Multi-agent routing simulation with partial smart vehicles penetration

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1. Introduction

Big cities suffer great economic losses and resident dissatisfaction from congestion and reliability issues (Inrix 2018). As a result, Traffic Management Systems (TMS) effectively increasing road network efficiency are in high demand. Although the vehicular technologies are in a period of an intense development, innovations require many years to become common in the automotive market. According to Lazard and Roland Berger, the penetration of highly automated vehicles in 2035 will reach between 5% and 26% accordingly in pessimistic and optimistic scenarios (Lazard and Roland Berger 2018). Since the transition from manual to automated vehicles will span many years, computer simulations provide valuable tool for testing the performance and the behaviour of novel systems. With the increasing smart cars penetration, beneficial effects of the underlying management system are expected to increase as well. However, this important issue is rarely addressed by researchers who tend to assume a full system coverage (Fiosins et al. 2011, Padgham et al. 2014, Desai et al. 2013).

The contribution of the research is to examine impact of changing smart cars penetration on various transportation system characteristics, in particular, the total travelling time. Experiments are conducted using an multi-agent routing simulation `SmartTransitionSim.jl` developed for this research project. The code is available with Open Source licence on GitHub[1].

[1] `https://github.com/KrainskiL/SmartTransitionSim.jl`

2. Simulation details

2.1. Traffic system

We assume that the road network is represented by a directed graph $G = (V, E)$ that consists of the set of n vertices $V = \{v_1, v_2, \ldots, v_n\}$ representing junctions, and the set of k edges $E = \{e_1, e_2, \ldots, e_k\}$ representing roads. Every edge (directed arc) e_i is described with road length ℓ_i, maximum allowed velocity $V_{\max}^{(i)}$ and maximum vehicles density $\rho_{\max}^{(i)}$. The road network is populated with agents which at any given time t, move towards ending vertex on the current edge with velocity calculated as follows:

$$V_t^{(i)} = \left(V_{\max}^{(i)} - V_{\min}\right) \cdot \max\left(1 - \frac{\rho_t^{(i)}}{\rho_{\max}^{(i)}}, 0\right) + V_{\min}, \tag{1}$$

where $\rho_t^{(i)}$ is the current density on the i-th edge at time t, and $V_{\min}$ is the fixed, minimum speed. The equation we use is a slightly modified version of the classical Lighthill-Whitham-Richards traffic flow model (Lighthill and Whitham 1955, Richards 1956).

2.2. Agent behaviour

Agents aim to select the optimal route that minimizes the travelling time between starting and destination nodes. Fastest route is determined using weighted A-star graph traversal algorithm. Each agent is generated with a fixed type: *smart* or *regular*. The type determines the individual's behaviour, available traffic information and route optimization mechanisms.

We assume that regular agents calculate travelling time with memorized short-term average speeds. However, the deterministic routing approach may lead to high routes overlap (Katrakazas et al. 2015). In order to reduce this undesired effect, we apply k-shortest path algorithm with probabilities based on Boltzmann distribution, see (2). Distribution characteristic is controlled with regularization parameter T.

$$p_i = e^{-t_i^{(N)}/T} \left(\sum_{j=1}^{k} e^{-t_j^{(N)}/T}\right)^{-1}. \tag{2}$$

Regular vehicles follow initial routes picked from k-shortest path algorithm until they reach destination node. We designed regular agents to provide a simple representation of currently used vehicular navigation systems.

The smart agents inherit all regular agents mechanisms and additionally utilize "smart" rerouting service provided inside Vehicular Ad-Hoc Network (VANET). We assume that smart vehicles receive full information about the current velocities with fixed time interval, and may reroute based on local, on-board calculations after receiving the data.

3. Simulation framework and experiment

As part of the research, we developed the simulation framework called `SmartTransitionSim.jl` in Julia language. Directed graph representation of road network is created based on OpenStreetMap data which is publicly available. The agents are generated with both starting and ending nodes chosen randomly from a given area, designated by a set of geographic coordinates. With that assumptions, the simulation emulates morning or evening rush hours when many vehicles move into the same direction. Input parameters for each simulation run are listed in Table 1.

Table 1 **Simulation input parameters and parameter sweep setup**

Parameter	Description	Min	Max	Step
N	Number of agents in simulation run	3000	7500	500
α	Smart agents penetration	0.05	0.85	0.05
U	Velocities update interval (seconds)	50	300	50
T	Boltzmann distribution regularization parameter	0.1	10.0	$\times 10$
k	Routes calculated in k-shortest path algorithm	1	5	1

The evaluation of the proposed model was conducted on a map of San Francisco in California, USA. We assumed scenario of evening commuting from financial (blue area) to residential district (red area) (Figure 1). The parameter grid was created as the Cartesian product of the parameters values described in Table 1. Simulations were repeated 3 times for each parameter combination–in total, 54,000 simulation runs were conducted. Repetitions value was deemed sufficient, considering moderate average coefficient of variation for time reduction (14%).

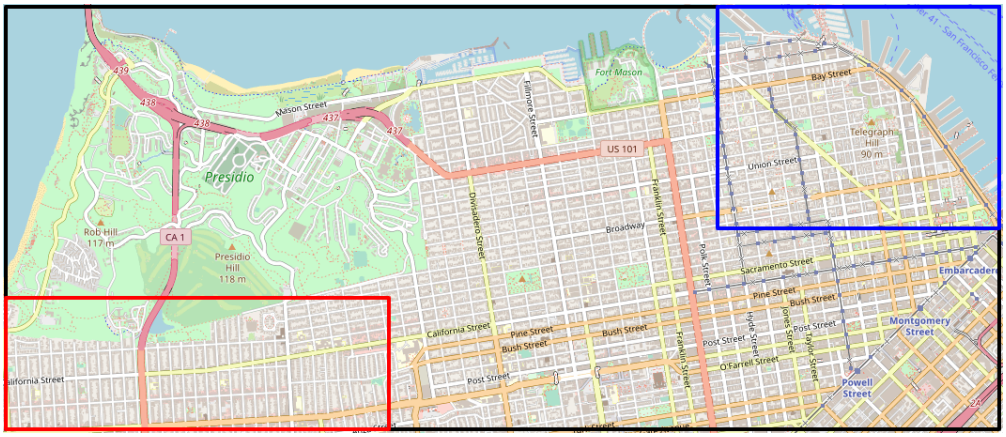


Figure 1 **Agents starting and ending area in San Francisco**

4. Results

In smart populations with the deterministic rerouting ($k = 1$), travelling time reduction effect is near 0% and exhibits high variance, but k-shortest paths algorithm efficiently alleviates detrimental effects of overlapping routes. Results also show that traffic is distributed less efficiently with smaller values of T which favour the fastest route.

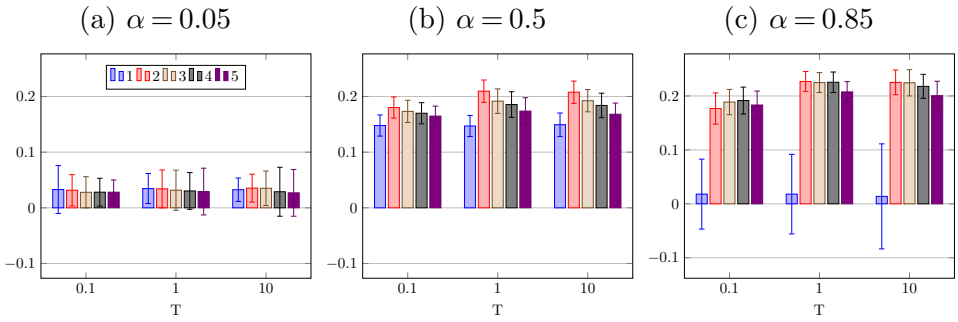


Figure 2 **Percentage travelling time reduction for Boltzmann distribution regularization, T and the number of routes calculated in k-shortest path algorithm, k. Averaged over all values of N and U parameters with error terms based on average coefficient of variation.**

As expected, time reduction effectiveness increases with the number of agents. With 3,000 vehicles, the travelling time was reduced up to 15% while with 7,500 agents maximum value reached 30%. The results also confirmed key role of update interval in boosting performance of the Traffic Management System. Additionally, with decreasing update interval, time reduction gain is diminishing and system reaches optimal performance near 50 sec interval.

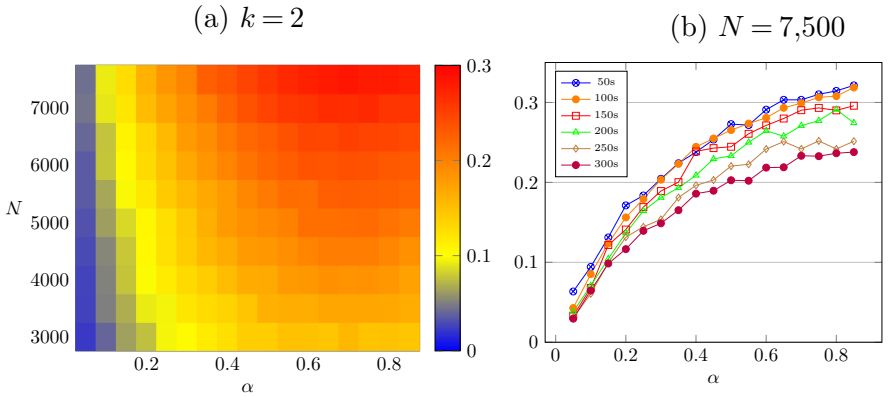


Figure 3 **Percentage travelling time reduction for a) the population size N and the smart agents penetration α b) different values of update interval U and the smart agents penetration α.**

5. Conclusions

The conducted experiments have shown that the proposed Traffic Management System can significantly reduce the travelling time in urban environment. By controlling the simulation parameters, the system performance may be fine-tuned. Moreover, the analysis revealed that an increasing smart cars penetration activates mechanisms connected with the underlying algorithms and the system characteristics may differ depending on the fraction of smart units. In particular, the optimality of the proposed parametrization of path selection probabilities depends on the level of smart car penetration. In practice, it means that the smart vehicle movement algorithm should be tuned when the transportation ecosystem changes. Hence, considering that the transition to fully automated vehicles will span a number of years, assessing intermediate effects should be an important stage of designing modern transportation systems.

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