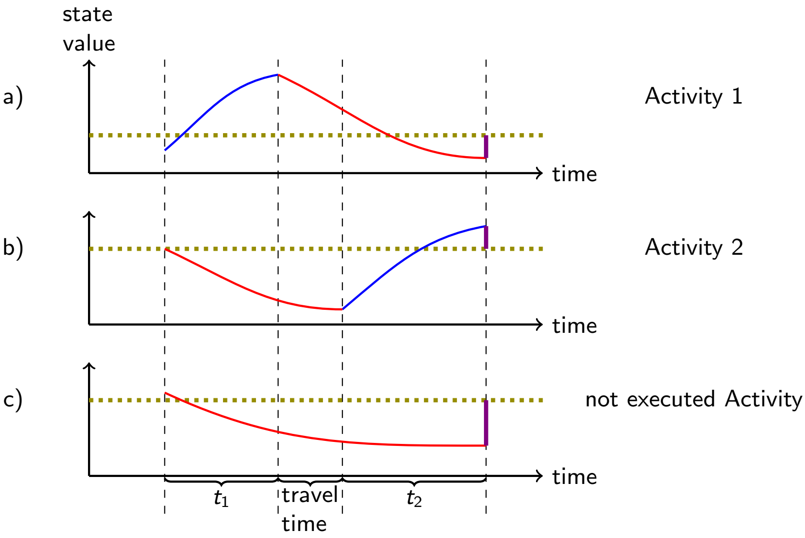
Model for the long term simulation:

- sum of all discomforts
- consider two or more activities

Long-Term-C-TAP Decision Model



Long-Term-C-TAP Decision Model



Optimization Process

Parameters:
Current time t_0 $\rightarrow$ is fixed.
Travel time t_t $\rightarrow$ is constant.
$\Longrightarrow$ discomfort depends on t_1 and t_2.

We fix the first Activity.
$\Longrightarrow$ n two-dimensional minimization problems.

Note:

- n is small.
- we assign just the first activity.

Model Validation - Used Data

Data Source:

- Survey from german INVERMO project (Chlond et.al. (2006)).
- 1944 people reporting in total 6593 long distance trips ($\geq$ 100km).

Calibration:

For each reported traveling purpose

- a percentage-of-time target (relative time spent),
- a duration target (average duration).

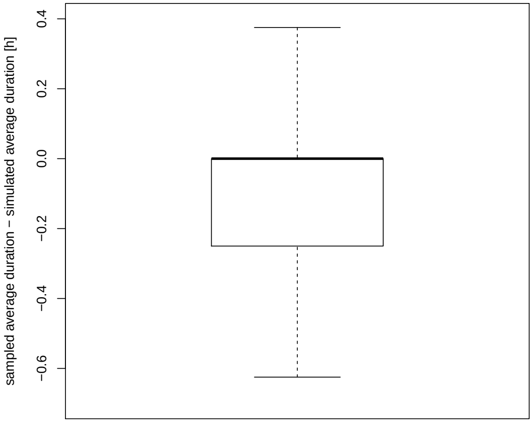
Additionally, we create also for the *daily life* activity one percentage-of-time target.

Validation - Number of Trips per Purpose

sampled trips - simulated trips	Trip Duration 0h-4h	4h - 4d	4d - 14d	14d - 30d	30d+
-10	1	0	0	0	0
-9	1	0	0	0	0
-8	0	0	0	0	0
-7	0	0	0	0	0
-6	0	0	0	0	0
-5	103	0	0	0	0
-4	239	0	0	0	0
-3	11	1	0	0	0
-2	30	22	0	0	0
-1	8	918	2	0	0
0	46	2431	955	77	6
1	101	101	138	39	1
2	4	0	0	0	0

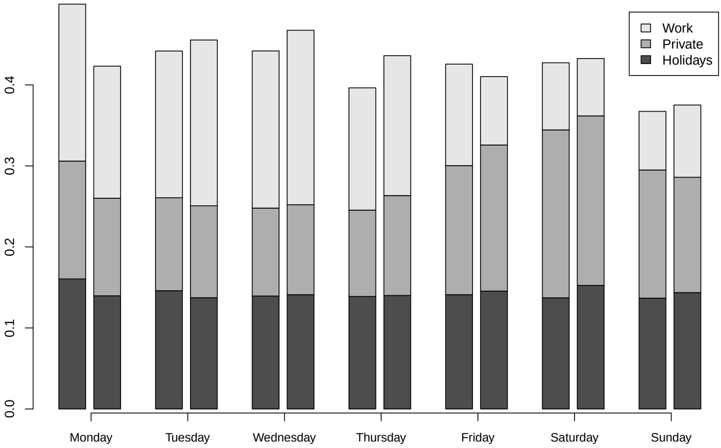
Validation - Average Trip Duration per Purpose

Boxplot of the difference between sampled average trip duration and simulated average trip duration



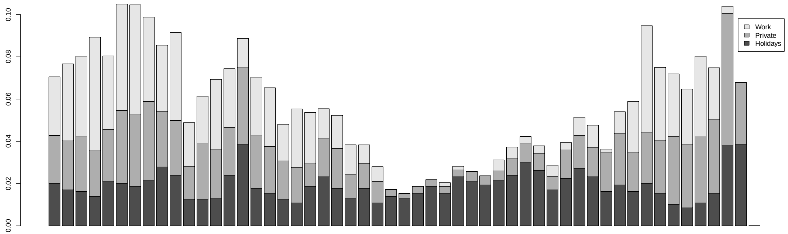
Validation - Out of House Days (Weekly Pattern)

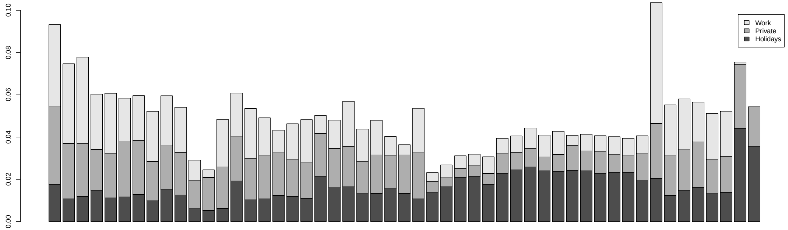
Relative Distribution of the Trips per Weekday and Purpose



Validation - Out of House Days (Yearly Pattern)

Relative Distribution of the Trips per Calendar Week and Purpose





Runtime Results

	Overall Runtime [h:min:s]	Optimization Steps
C-TAP	19:05:31	7451489
Long-Term C-TAP	00:01:14	19764

Runtime Results

	Overall Runtime [h:min:s]	Optimization Steps
C-TAP	19:05:31	7451489
Long-Term C-TAP	00:01:14	19764

Not necessary a hint of a high accelaration, but a hint of an implementation with a much smaller number of parameters needed for a simulation in reasonable runtime.

Future Work

Short Term:

- Improve Reproduction of Seasonal Effects

Mid Term:

- Location Choice
- Mode Choice
- Budget Restrictions

Long Term:

- Traffic Simulation

Thank You!