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Melnikov, V.R.; Krzhizhanovskaya, V.V.; Lees, M.H.; Boukhanovsky, A.V.

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Data-driven travel demand modelling and agent-based traffic simulation in Amsterdam urban area

V.R. Melnikov^{1,2}, V.V. Krzhizhanovskaya^{1,2}, M.H. Lees^{1,2,3},
A.V. Boukhanovsky¹

¹*ITMO University, Saint-Petersburg, Russia*

²*University of Amsterdam, the Netherlands*

³*Nanyang Technological University, Singapore*

mail@valmelnikov.ru, V.Krzhizhanovskaya@uva.nl, M.H.Lees@uva.nl, avb_mail@mail.ru

Abstract

The goal of this project is the development of a large-scale agent-based traffic simulation system for Amsterdam urban area, validated on sensor data and adjusted for decision support in critical situations and for policy making in sustainable city development, emission control and electric car research. In this paper we briefly describe the agent-based simulation workflow and give the details of our data-driven approach for (1) modeling the road network of Amsterdam metropolitan area extended by major national roads, (2) recreating the car owners population distribution from municipality demographic data, (3) modeling the agent activity based on travel survey, and (4) modeling the inflow and outflow boundary conditions based on the traffic sensor data. The models are implemented in scientific Python and MATSim agent-based freeware. Simulation results of 46.5 thousand agents -with travel plans sampled from the model distributions- show that travel demand model is consistent, but should be improved to correspond with sensor data. The next steps in our project are: extensive validation, calibration and testing of large-scale scenarios, including critical events like the major power outage in the Netherlands ([doi:10.1016/j.procs.2015.11.039](https://doi.org/10.1016/j.procs.2015.11.039)), and modelling emissions and heat islands caused by traffic jams.

Keywords: transportation systems, agent-based modelling, travel demand, traffic flow, large-scale simulation

1 Introduction

Automobile transport is an integral part of today's urban transportation systems. It influences different parts of megapolis life: economy, daily commuting, accessibility of infrastructure, ecology. That makes it necessary to study in detail traffic flow on the scale of the whole city or even country. Different models are proposed to model traffic flow varying in level of detail (macro-, meso- and micromodels) and scale of modelling (road segment, intersection, roundabout, network of roads) [1]. Recent developments in these models allow to reproduce realistically traffic flow and its microscopic features [2]. However, sophisticated detailed macro- and microscale models are computationally

prohibitive and are used either in relatively small simulations [3] or in large-scale simulations where research problem, such as e-vehicle infrastructure planning [4] or emergency evacuation simulation [5], requires the highest level of detail. For more global research purposes models are simplified as, for example, macroscale modeling of motorways in Amsterdam [6], where to perform macroscale simulation of traffic flow, road network was reduced to the big motorways with few junctions. Another study demonstrated an improved static traffic assignment technique also on example of Amsterdam urban area [7] with more complete but still degenerated road network, which allowed to determine the most loaded segments of network and segments with decreasing traffic speed caused by intense flow.

These studies can answer research questions on a scale of a city, but fail to give insight into the more detailed levels important for such complex systems as transportation systems, where small changes in some place of a system can lead to the unpredictable results for the performance of the whole system. To simulate traffic flows on a large scale with complete road networks consisting of thousands of nodes, it makes sense to use simplified models, which do not use computationally expensive fluid dynamics or car-following principles, but are able to reproduce basic traffic flow features.

The agent-based traffic flow is the most natural representation of the real-world traffic: every agent symbolizes a real driver making a trip on the road network. Agents can interact on a road according to car-following models, but for the feasible large-scale simulation drivers behavior and interaction is usually omitted, only queueing to preserve vehicles order and sometimes lane changing are used to simulate traffic flow. By the underlying microsimulation principle these models can be divided into cellular automata and queueing models. Queueing model is more computationally efficient since for cellular automata every cell should be processed every time step. There is also a difference between models in travel demand composition: some use trip-based traffic, whereas others utilize activity-based approach [8], which is more realistic because of additional constraints on trips of one agent (start and end of the agent's day is in the same place -home- and next trip cannot start before the previous ends). From open source agent-based traffic flow simulation packages (TRANSIMS [9], MATSim [10] and SUMO [11]) we chose MATSim due to its usage of a queueing model, activity-based agent trips, exhaustive documentation and wide community support (detailed comparison analysis can be found in [12]) to continue our research in data-driven traffic flow modeling for Amsterdam urban area and case study of blackout impact on transportation system [13].

In this work we describe our methods and first results in traffic flow modelling in the scale of city of Amsterdam. Section 2 contains general description of agent-based model of used simulation package. In Section 3 we describe models on population synthesis, agent activity, road network and flows from and to the main simulations area. Section 4 reports results of implementation of models mentioned above and simulation run and validation. Conclusions and future research direction are the subject of Section 5.

2 Agent-based model description

In this section we describe the underlying modeling principles and data required to run agent-based traffic simulation. MATSim offers a microsimulation engine based on queues and agent activity chains instead of separate trips. Queue traffic flow model can be simply described as follows: once an agent enters a link (road), it is put into a queue; agent leaves a link queue after the time required to travel through the link with a free-flow speed if it is in the head of the queue or otherwise as soon as it reaches the head of the queue. In both cases, transition is possible if capacity of the subsequent link allows to enter it (see left scheme on Figure 1).

The standard scenario is a one-day scenario, but there are no hard constraints, which makes it possible to perform multi-day simulations. A simulation workflow is shown in Figure 1 (right): in one iteration, agent plans are re-planned to produce better score, which is an econometric measure of system utility. Replanning means four types of changes in a plan: departure time (activity duration), travel mode

(car/public transport), route, and destination (where agents perform extra activities like sport, shopping, etc.).

A simple scenario used in this paper requires the following input data:

- road network;
- agent plans, containing whole-day activity chain of every agent.

Additional layers can be added to make simulation more flexible and results closer to real life:

- facilities layer allows to add extra activity destinations [14];
- counts layer allows to perform comparison analysis of intensities on road segments from sensor data and simulation.

In the next section we describe the methods and results of modelling the road network and travel demand.

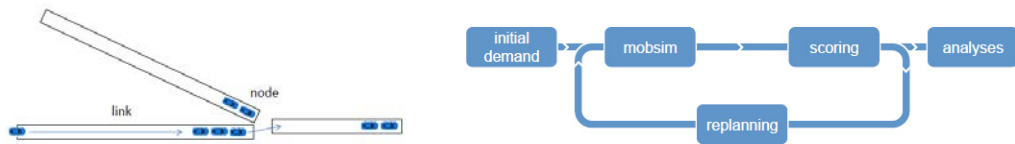


Figure 1. Queue traffic flow model (left). MATSim loop (right).

3 Data-driven modelling of road network and travel demand

3.1 Road network model

Road network constructed in our previous study [13] turned to be insufficient for the large-scale microsimulations, since it represented a degenerated arterial road network graph. That is why OpenStreetMap (OSM) was used to obtain road network of Amsterdam urban area. With increasing quality of collected geospatial data, OSM becomes a reliable source of data for transportation research.

Using OSM data snapshot for the Netherlands and Osmosis tool full road network for Amsterdam urban area (rectangle with GPS-coordinates [52.4786, 4.6960] and [52.2778, 5.0201] of northern-west and southern-east corners, which results in 22.02 km in width and 22.34 km in height). Then it was merged with network of major roads of the Netherlands. Next this graph was transformed from spherical to local Cartesian coordinate system, which is Dutch a RD (Rijksdriehoeksmeting) coordinate system. MATSim requires any spatial data to be converted into local Cartesian, since it significantly decreases computational costs of calculations (simple geometry is used instead of spheroid).

The technical details of road network extraction from OSM and its conversion to MATSim data file format can be found at [15].

Full road network used in simulation is shown in Figure 2 (right), it consists of 118577 nodes and 207577 links including 30223 nodes and 64078 links, which belong to the complete road network of Amsterdam urban area (left).



Figure 2. Amsterdam urban area road network (left); Amsterdam urban area road network extended by the major roads of the Netherlands.

3.2 Travel demand model

This section describes model of travel demand composition we used to generate realistic traffic flow of private cars in Amsterdam during normal working day.

Algorithm of agents plans generation consists of the following steps:

1. Define following variables:
 - N — car owners population size (number of agents);
 - α — fraction of agents living outside main simulation area;
 - $N_{in} = (1 - \alpha) \cdot N$ — number of agents living inside main simulation area;
 - $N_{out} = \alpha \cdot N$ — number of agents living outside main simulation area;
 - μ — mean trip duration;
 - δ — road curvedness coefficient (determine experimentally).
2. Randomly choose home locations for N_{in} car owners from the total population $P_{home}(x, y)$.
3. For each living inside agent $a_{in}^{(i)}$ select departure time $t_{fromHome}^{(i)}$ from home to work, from the modeled distribution $P_{HW}(t)$.
4. For each $a_{in}^{(i)}$ select departure time from work equal to $t_{fromWork}^{(i)} = t_{fromHome}^{(i)} + \mu + t_{workDuration}^{(i)}$, where $t_{workDuration}^{(i)}$ is working day duration sampled from distribution $P_{workDuration}(t)$.
5. For each $a_{in}^{(i)}$ sample trip distance $l^{(i)}$ to/from work from distribution $P_{distIn}(l)$, Set straight distance between work and home $d^{(i)} = \delta \cdot l^{(i)}$.
6. For every agent select work location:
 - a. If $d^{(i)}$ fits simulation boundaries then randomly sample from the distribution of work locations lying in the simulated domain on a distance of $d^{(i)}$ from $P_{work}(x, y)$.
 - b. If $d^{(i)}$ does not fit the simulation boundaries then select a work location along the major road chosen randomly corresponding to outflow probabilities.
7. Randomly choose N_{out} work locations for outside car owners from $P_{work}(x, y)$.
8. For each living outside agent $a_{out}^{(i)}$ select departure time $t_{fromHome}^{(i)}, t_{fromWork}^{(i)}$ in the same manner as for living inside agents, sample trip distance $l^{(i)}$ to/from work from distribution $P_{distOut}(l)$, set straight distance between work and home $d^{(i)} = \delta \cdot l^{(i)}$. Sample home location from road network nodes on a distance of $d^{(i)}$.

All distributions mentioned are presented in subsequent sections: population distribution $P_{home}(x, y)$ in Section 3.3, other in Section 3.4. In- and outflows analysis is the content of Section 3.5.

3.3 Population synthesis model

Population synthesis is a non-trivial scientific task: it requires both data and model to populate the area realistically. In our case study we are interested not in residents spatial distribution, but in car owners distribution. We used as the first approximation of residents, owning cars, distribution the following model: having neighborhood map data for year 2014 [16] which also contains number of registered personal cars, we distributed uniformly this number of vehicles over the area of neighborhood. Figure 3 demonstrates car owners density on the scale of neighborhoods, which was used to distribute uniformly future agents homes. Randomly sampling from generated points we get this distribution, which makes generation of population of any size really computationally efficient.

For Amsterdam urban area we received total count of households automobiles equal to 314408, which is a good estimate of total number of agents for full-size simulation.

This approach, however, has several drawbacks: it uses number of registered cars in neighborhood, which is not always and not precisely reflects the actual number of cars, uniform distribution leads to non-probable resident house locations (such as park or water zones), living areas are usually not uniformly distributed within the neighborhood. Nevertheless, we assume this model for population generation fair enough for the first experiments.

Right picture in Figure 3 shows an example of random uniform population of neighborhood.



Figure 3. $P_{home}(x, y)$ — personal cars density per ground square meter used to generate agents homes (left) and example of randomly and uniformly populated neighborhood with 165 cars (right).

3.4 Agent activity model

Once agents homes are generated, it is necessary to generate a daily activity plan for every agent. For these purposes, travel demand models are used. Any travel demand model is based on travel survey for particular area for which this model is utilized. For the Netherlands ALBATROSS agent-based travel demand generation model was created [17] based on data containing activity diaries for two consecutive days. In this work we used travel survey (OVIN-2014 [18]) conducted by Dutch authorities every year with over 42 thousand daily travel diaries of randomly chosen citizens, describing the trip itinerary (see Table 1) and giving some personal information: age, gender, origin/destination postal code, etc.

For the first simulation runs and peak hours study, it is appropriate to build simple activity chains for agents: home-work-home chains. To construct such plans the following models are required:

- temporal distribution of departure time from home;
- temporal distribution of departure time from work (or work duration distribution);
- spatial distribution of working places;
- trip distance distribution.

For the departure time distributions, Gaussian mixture models (GMM) [19] were built based on the records of travelling by car on working days. Left plot in Figure 4 shows a histogram of real data and a general mixed Gaussian distribution of departure times. The middle and right plots demonstrate that the two peaks in general distribution are contributed by the departures from home and from work. It is interesting to mention that the distribution built on travel survey data prove to be correct by comparing it to the NDW (Dutch National Data Warehouse for Traffic Information) [20] traffic intensity data. Left plot in Figure 5 shows the traffic flow intensity on five major roads heading to Amsterdam. Peak locations and hill shapes correlate with the distribution shown in the left plot of Figure 4.

Departure time	Destination	Mode	Distance	Arrival time
7:20	walk with dog	on foot	1.5 km	7:35
8:05	pick up passenger	automobile	< 1 km	8:10
8:15	put out passenger	automobile	1 km	8:20
8:30	work	automobile	26 km	9:05
17:10	pick up passenger	automobile	26 km	17:50
17:55	home	automobile	1 km	18:02
19:27	ride bicycle	by bike	19 km	20:43
23:55	walk with dog	on foot	2 km	0:20

Table 1. Example of one day travel log from OViN-2014 database

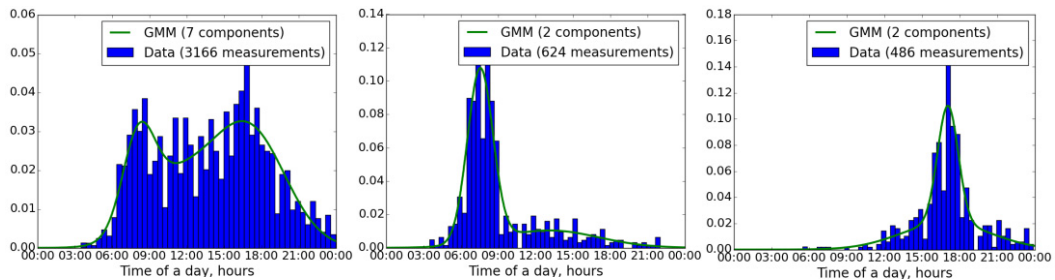


Figure 4. Car trips departure times on working days (left), $P_{HW}(t)$ — departure times to work (middle) and departure times from work (right) distributions for province Noord Holland fitted by Gaussian Mixture Model (GMM)

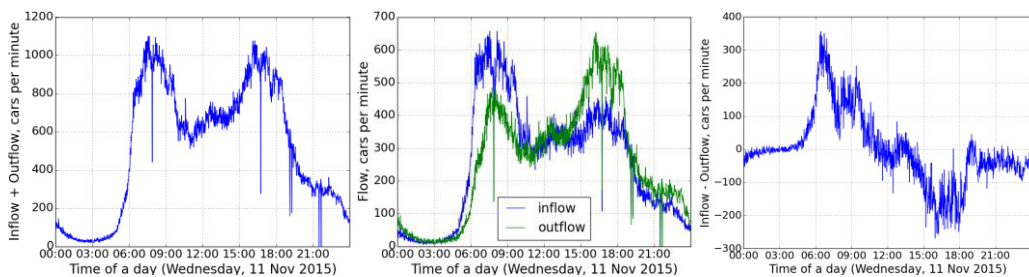


Figure 5. Traffic inflow and outflow (middle), inflow plus outflow (left), inflow minus outflow (right) in Amsterdam on major roads to/from Amsterdam urban area on November 11th 2015.

To populate Amsterdam area with working places, an approach similar to automobile population synthesis is used. Two sources of data were combined to build spatial distribution of working places: (1) data on special industrial and office zones and (2) land use data. Data of province Noord Holland about special business zones for each entry contains location, shape, type (industrial or offices), and number of working places (see Figure 6 middle). As it contains information only about special zones and does not cover the whole Amsterdam area, this data alone is not enough. It was used to obtain distributions of number of working places per ground square meter for industrial and office to populate

areas from land use data (see Figure 6 left) with a building resolution covering the whole simulation domain.

Right graph in Figure 6 shows that from more than 564 thousand working places in Amsterdam the majority (370 thousand) are located outside the special zones. To estimate the spatial density of working places for the whole city, half-normal distributions were built (see Figure 7). Using these distributions and the land use data [21], corresponding areas throughout the city were populated with working places. The remaining number of working places was distributed in living areas. The density was assumed to be linearly decreasing with distance from the city center (GPS-coordinates: [52.3754, 4.9015]). The resulting distribution of working places is demonstrated in Figure 7 (right). Since this approach is stochastic, several algorithm runs have been averaged to obtain a statistically valid model.

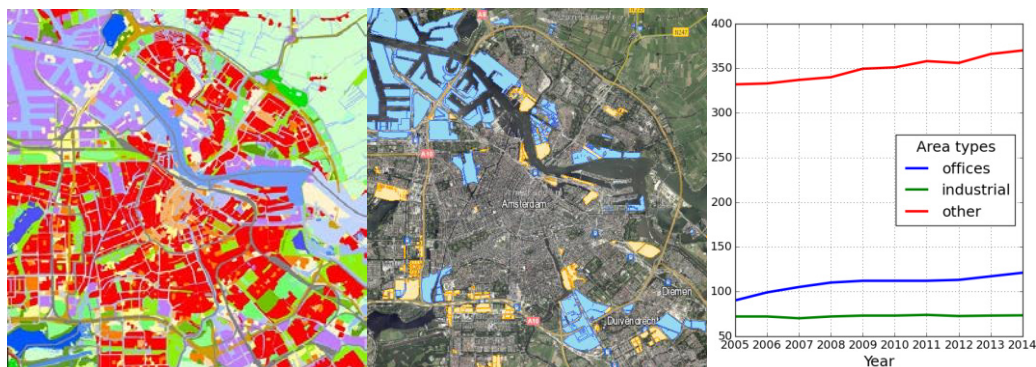


Figure 6. Land use data (left); work locations data (middle): blue – industrial zones, yellow – offices; dynamics of working places count (thousands) in special industrial, offices zones and other locations (right).

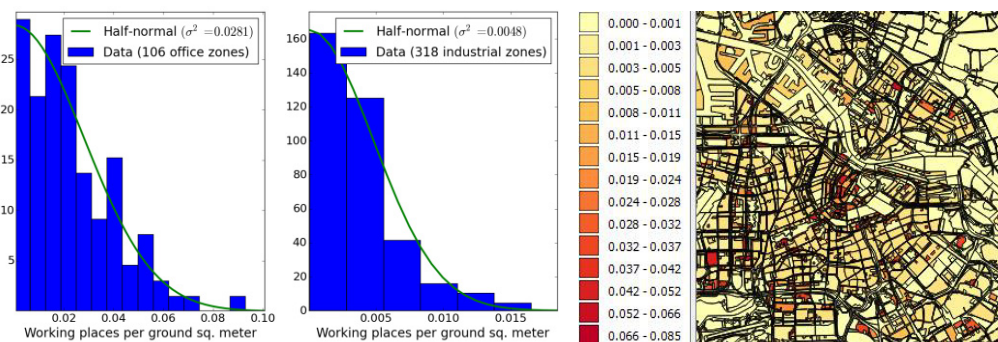


Figure 7. Distribution of working places density per ground square meter for offices (left) and industrial areas (center), $P_{work}(x, y)$ — modeled spatial distribution of working places in Amsterdam urban area.

3.5 Inflow and outflow models

Histogram of distance traveled to work from Amsterdam urban area is shown in Figure 8 (left). Since the mean trip length is greater than the simulation domain, the agents should be allowed to cross simulation border in both directions. To implement this, travel distance is sampled from the distribution (Figure 8), then the agent is either assigned to a working place inside the simulation domain (if the travel distance does not exceed maximum distance from home to any border) or assigned to leave the simulated domain along one of the major roads. A direction is chosen according to a probability obtained from the NDW data. Figure 10 (left) shows a map with five NDW sensors on five primary roads heading to Amsterdam. The middle graph shows the traffic outflow from Amsterdam registered every minute on a

typical working day. Time dependent probabilities of outflow in particular direction in the right graph are obtained from the middle graph by calculating the fraction of each point flow in total flow.

To estimate the inflow traffic load on transportation system in Amsterdam, the inflow-outflow difference plot (Figure 5, right) was integrated over time from 00:00 to time t . The resulting dynamics of the number of accumulated cars (Figure 9, right) demonstrates that during the working day, over 59 thousand extra vehicles operate in Amsterdam. The curve returns to the starting value at the end of the day, which shows that inflow and outflows are balanced within the 24-hour timeframe.

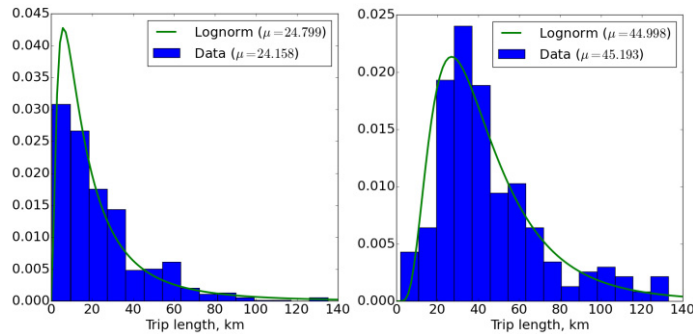


Figure 8. $P_{distIn}(l)$ — distribution of trip distance to/from work for agents living inside Amsterdam (left), $P_{distOut}(l)$ — distribution of trip distance to/from work for agents living outside Amsterdam but working inside

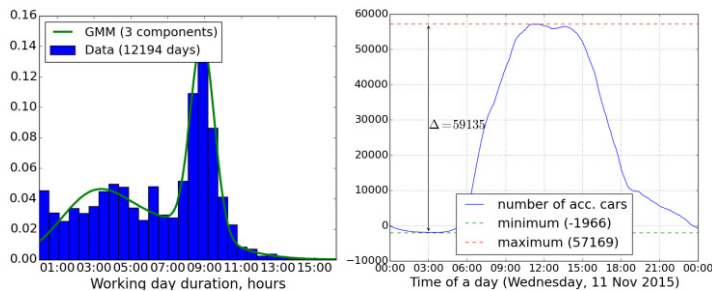


Figure 9. $P_{workDuration}(t)$ —working day duration distribution (middle); number of cars exceeding internal Amsterdam cars population during the working day(right).

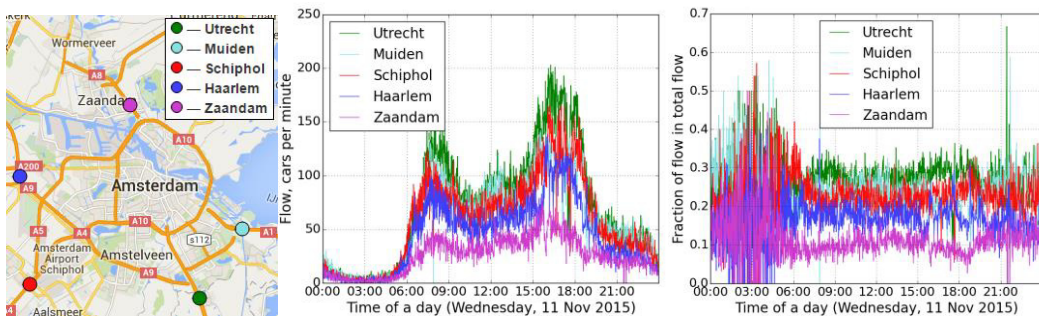


Figure 10. Traffic flow sensors locations chosen for inflow/outflow calculation (left); traffic outflow from Amsterdam (middle), probability of outflow in particular direction (right)

4 Simulation results and discussion

We ran a simulation of home-work-home scenario with 41 thousand agents, which is 10% of estimated total population of 410 thousand agents. We estimated this number in a following way:

- We took $N_{in} = 315000$, which is a total number of car owners inside simulation area found in Section 3.3. We assumed that number of those cars which are not used for daily commute is compensated by number of non-personal cars used by businesses.
- We set fraction of agents living outside main simulation area $\alpha = 0.23$ based on travel survey fraction of outside trips in all trips made to Amsterdam for work, i.e.

$$N_{out} = \frac{0.23}{1-0.23} \cdot 315000 \approx 95 \text{ thousand agents.}$$
- $N = N_{in} + N_{out} = 410 \text{ thousand agents.}$

To take into account reduced number of agents, road capacities were adjusted according to sample size fraction in total population size: multiplied by 0.1. Road curvedness coefficient was set $\delta = 0.75$.

Visualization of simulation results is presented on Figure 11, it demonstrates that during morning rush hour agents experience traffic congestion that lead to speed drop in some parts of road network, including not only city center, but also a ring road.

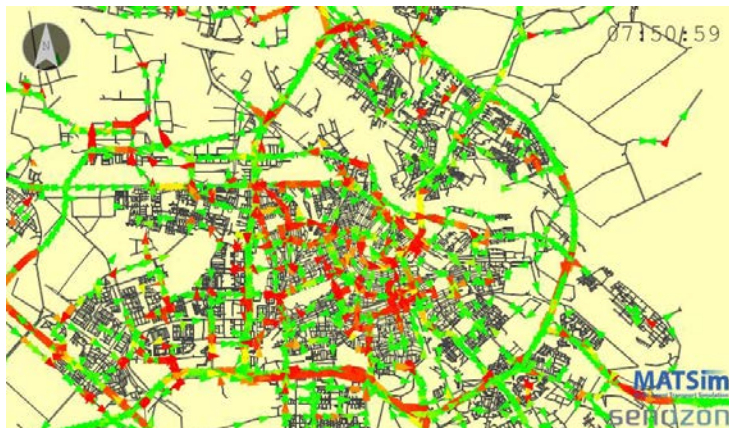


Figure 11. Visualization of simulation results.

To analyze the validity of results we compared simulated average trip distance and travel time with those from travel survey data. Comparison of average trip distance shows that agent plans were generated generally correctly, but it has sense to use separate road curvedness coefficient for generation of plans of agents living outside main simulation domain.

Difference in more than quarter in average travel times demonstrates that even with observed traffic congestions traffic load on road network is lower than real level.

	Agents	Travel survey	Simulation	Difference
Average trip distance, km	all	30.6	32.33	1.73 (+5.65%)
	insiders	24.16	23.9	0.26 (+1%)
	outsiders	44.5	48.1	3.6 (+8%)
Average travel time, minutes	all	33.8	25.2	8.6 (-25.4%)
	insiders	28.8	20.4	8.4 (-29.16%)
	outsiders	44.8	37.8	7 (-15.62%)

Table 2. Simulation average trip characteristics compared to travel survey data.

Another type of validation is comparison of traffic flow intensities from simulation and from road sensors. Left plot in Figure 12 demonstrates that simulated traffic flows during morning rush hour are from 7% to 50% less than those provided by sensor data.

These results imply that described travel demand model should be improved to be able to reproduce real world traffic flows. Further model improvements include:

- More precise estimation of total population size;
- Calibration of inflow-outflow agents ratio based on flows analysis;
- Multiscale travel-demand model: we did not take into account transit traffic which take a big part in case of Amsterdam urban area. By introducing additional layer of transit traffic we will be able to meet simulated and real intensities and also increase density on a ring road, which will result in more realistic travel times;
- Multi-activity travel demand model: by usage of more sophisticated agent activity patterns, containing secondary activities we will be able to meet intensities in mid-peak hours period of a day (Figure 12 right);
- More precise model of work locations distribution.

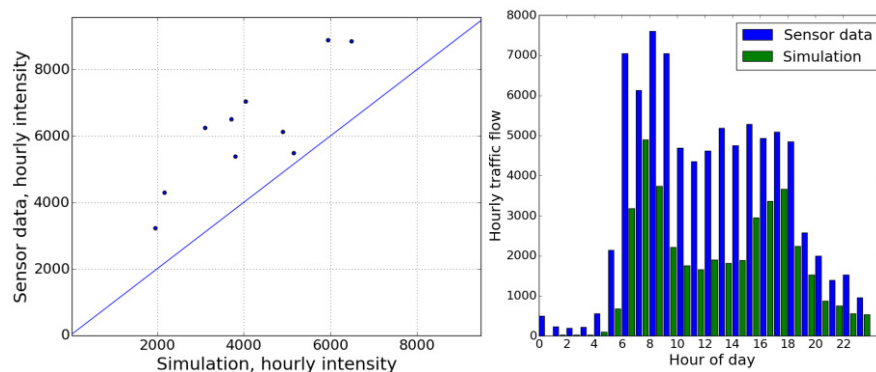


Figure 12. Sensor and simulation intensities for 10 sensors from 5 points on major roads around Amsterdam during morning rush hour from 7 till 8 AM (left), within day hourly intensity rates from sensor and simulation data of road heading from Muiden to Amsterdam (right).

5 Conclusions and future work

In this work we described models and approaches used to perform agent-based large-scale traffic simulation of Amsterdam urban area. This included: road network model, population synthesis, agent activity model and model of inflow and outflow traffic.

For morning rush hour study as well as blackout case study, home-work-home agent plans are appropriate. We ran simulation with 46.5 thousand of agents with such plans, basic validation techniques showed that travel demand model is basically correct, but should be improved, to meet real world data. Several improvements are planned, including transit traffic layer, better estimation of parameters (such as population size, in- and outflow agents number ratio) and introduction of secondary activities of agents.

Our next steps are: to improve travel demand model, to run simulation in even larger scale with number of agents comparable to estimates of real traffic flow in area; to analyze rush hour traffic flows in Amsterdam; to try to reproduce blackout period flow by increasing intensity of automobile traffic, this also can answer the question how sustainable transportation system in study area is, what are critical components in it.

By making agent plans more complex and realistic, and by calibrating model on NDW traffic data, we will be able to simulate precisely the full-day traffic flow. This will be used for ecological research and policy testing, for example, electric vehicles program aimed at emission-free city center of Amsterdam [22].

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