Agent-Based Simulation Model for Real-Time Traffic Analyses

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Abstract*. Densely populated areas usually have problems with commuting, especially during morning rush hours. This paper presents an agent-based simulation model for real-time traffic analyses. The built simulation model is representing the part of Belgrade during morning rush hours with major traffic participants involved. The model is used to conduct simulation experiments and based on results, improvement measures are suggested.*

Keywords. agent-based model, agent-based simulation, traffic analyses, real-time decision-making

1 Introduction

Citizens in big cities are making a lot of traffic-related decisions during the day. Some of the most important ones are made during the morning rush hours. Most of these decisions are made based on experience and not based on current traffic data.

In this paper, the model of smaller part of Belgrade during morning rush hours is presented. The model includes a proposal for a system that enables real-time traffic information sharing and drivers' real-time decision making based on that information. The main purpose of this model is to conduct traffic analyses and suggest the measures for shortening the time needed to travel from one distanced point to another. The agent-based modelling and simulation (ABMS) is chosen as the most appropriate methodology.

Over the last two decades, the application of ABMS is making vigorous development. Taking into account only papers indexed in Science Citation Index Expanded (SCI-EXPANDED) and Social Sciences Citation Index (SSCI), their number increased from 15 to 449 in period 2000-2015 (Markovic & Zornic, 2016).

Agent-based modelling and simulation can be used to reproduce systems related to economy (Čavoški & Marković, 2016; Marković, Čavoški, & Novović, 2016; Shafiei et al., 2012), ecology (Gerst et al., 2013), agriculture (Rebaudo & Dangles, 2013), medicine (Kasaie, Andrews, Kelton, & Dowdy, 2014), to solve optimization problems (Nikolopoulou & Ierapetritou, 2012), and many others.

Meignan, Simonin, and Koukam (2007) used ABMS to model bus-networks, including a road traffic model and showed that this approach is able to give solution for authorities to design new transportation solutions. Hashmi Syed et al. (2017) presented traffic route analyser together with the custom-built mobile application for collecting the traffic data.

Every agent-based model has three elements (Macal & North, 2010):

- A set of agents with their attributes and behaviours.
- A set of agent relationships and types of interaction.
- The agent's environment, as agents interact with their surroundings in addition to other agents.

The most important characteristic of the agent, also often used in literature to justify the usage of ABMS over other methods, is its independence and capability to act autonomously (Macal & North, 2014; Wooldridge & Jennings, 1995).

After defining agent-based modelling and simulation, the paper is organized as follows. Model for real-time traffic analyses is presented in section two, including the description of model variables and analyses of simulation results. Finally, conclusions and some directions for future research are provided in section three.

2 Model for real-time traffic analyses

As it can be seen in Figure 1, the presented traffic model features two parts of the route from *START* to *FINISH*, each with two alternative sub-routes. The first part, from point *A* to traffic light 14 (*TL14*) can be travelled using the blue route (2.0 km) or the red route (2.7 km). The following part, from point *B* to *TL12* can be travelled using the green (2.5 km) or the brown (3.1 km) route.

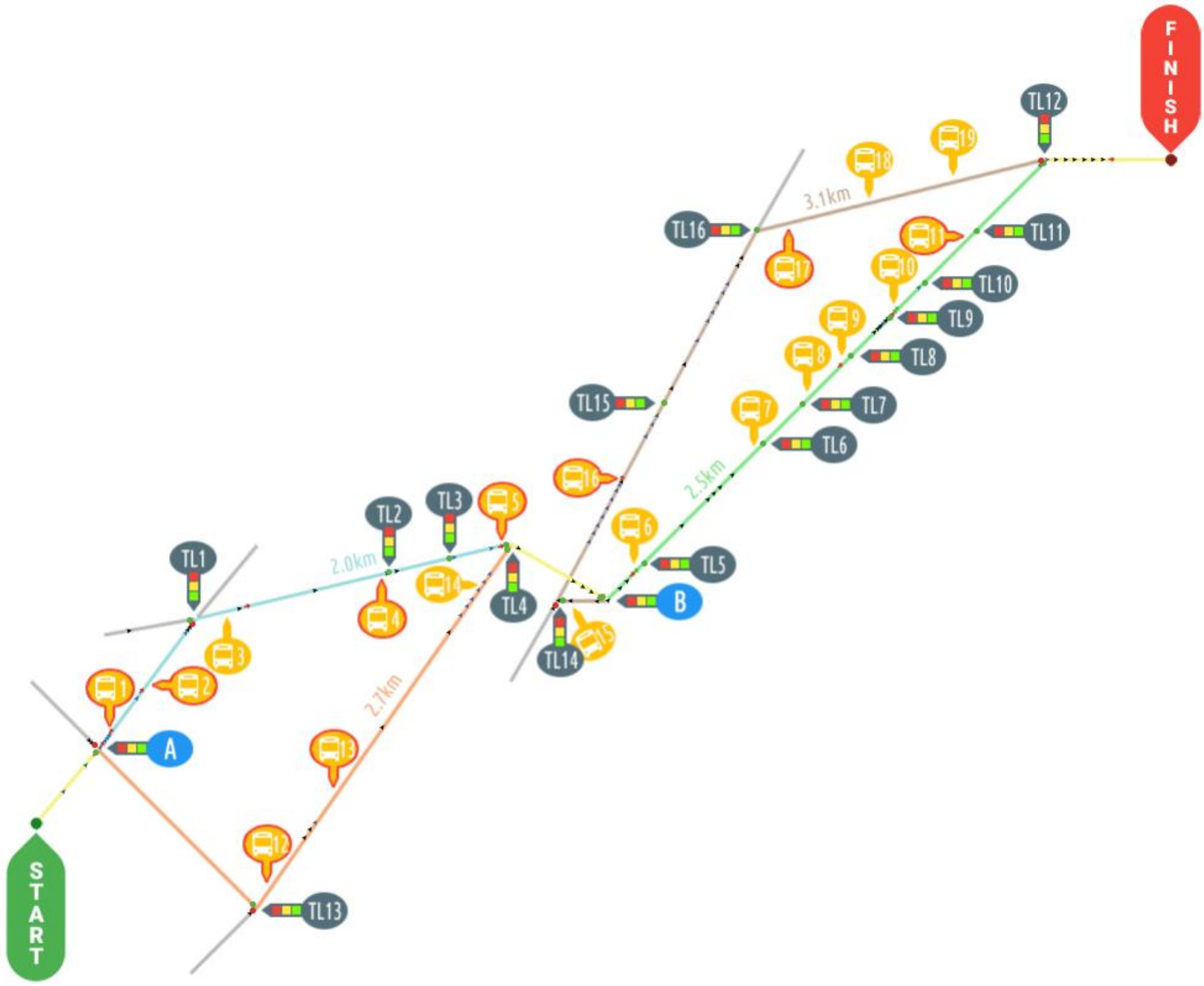

Figure 1. Traffic model

Besides roads, the model features 18 traffic lights (*TL*) and 19 bus stops (bus icon). Bus stops with a red border are stops on-street and buses are blocking the traffic while passengers are boarding. Yellow-only bus stops are bus turnouts, where two buses can board passengers without blocking the traffic.

While modelling the behaviour of traffic participants, the abilities of agents are well-employed. Namely, every car is aware of its surrounding: other cars, traffic lights, and buses. The same accounts for buses, they are aware of cars, other buses, traffic lights and bus stops. The model is built keeping flexibility in mind. Namely, the behaviour of model participants is described using more than 400 adjustable variables.

Besides observed cars travelling from *START* to *FINISH*, other cars are present also. It is assumed that all the cars are respecting the speed limit in the populated area of 50 km/h and there is no overtaking. Speeding up and slowing down is modelled, also.

There are multiple bus lines present in the observed traffic system but also included in the model. Those are presented in Table 1.

The model includes the possibility for drivers to receive information about routes to their destination. Herrera et al. (2010) proved that only 2-3% penetration of cell phones in the driver population is enough to provide accurate measurements of the velocity of the traffic flow.

Table 1. Bus lines

No.	Route	Interval [minutes]	Deviation ± [minutes]
23	*START-TL1*	6	0.5
37	*TL1-TL4-B-TL14*	7.5	1
42	*TL13-TL4-B-TL14-TL16-TL12-FINISH*	14	1
47	*B-TL12-FINISH*	6	0.5
48	*TL8-TL12-FINISH*	7.5	1
50	*TL1-TL4-B-TL12-FINISH*	6	0.5
53	*START-TL1*	8	1
59	*START-TL1-TL4-B-TL12-FINISH*	7.5	1
89	*START-TL1*	12	1
94	*TL6-TL12-FINISH*	11	1

In Serbia in 2015 35% of individuals aged 16 to 74 were using mobile devices to access the internet on the move (Eurostat, 2016). Thus, we suggest introducing the mobile application for real-time traffic information sharing. This application should be able to provide the driver with information about alternative routes to their destination and travel time for each route. Based on this information driver is able to choose the faster one. In the model, the average travel time for a selected number of cars is calculated every time the new car finishes the section.

The model is built using NetLogo software (Wilensky, 1999).

Some of the most interesting variables are made adjustable using graphic input elements, switches and sliders and are explained in order from Fig. 2:

- *speed-limit*, for setting the speed limit for cars and buses.
- *add-car-constantly*, for controlling the creation of new cars in the model.
- *add-car-unobserved*, for enabling/disabling the appearance of unobserved cars from different parts of traffic grid.
- *add-bus-constantly*, for controlling the creation of new buses.
- *get-traffic-info* is controlling whether drivers will get information about mean travel time when choosing the sub-route.
- *mean-time-last-cars* is slider for defining for how many last cars that finished the specific sub-route we will calculate the mean travel time.
- *blue-over-red*, chance to choose blue route, and not the red one.
- *green-over-brown*, chance to choose green route, and not the brown one.
- *bus-stop-{1, 2, 4, 5}-turnout*, for adding the turnout to corresponding bus stops.
- *tl-12-brown-side-green-light* is for controlling the duration of green light on the brown-route side for *TL12*.

Most of the input variables are set based on authors' approximation (like introduction of new cars to the model, *blue-over-red* and *green-over-brown*, and bus boarding time on bus stops) and some based on system observation (most of the traffic lights' green/red light duration). Additionally, bus departure times are taken from official timetable (Sekretarijat za javni prevoz, 2017).

As stated in the introduction, the purpose of this model is to conduct traffic analyses and suggest the improvement to shorten the time needed to travel from *START* to *FINISH*, including all the route subsections. We conducted a series of experiments and will present some of the interesting results and conclusions in the following section.

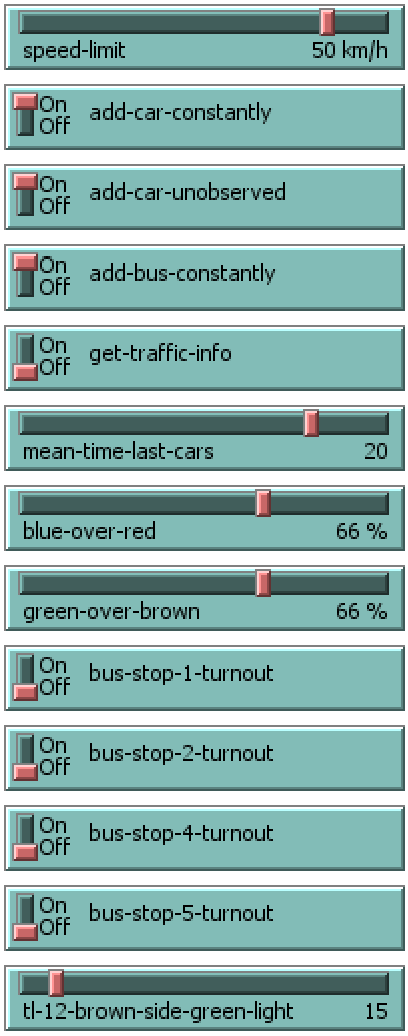

Figure 2. Model controls

2.1 Simulation results

Simulation experiments are run for the approximate duration of morning rush hours (from 07:00 to 09:00).

Input variables for the first (*base case*) experiment are presented in Figure 2. From the *base case* experiment results, we noticed that the blue route had a problem with most of the bus stops being on the traffic lane, while the part of this route from *A* to *TL1* has four buses with interval 6-12 minutes each. Besides this, the average waiting time is 3.38 minutes and travel time (from start to finish) is 10.26 minutes. Selected indicators for all experiments are presented in Table 2.

In the next experiment (*traffic info*), the *get-traffic-info* switch is turned on, meaning that drivers coming from *START* are getting information about average time needed to travel from point *A* (using blue/red route) and from point *B* (using green/brown route) for the last 20 cars (*mean-time-last-cars* slider). Based on that information they are taking a faster route. The slight improvement is visible in the system. Namely, the average travel time from start to finish is now 9.85 minutes and average waiting time is 2.67 minutes. This is mostly because majority of the cars avoided blue and used a red route instead. The red route is burdened with only one bus that has interval of 14 minutes.

During the previous simulation experiments we noticed that bus stops 1, 2, 4, and 5 are causing traffic jams. In experiment *bus stop turnout 1* we turned on the switch *bus-stop-1-turnout* to check the influence of adding turnout to this bus stop on travel time. Results presented in Table 2 show that there is slight improvement regarding the blue route. This is expected, as bus stops 1 and 2 are ones with most buses operating and longest boarding times. What we noticed during this experiment is that bus stop 2 is one of the major bottlenecks in the system. The next experiment will consider introducing turnout to the mentioned bus stop.

Table 2. Simulation results

Experiment	Average waiting time [minutes]	Average travel time (start - finish) [minutes]	Blue route average travel time [minutes]	Red route average travel time [minutes]	Green route average travel time [minutes]	Brown route average travel time [minutes]
base case	3.38	10.26	4.47	3.25	4.11	4.77
traffic info	2.67	9.85	4.00	3.30	4.23	5.79
bus stop turnout 1	3.05	9.96	3.76	3.23	4.34	4.63
bus stop turnouts 1&2	2.73	9.59	3.32	3.26	4.30	4.53
bus stop turnouts	2.08	8.85	2.27	3.25	4.07	4.65

In experiment *bus stop turnouts 1&2* both *bus-stop-1-turnout* and *bus-stop-2-turnout* are switched on. This resulted in a reduction of average waiting time to 2.73 minutes and average travel time to 9.59. At this point, we can say that the similar result is achieved by equipping drivers with a mobile application for traffic information sharing and by introducing one or two mentioned turnouts.

With the next experiment, *bus stop turnouts*, we are analysing the influence of adding turnouts to bus stops 1, 2, 4 and 5 to travel time – *bus-stop-{1, 2, 4, 5}-turnout* switches are turned on. This experiment showed the best results. Namely, the average waiting time is 2.08 minutes now and average travel time from start to finish is 8.85 minutes (more than a minute, or 14% less than in the *base case*). The result is improved mostly because bus turnouts keep buses off the road during boarding time and cars can freely pass by.

Based on presented experiments bus turnouts should be introduced wherever possible and in the case of bus stops 1, 2, 4 and 5 it certainly is. This investment would greatly shorten the time needed to reach the desired destination, but also decrease gas consumption and CO_2 emission (Shang, Zheng, Tong, Chang, & Yu, 2014).

3 Conclusion

This paper is presenting the usage of agent-based modelling and simulation for analysing traffic system. Traffic system is modelled keeping in mind possible improvements, both those depending on drivers and policy makers. Namely, drivers can be equipped with a mobile application capable of receiving traffic information and choosing the faster route in real time. This solution can shorten the time needed to reach the destination by 5% in regular conditions. On the other side, policy makers can use the model to analyse the impact of bus stops on traffic overall.

The flexibility of the model enabled us to conduct series of experiments and notice bottlenecks of the traffic system. In some of our experiments, we suggested improvements which demonstrated that small changes could have a great impact on system efficiency. Namely, the introduction of only four bus turnouts resulted in 14% reduction of time needed to pass the same route.

We can conclude the designed model for traffic analyses is providing a better insight into problems of reaching a desired destination during rush hours. Future research will be devoted to model even more complex systems with larger number of participants.

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