# Information impact on transportation systems

Litescu, S.; Viswanathan, V.; Lees, M.; Knoll, A.; Aydt, H.

**DOI**
10.1016/j.jocs.2015.04.019

**Publication date**
2015

**Document Version**
Final published version

**Published in**
Journal of Computational Science

**License**
CC BY

Journal of Computational Science 9 (2015) 88–93

Contents lists available at ScienceDirect

Journal of Computational Science

journal homepage: www.elsevier.com/locate/jocs

# Information impact on transportation systems☆

Sorina Litescu[a,*], Vaisagh Viswanathan[a], Michael Lees[b], Alois Knoll[c], Heiko Aydt[a]

[a] TUM CREATE, Singapore
[b] University of Amsterdam, The Netherlands
[c] Technical University of Munich (TUM), Germany

ARTICLE INFO

*Article history:*
Available online 18 April 2015

*Keywords:*
Information dissemination
Information control
Modelling and simulation
Agent based simulation
Transportation systems
Human complex systems
Network performance
Traffic

ABSTRACT

With a broader distribution of personal smart devices and with an increasing availability of advanced navigation tools, more drivers can have access to real time information regarding the traffic situation. Our research focuses on determining how using the real time information about a transportation system could influence the system itself. We developed an agent based model to simulate the effect of drivers using real time information to avoid traffic congestion. Experiments reveal that the system's performance is influenced by the number of participants that have access to real time information. We also discover that, in certain circumstances, the system performance when all participants have information is no different from, and perhaps even worse than, when no participant has access to information.



## 1. Introduction

With a larger distribution of personal smart devices and navigation tools, there are several novel sources for real time data collection and better means for information transmission. At the same time, Intelligent Transportation Systems (ITS), applying information processing, communication, sensing, and control technologies [21], have become more advanced and play a key role in improving transportation [20]. In this context, large amounts of data are processed and presented to the participant vehicles through their navigation systems. Surveys show that, in most of the cases, drivers trust real time information and follow the navigation recommendations [6]. However, the consequences of providing real time information to drivers, who are themselves participants in the data collection process, has not been investigated in much detail.

Information dissemination with feedback loops is a fundamental topic in all human complex systems where people make decisions by accessing real time information. Knowing details of future problems modifies people's behaviours and this possibly affects the entire system. This effect has been studied in several areas of human activity. For example, in financial markets, has been analysed the effect of private and public information. In [8], the market dynamics is explained by phases: boom, euphoria (with informational cascades), trigger and panic (with information avalanches). Another example is analysing the effect of transaction costs on the overall market efficiency when aggregating private information [3].

In this paper, we investigate the effect of information dissemination on transportation systems. The annual Traffic Report released in 2014 by the navigation device maker, TomTom, after analysing real world traffic data, reveals that the travel time is increased by 50% because of the common traffic shortcuts drivers take to avoid congestion [16]. The effect can be empirically observed, for instance, during daily commutes, when multiple drivers make the simultaneous decision to take the same alternative route, thus simply moving the congestion to the new road.

Unlike in existing research, [14,15,1,11] discussed in more detail in Section 2, we are particularly interested in investigating how the traffic is affected by the amount of drivers that receive information about the traffic situation. Intuitively, the more drivers are informed, the better the traffic situation should be. We investigate and analyse the conditions under which, drivers having knowledge of the current situation of the traffic system is detrimental to the system as a whole. For this, we built an experimental set-up based on a microscopic traffic simulation. The transportation system and the information dissemination in it is modelled and analysed in this paper through an agent based simulation.

This paper is organised as follows: Section 2 introduces related work done on the effect of information dissemination over

☆ This work was financially supported by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) programme.

* Corresponding author.
*E-mail address:* sorina.litescu@tum-create.edu.sg (S. Litescu).

http://dx.doi.org/10.1016/j.jocs.2015.04.019
1877-7503/

transportation networks. Section 3 and Section 4 describe the computational model, experimental set-up and the numerical results. Section 5 presents the conclusion and the significance of our study.

## 2. Related work

There are some relevant studies on information dissemination in transportation systems using simulations. One category of studies look at how either local information (only about the neighbours) or global information (about the entire network) affects the global network performance. Our approach is different in the sense that we investigate the impact of information on the global network performance depending on the fraction of people that receive information. We analyse what is the effect of real time information dissemination and explain why this effect appears. Information is disseminated in real time and contains global details about how congested the roads are. This approach is important as it gives insights on the impact that massive use of real-time information can have on traffic. This can be useful for building more intelligent traffic control mechanisms where information is a steering tool.

Models of information dissemination have also been studied for networks with congested and uncongested nodes [14,15]. The information (details such as congestion, flow or occupancy) was either local or global. Information is used to control the node's outgoing traffic flow, influencing this way the routing choice for vehicles. In [15], urban street models were implemented for various topologies ranging from naturally evolved ones such as Bologna or London to grid-like cities such as Los Angeles or Washington. Both [15] and [14] show that the best performance is achieved when local information is used.

Information control systems for traffic planning in the presence of congestion has been researched by [1,9–11]. In [1], a fleet of taxi drivers from Singapore used a Web based application to specify trip origin, destination and departure time and receive route recommendations. Congestion was modelled as a relationship between flow and delay, model proposed by the Bureau of Public Roads (BPR). Congestion is estimated using traffic data from loop detectors, GPS location and time data from a roving fleet of taxis. The learned congestion model is used in multi-agent system (computing socially optimal paths) and also in a single agents route planning (computing greedy path). The study proposes an experimental comparison between actual taxi paths, with socially optimal and greedy path congestion-aware planning. The results show that socially-optimal congestion aware routing achieves 15% reduction in travel time.

Our approach is similar because we also select a fraction of drivers to receive recommendations. However, in the previous studies, the number of informed drivers is fixed to the taxi fleet. We investigate in more detail what happens when different percentages of traffic participants receive information. Another difference is that we do not estimate congestion, because, the fact that traffic participants use information makes the congestion prediction invalid.

Other similar studies analysing the effect of information on a traffic simulation are inspired from biological ants systems [4,5]. Information consists of route recommendations. There are infrastructure agents (roads) and vehicle agents. The vehicle agent knows the destination of the car, asks the environment for routing options and informs the road agent of its intention. Based on these details, the road agent estimates the future traffic intensity and gives a recommendation to the vehicle agent. This mechanism provides a better routing choice to drivers.

Understanding congestion is an important aspect in our study. In transportation systems, there are two parameters that are usually taken into consideration when defining congestion: the amount of traffic flow and the strength or the degree of congestion [17]. There are multiple causes for congestion: high traffic flow, bottlenecks (local reduction of the road capacity) and local disturbances of individual drivers in the flow [17,19]. While bottlenecks (caused by road obstructions or lane narrowing) are considered to be spatial and deterministic, local disturbances in the flow are stochastic (spontaneous and unpredictable). They can be triggered, for instance, by an abrupt break or by two trucks overtaking each other at different speeds or several other factors. In our experiments we create congestion using local disturbances.

Network performance is defined by transportation engineers combining the analysis of individual traffic elements. The most common variables used are speed calculated usually as travel time or the delays defined as additional travel time experienced by the traffic participants. The global network performance is then obtained by aggregating the individual travel times across the entire network [12]. A similar performance indicator was selected for our study. Another approach would be to calculate the fundamental diagram of the network mean flux and a function of traffic load [15]. In other studies network performance is defined as the relation between the filled fraction of the total network capacity and the jammed population of nodes [14].

## 3. Computational model

We investigate the effect of information dissemination on transportation systems when different fractions of drivers are informed. In order to gain an understanding of this effect, we use a computation model of the traffic flow, congestion formation and information dissemination.

The transportation system is simulated using an agent-based simulation. The system consists of agents (vehicle driver units) operating and interacting in a shared environment (road network). The behaviour of the entire system is the emergent behaviour of all its interacting elements. The agents know the road network, perform route calculations and move forward on their route with a certain speed and acceleration determined by a time-stepped car following model [2]. For this, the Intelligent Driver Model (IDM) is used [18,7].

A road $Y$, is characterised by a tuple with road length, minimum speed and maximum speed: $Road_Y = \langle v_Y^{\min}, v_Y^{\max}, L_Y \rangle$. Fig. 1 illustrates a typical IDM scenario. A vehicle $i$ follows the car in front vehicle $i+1$ at a speed less than the desired speed of the road $v_d$, which is a value between $v^{\min}$ and $v^{\max}$. The current speed of car $i$, $v_i$ is adapted to the speed of car $i+1$, $v_{i+1}$ in order to maintain a gap distance greater than $D_{gap}$. Where $D_{gap}$ is a parameter of the IDM model that specifies the preferred distance between cars. IDM calculates a realistic instantaneous acceleration (or deceleration) and displacement of vehicle $i$ for a time step $\delta t$ by taking into consideration its current speed and position ($v_i$ and $x_i$), the desired speed ($v_d$), the current speed and the position of the car in front ($v_{i+1}$ and $x_{i+1}$). In addition, there are parameters that specify vehicle length ($L_{vehicle}$), time headway ($t_h$) for safe acceleration and deceleration (to avoid collisions), and maximum acceleration and deceleration ($a_{max}$, $d_{max}$).

We analyse the effect of traffic information dissemination in the presence of congestion. For this, we introduce stochastic disturbances in the traffic flow to create a controlled scenario where congestion is persistent. Congestion is produced naturally as an emergent behaviour of cars interacting on roads (for example it can create self-organised stop-and-go waves, as described in [7]). This congestion naturally appears and disappears through the evolution of the traffic. For our study we need to regulate congestion and for this reason we artificially introduce disturbances.

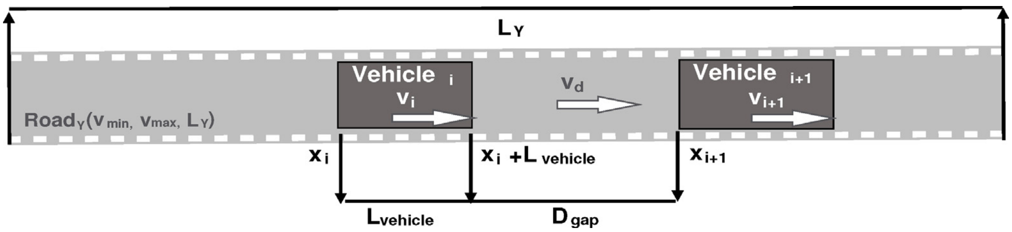



**Fig. 1.** In an IDM scenario, a vehicle $i$ is characterised by the current position $x_i$ and the current speed $v_i$. $D_{gap}$ is the gap distance between vehicles. The road is characterised by minimum and maximum speed, length and desired speed $v_d$: $Road_Y = \langle v^{\min}, v^{\max}, L_Y \rangle$.

Information dissemination is simulated by sending updates to only a fraction of the agents. Information contains details about current travel times on links and is used by informed agents to estimate the fastest path (as defined by travel time). Route calculation is done using Dijkstra's algorithm. We therefore have two types of agent, *informed* and *uninformed*. The only difference between these two agents is that one calculates the best route using a road network of *current* travel time (these are the informed agents). The other agents calculate the best route assuming free flowing traffic, i.e., they estimate travel time by dividing the length of the road by the maximum speed of that road: $L_Y/v_Y^{\max}$. This way, the congested roads may have a lower priority in the informed driver's choice.

## 4. Experiments

We are particularly interested to evaluate the effect caused on traffic by real time information dissemination in the presence of congestion (generated by local disturbances). For this, we define the experimental setup with the network graph, parameters, metrics and indicators.

For the experiments we consider a simplified scenario using a road network as shown in Fig. 2. Every agent starts at the origin and moves towards the destination. The agents have 2 choices in terms of the routes they take: $Road_A = \langle 11\,[\text{m/s}], 19\,[\text{m/s}], L_A \rangle$ and $Road_B = \langle 11\,[\text{m/s}], 19\,[\text{m}], L_B \rangle$, where $L_A$ is fixed at 500 [m] and $L_B \geq L_A$. Both roads are single lane. As described in Section 3, each car applies the IDM model and the parameters used are: $L_{vehicle} = 3\,[\text{m}]$, $a_{max} = 3\,[\text{m/s}^2]$, $d_{max} = 5\,[\text{m/s}^2]$, $t_h = 1.5\,[\text{s}]$, $\delta t = 250\,[\text{ms}]$.

Agents are created by a Poisson process with a mean inter arrival time of 1700 [ms]. This value is chosen as the minimum inter arrival time so as to maximise traffic, while not causing congestion on Road C (i.e., before the decision point, marked in Fig. 2). Each informed agent receives updates about the traffic situation every 2 [s]. At the *decision point*, the agents select either Road A or Road B, whichever gives the fastest route time. We simulate 40 min which implies about $N = 1000$ agents in total that finish trips. From this amount, we consider the last 800 vehicles to complete their trip $N_c$, giving a warm-up period of 10 min.

Congestion is created by introducing disturbances in the *disturbance area* (the last 150 [m] of Road A), marked on Fig. 2. In order to create a disturbance, a random vehicle $i$ driving on the disturbance segment of the road is chosen every 2 [s] and forced to brake immediately ($v_i = 0\,[\text{m/s}]$).[1] The car takes some time to accelerate and once again reach full speed, thus causing a temporary congestion on the link.

Each experiment is characterised by two parameters: $L_B$, the length of Road B and $p$, the percentage of informed agents. $L_B$ varies from 500 [m] to 1250 [m], while $L_A$ is fixed to 500 [m]. $p$ varies from 0% (no agent is informed) to 100% (all agents receive information). Each experiment is repeated 10 times.

[1] We use a simplification of instantaneous deceleration.

In order to quantify the effect of information dissemination, we characterise network performance as $T$, the average travel time of all agents in one experiment.

$$T = \frac{1}{N_c} \sum_{i=0}^{N_c} t_i, \tag{1}$$

where $t_i$ is the trip duration of an agent $i$ and $N_c$ is the last 800 agents to complete their trip. $T$ is analysed for different groups of agents. We calculate a global $T$ over all agents and $T_U$, $T_A$ and $T_B$ for the different groups of agents: uninformed, informed agents on Road A and informed agents on Road B.

For each $L_B$ we can calculate the maximum improvement across all levels of informed agents, i.e., $p \in (0, 100]$. The information impact indicator for a road length $L_B$, $I_{L_B}$, quantifies the maximum improvement (negative change) on $T$ when compared to the case of no information. This is actually the value of $p$ at which we see the smallest value of $T$, which we define as $p_{min}$.

$$I_{L_B} = \max(T_{0,L_B} - T_{p_{\min},L_B}), \tag{2}$$

where $T_{p_{\min},L_B}$ is the minimum $T$, obtained for $p_{min}$. $T_{0,L_B}$ is $T$ for $p = 0\%$.

As we increase $p$, for some road lengths $L_B$ the average trip time will initially decrease (i.e., performance improves) to a minimum at $p_{min}$, beyond which average trip time will increase. We define this degradation in performance (increase in average travel time) as $D_{L_B}$.

$$D_{L_B} = \max(T_{p_{\max},L_B} - T_{p_{\min},L_B}), \tag{3}$$

where $p_{max}$ gives the longest average trip time and $p_{max} > p_{min}$. Note that for $L_B = 625\,[\text{m}]$, $p_{max} = 100\%$ and $p_{min} = 60\%$, $I_{625} = 98.1 - 85.8 = 12.3\,[\text{s}]$ and $D_{625} = 91.06 - 85.85 = 5.21\,[\text{s}]$.

It is interesting to note that $T$ is influenced both by $p$ and by $L_B$, shown in Fig. 3. We illustrate in Fig. 3(b) the impact of information on $T$ as we vary $L_B$. For this we calculate the improvement indicator $I_{L_B}$ (defined in Eq. (2)) and the degradation indicator $D_{L_B}$ (defined in Eq. (3)). We see that the information produces the biggest improvement, $I_{L_B} = 12.3\,[\text{s}]$, for $L_B = 625\,[\text{m}]$ and the most significant degradation, $D_{L_B} = 6.7\,[\text{s}]$, for $L_B = 875\,[\text{m}]$.

Next, we explain why there is a significant improvement on $T$ for $L_B = 625\,[\text{m}]$ and a significant degradation on $T$ for $L_B = 875\,[\text{m}]$. For this, we define $F_Y$ as the fraction of informed agents that select Road Y:

$$F_Y = N_Y/N_I, \tag{4}$$

where $N_Y$ is the number of informed agents that select Road Y and $N_I$ is the total number of informed agents.

Fig. 4 shows how $p$ affects $F_A$ and $F_B$ for the two values of $L_B$. In Fig. 4(a) we observe that, for $L_B = 625\,[\text{m}]$, $F_A < F_B$. This happens because Road A is congested (we introduce artificial disturbances) and therefore Road B, with $L_B = 625\,[\text{m}]$, is the fastest option. The agents that select Road B don't experience a significant increase in distance and therefore no severe degradation on travel times. In this case $T$ has a big improvement. On the other hand, in Fig. 4(b)

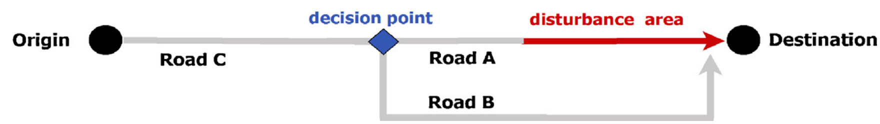



**Fig. 2.** The following network graph is used in experiments. Agents travel from origin to destination on the fastest recommended option. Agents select either Route A or Route B at the *decision point*. Congestion is obtained by introducing disturbances on *disturbance area* (the last 150 [m] of Road A). $L_A$ is fixed to 500 [m], while $L_B$ varies between 500 [m] to 1250 [m].

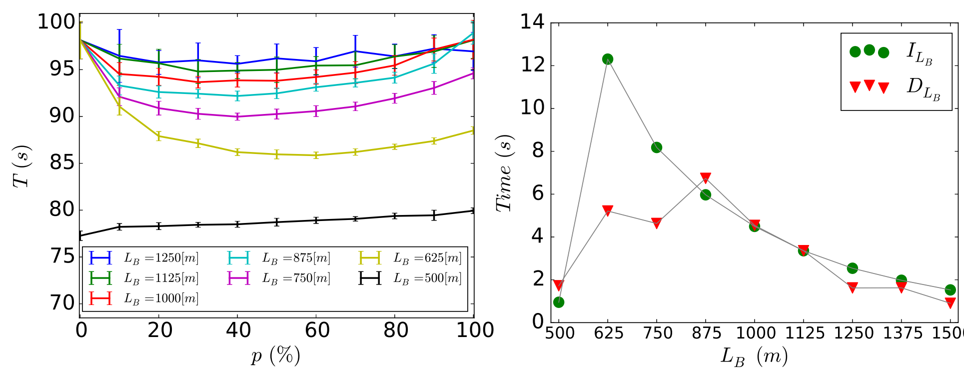



**Fig. 3.** Information impact on $T$ (defined in Eq. (1)) depending on $p$ and $L_B$.

we see that, for $L_B = 875$ [m], $F_A \geq F_B$. The reason is that $L_B$ is long enough that it is better to choose Road A, even though this road is congested. The informed agents that select Road B experience longer trip durations, producing a significant degradation on $T$.

Based on the results illustrated in Figs. 3 and 4, we focus further investigation in the case of $L_B = 875$ [m]. This case is interesting as it contains a significant improvement ($I_{875} = 6$ [s] for $p_{min} = 40\%$) but also significant degradation ($D_{875} = 6.7$ [s] for $p_{max} = 100\%$). Even though intuitively, one would expect that more agents using information would improve traffic conditions, our results show the opposite in some cases. Fig. 5(a) shows $T$ as a function of $p$ in the case of $L_B = 875$ [m]. We notice that by increasing $p$, first $T$ improves and afterwards it decreases to almost the same level as if no agent is informed.

In order to explain this effect, we analyse the average speed for roads A and B, and we evaluate $T_U$, $T_A$ and $T_B$ for uninformed, informed agents that select Road A and informed agents that select Road B. We notice in Fig. 5(a) that $T_U$ and $T_A$ have smaller values than $T_B$. The informed agents select Road B because it is recommended by Dijkstra's algorithm as the best route at that moment. After a while, the situation improves on Road A, the informed agents find out about this change. The agents from Road B are not able to return on Road A and their trips take significantly longer, causing a severe degradation on the global $T$.

We define $S_A$ and $S_B$ as the average speed on Road A and on Road B for one experiment. In Fig. 5(b) we see that $S_B$ decreases for higher values of $p$. This is caused by the increasing number of agents that select Road B as illustrated in Fig. 4(b). $S_A$ remains almost the same, regardless of the fact that the number of agents on Road A is getting smaller as $p$ increases. This happens because on Road A we introduce disturbances to regulate congestion.

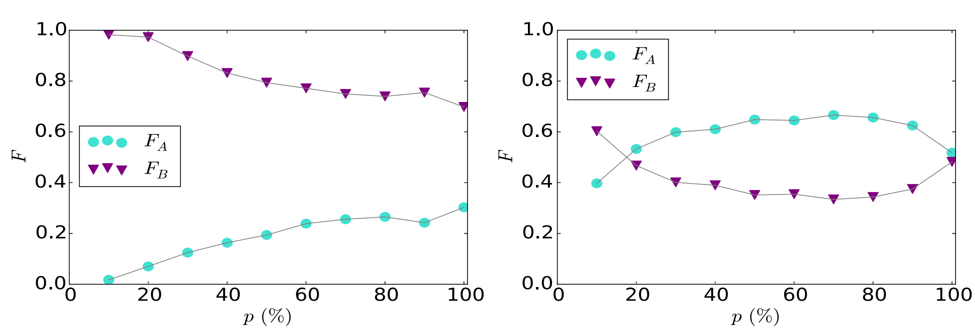
The average speed on roads influences the way Dijkstra's algorithm produces route recommendations. In Fig. 6 it is shown that $SD$ (standard deviation) of $N_A$, $N_B$, $S_A$ and $S_B$ becomes bigger when we increase $p$. This means that the recommendations from Dijkstra's algorithm change more frequently for bigger $p$. Some informed agents are recommended to select Road B, even though very soon afterwards, the recommendation is no longer valid. Nevertheless, the agents that selected Road B are not able to move Road A, even though they may receive new recommendations later.

The congestion indicator $C_Y$ for a Road $Y$ is defined as follows:

$$C_Y = (1 - v_Y^{avg} / v_Y^{\max}), \quad (5)$$

where $v_Y^{avg}$ is the average speed on Road $Y$ at the moment when agents select their route (at *decision point* marked on Fig. 2) and $v_Y^{\max}$ is the maximum speed for the road.

Fig. 7 illustrates $F_A$ and $F_B$ (defined in Eq. (4)) depending on $C_A$. We notice in Fig. 7(a) and (b) that for higher $p$, agents experience




(a) $F_A$ and $F_B$ for $L_B = 625m$ (b) $F_A$ and $F_B$ for $L_B = 875m$

**Fig. 4.** $F_A$ and $F_B$ (as defined in Eq.(4)) illustrates the fraction of informed agents that select either Road A or Road B, depending on $p$.

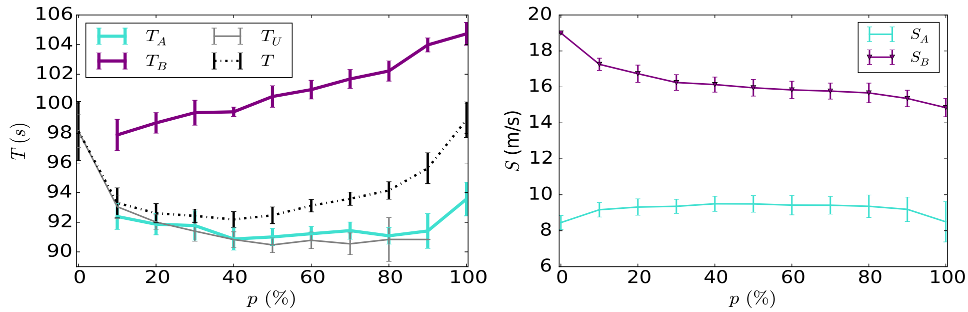
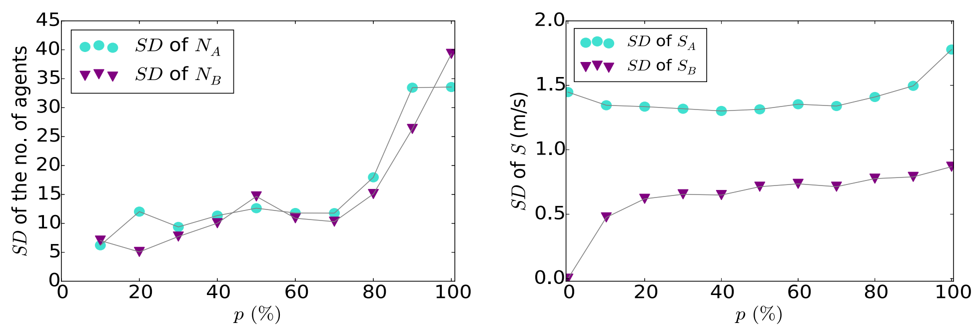
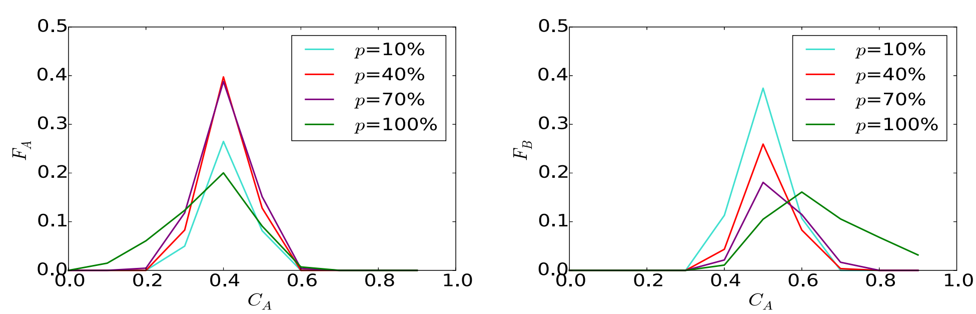



**Fig. 5.** Information impact on $T$(defined in Eq. (1)) (average trip duration) and on $S$ (average speed on roads) depending on $p$. $L_B$ = 875 [m].




(a) $SD$ of $N_A$ and $N_B$ (b) $SD$ of $S_A$ and $S_B$

**Fig. 6.** SD(standard deviation) of $N_A$ and $N_B$ (numbers of the informed agents that select Road A and Road B) and SD (standard deviation) of $S_A$ and $S_B$ (average speed on Road A and Road B), depending on the $p$. $L_B$ = 875 [m].




(a) $F_A$ for Road A depending on $C_A$ (b) $F_B$ for Road B depending on $C_A$

**Fig. 7.** $F_A$ and $F_B$ (fraction of informed agents that select Road A and Road B, defined in Eq. (4)) calculated for the congestion indicator $C_A$ for Road A (defined in Eq. (5)). $L_B$ = 875[$m$].

$C_A \in (0, 1)$, while for smaller $p$, $C_A$ interval is narrower. Road A is selected when $C_A$ has smaller values (the congestion is smaller on Road A), while Road B is selected when $C_A$ is bigger (the congestion on Road A is higher).

It is important to notice that traffic is influenced both by $p$ and by $L_B$. Unlike the common intuition, there are cases when more information becomes detrimental. Also, we show that among the informed agents some experience worse $T$ than others, even though one would expect to have similar performances. This phenomenon is explained in an abstract manner as follows: the transportation system provides data coming from fixed or mobile sensors. Information is processed from data and sent back into the system in real time. People make new routing decisions and change their behaviour. These new routing decisions, result in the original model of the transportation system, which produced the routing recommendations, to be invalid because the participants changed their behaviour.

## 5. Conclusions

We present our experimental results involving information dissemination in transportation systems. These results show that informing drivers about congestion in the transportation system will affect the overall performance. In some cases, if most of the traffic participants receive information (for example trough navigation tools and applications on personal smart devices) traffic can become worse, contrary to common expectation. There are cases when giving more information does not make a difference on the network performance and cases when it gets improved.

It is important to note that our model of disseminating information consists in selecting specific numbers of traffic participants to receive details about congestion. We calculated the network performance when varying the amount of informed agents and the length of the alternative road selected to avoid the congested area. For this study, it was assumed that all agents are rational and decide to use the information about congestion to improve their travelling time.

Future work will aim to extend the existing models of information dissemination by introducing among others time delays and information errors. Also, we plan to use more realistic city networks and human behaviour models in order to determine how agents decide to use the real time congestion awareness information.

The findings of our study are relevant in the context of information based solutions for ITS [21], involving information processing, advanced communication and sensing. There are significant amounts of money that governments and private industry invest in developing such systems. ITS are expected to play even a more important role in the future [20]. It is useful to anticipate the impact that the massive use of real time information can have on traffic.

Particularly, understating the effect of real time information disseminated in traffic can help solving problems related to congestion. A practical solution to improve congestion should take into consideration not only the travel time but also reliability, predictability, recurrence,peak-spreading or the geographic extent [13]. This will be analysed in future work.

For planning efficient future ITS, it is necessary to consider the negative and the positive effects that real time congestion awareness information can have. Our study illustrates that the real time information has a great impact on a transportation system. Understating what the effect is and why it occurs can help decreasing the likelihood of congestion, therefore it is worth exploring further details.

## References


[1] Javed Aslam, Sejoon Lim, Daniela Rus, Congestion-aware traffic routing system using sensor data, in: 2012 15th International IEEE Conference on Intelligent Transportation Systems (ITSC), IEEE, 2012, pp. 1006–1013.

[2] Heiko Aydt, Yadong Xu, Michael Lees, Alois Knoll, A multi-threaded execution model for the agent-based semsim traffic simulation, in: AsiaSim 2013, Springer, 2013, pp. 1–12.

[3] Marco Cipriani, Antonio Guarino, Herd behavior and contagion in financial markets, BE J. Theoret. Econ. 8 (1) (2008).

[4] Rutger Claes, Tom Holvoet, Maintaining a distributed symbiotic relationship using delegate multiagent systems, in: Simulation Conference (WSC), Proceedings of the 2010 Winter, IEEE, 2010, pp. 2981–2990.

[5] R. Claes, T. Holvoet, D. Weyns, A decentralized approach for anticipatory vehicle routing using delegate multi-agent systems, in: IEEE Transactions on Intelligent Transportation Systems, vol. 12 (2), IEEE, 2011, pp. 364–373.

[6] Verena Franken, Transportation Research Board, Use of navigation systems and consequences for travel behaviour, in: ECTRI-FEHRL-FERSI Young Researcher Seminar, Brno, Czech Republic, 2007.

[7] A. Kesting, M. Treiber, D. Helbing, Agents for Traffic Simulation, 2008, arXiv preprint arXiv:0805.0300.

[8] In Ho Lee, Market crashes and informational avalanches, Rev. Econ. Stud. 65 (4) (1998) 741–759.

[9] S. Lim, H. Balakrishnan, D. Gifford, S. Madden, D. Rus, Stochastic motion planning and applications to traffic, in: Algorithmic Foundation of Robotics VIII, Springer, 2009, pp. 483–500.

[10] S. Lim, D. Rus, Stochastic motion planning with path constraints and application to optimal agent, resource, and route planning, in: 2012 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2012, pp. 4814–4821.

[11] S. Lim, D. Rus, Congestion-aware multi-agent path planning: distributed algorithm and applications, Comput. J. (2013) bxt067.

[12] Highway Capacity Manual, Highway Capacity Manual, 2000.

[13] The European Conference of Ministers of Transport (ECMT), Managing Urban Traffic Congestion, 2007 (Online). Available at http://www.internationaltransportforum.org/Pub/pdf/07Congestion.pdf

[14] G. Petri, J.H. Jensen, J.W. Polak, Global and local information in traffic congestion, Europhys. Lett. 88 (2) (2009) 20010.

[15] S. Scellato, L. Fortuna, M. Frasca, J. Gómez-Garde nes, V. Latora, Traffic optimization in transport networks based on local routing, Eur. Phys. J. B: Condens. Matter Complex Syst. 73 (2) (2010) 303–308.

[16] TomTom, 4th Annual Traffic Index, 2014 (Online). Available at http://corporate.tomtom.com/releasedetail.cfm?ReleaseID=851820

[17] M. Treiber, A. Hennecke, D. Helbing, Congested traffic states in empirical observations and microscopic simulations, Phys. Rev. E 62 (2) (2000) 1805.

[18] M. Treiber, A. Hennecke, D. Helbing, Congested traffic states in empirical observations and microscopic simulations, Phys. Rev. E 62 (2) (2000) 1805.

[19] M. Treiber, A. Kesting, Traffic flow dynamics, in: Traffic Flow Dynamics: Data, Models and Simulation, Springer-Verlag, Berlin, Heidelberg, 2013, p. 1, ISBN 978-3-642-32459-8.

[20] Futurium, European Union Smart mobility – Intelligent Transport, 2014 (Online). Available at http://ec.europa.eu/digital-agenda/futurium/en/content/smart-mobility-intelligent-transport

[21] T.A. Dingus, W. Barfield, Human Factors in Intelligent Transportation Systems, Psychology Press, 2014.