

CELLULAR AUTOMATON URBAN TRAFFIC MODEL

Felix TOTIR¹, Ștefan CANTARAGIU², Tudor POPESCU³

Rezumat. *Articolul abordează modelarea traficului urban de automobile. Principalele caracteristici ale metodei expuse sunt utilizarea unui automat celular pentru modelarea distribuției autovehiculelor de-a lungul a două străzi între care este interpus un semafor. Se analizează astfel apariția și incidența fenomenelor de ambuteiaj. Modelarea comportamentului conducătorilor auto se face probabilist. Rezultatele prezentate pot fi utilizate atât în vederea asigurării unei fluențe sporite, cât și a optimizării consumului de combustibil, controlul nivelelor de poluare chimică și fonică.*

Abstract. *The paper presents an approach for urban vehicle traffic modeling. Main characteristics of the exposed method are the use of a cellular automaton in order to model the vehicle spreading over two streets interconnected with the help of a traffic light. The apparition and the incidence of bottlenecks phenomena are thus analyzed. Drivers' behavior is modeled probabilistically. Obtained results are valuable for increasing traffic fluency, optimizing fuel consumption and controlling chemical and phonic pollution levels.*

Keywords: urban vehicle traffic, cellular automata, intelligent transportation

1. Introduction

Appropriate modeling of urban traffic is of extreme importance in the modern days. Heavily crowded, cities must cope with a growing number of cars, the level of traffic continually increasing. Fluency of vehicle traffic is not the only issue: levels of phonic and chemical pollution are also to be addressed. Fuel consumption is another first-hand issue, especially with the non-renewable, fossil resources showing their limits.

Modeling a city's vehicle traffic is, quite often, a particular and stand-alone problem. This is because, for the vast majority of cases, no networks of roads are the same for any two cities. To further complicate the issue, one has also take into account weight limits, forbidden ways, obligated passages for some categories of vehicles, but also many psychological factors such the driver predilection for large, high-capacity freeways, the attraction exercised by some areas of the city for tourists, seasonal loading of the roads etc.

¹Dr. Eng., Military Technology and Equipment Research Technology, Bucharest, Romania.

²Dr. Eng., Chief Technology Officer, UTI Group, Bucharest, Romania; corresponding member of the Academy of Romanian Scientists (stefan.cantaragiu@uti.ro).

³Dr. Eng., Systems Integrations and Development, UTI Systems, Bucharest, Romania.

On the other hand, beyond accuracy, a useful traffic model should also be evolutionary. Nowadays, the city skyline is continuously changing. Even if large freeways do not change for long periods of time, different restrictions based on weight and category may be made for vehicles (by example, reserving particular lanes for bus traffic only). Also, infrastructure maintenance interventions, natural disaster, all require reconfiguring the traffic model, the time being a critical issue.

A flexible and appropriate model is useful not only for understanding the city fluxes of vehicles and analyzing the apparition of bottlenecks and of heavy-traffic areas. Ideally, it should also allow the legal authorities to properly react in order to minimize the negative (for traffic fluency) effects of unexpected incidents, such as collisions, ambulance, police or firemen interventions, or simply to help flushing the formed bottlenecks. This issue is even more important as the congestions caused by the above-mentioned usually have side effects, sometimes reverberating into the whole traffic. Although the basic causes are usually quite simple (by example, one driver may just attempt to use a different route or to turn around), the outcome may be a domino-like effect. These interdependencies and resulting difficulties mean that the separate modeling of different areas of the city is no longer appropriated.

The unpredictability of city traffic, directly caused by the unpredictability of drivers' intentions and behavior, called for the use of various techniques, ranging from statistics to hydrodynamics and mean field approaches [1-8] or chaotic models [9] [10]. The latter, by example, is a promising tool to rapidly assert, even if with an underlying probability, the effects of events such as car collisions, blockages etc. at the level of the entire city.

2. Peculiarities of city traffic modeling

Regarding city traffic modeling, an essential requirement is to be able to produce a dynamically correct representation of the transportation system. A simple average of streets loading will not provide a valuable measure of peak-hours traffic and will fail to predict congestions caused by such general hurries as going to work and coming back home. Thus, dynamical correctness, along with wide temporal and spatial scales is required for the traffic model. Such are the microscopic approaches, based on the individual description of the cars, seen as the smallest particles in traffic, unlike the method of aggregated traffic flow.

The microscopic approach has a number of advantages, such as allowing including individual route choice behavior for each car. However, even if individual car models are rather simple, they quickly sum up, so that modeling of large transportation systems [11] may prove computationally very intensive.

An intermediate way is to provide detailed, i.e. microscopic modeling for critical traffic points only. Such are the transitions between the roads of the city. The

dynamics of these transitions is important, particularly since it is at the level of these transitions that the bottlenecks and traffic congestions tend to occur.

In urban systems, probably the most important bottlenecks are the traffic lights. Usually, these are studied via queuing-type models [12-14]. In order to account for the road capacity, a limited service rate is introduced for each link. When the time necessary for a car to arrive at the end of the link is reached, the car is added to the queue in front of the traffic light.

A different approach, presented in [15] and reviewed here, makes use of simple single-lane micro-simulations in order to capture the dynamics of the traffic on the link itself.

A simulation model of urban traffic is presented below, using a combination of stochastic cellular automata and probabilistic transitions between streets. The urban road network is represented via an associated graph, where a link means a directed street segment (a two-direction road will be divided in two such oriented links) and a node models an intersection. Each link of the graph will be bounded by an input node and an output node. Vehicles are moved on the links according to an underlying cellular automaton model described below, and are transferred between two paired links (i.e. having the same input and output nodes) probabilistically, based in the link's capacity.

3. Models for links and transitions

Roads (and corresponding links) have different characteristics, modeling their physical parameters: length, speed-limit, number of lanes, maximum capacity etc. In the approach presented here, from the length of the road and the speed limit follows the time necessary for the car to arrive at the end of the road. But, the road's length will also determine the number of the sites (cells of the cellular automaton) allowable for the cars on the given road.

Similarly to [16], the length of one site is assumed to be 7.5 m. Each such site (cell) can be either empty or occupied by a vehicle. The latter has a state defined by its quantified velocity $v \in \{0 \dots v_{\max}\}$. A typical choice [15] is to use 5 quantification levels, so that $v_{\max} = 5$.

Recall that each link is, in fact, a one-lane segment. Based on this assumption, it is assumed that the vehicles are moving using the Nagel-Schreckenberg model [16]. The number of unoccupied sites in front of a vehicle is denoted by *gap*. Normally, a large *gap* will encourage the driver to accelerate. However, there is also the possibility for this expected behavior to no occur. This case, i.e. having a driver slower than he could, is modeled by the probability p_{noise} .

The model (and its simulation) is iterative. Let us denote by *rand* a normalized (i.e. between 0 and 1) random number, generated at each iteration. One such

iteration of the traffic model consists of the following three sequential steps, applied in parallel to all cars:

1. all free (having a strictly positive gap) vehicles are accelerated at the next level of speed, provided that the maximum allowed speed is not already reached: if($v < v_{max}$) then $v = v + 1$;
2. the effect of the other cars is taken into account by slowing all the cars which are too close of their forerunners: if($v > gap$) then $v = gap$;
3. driver decelerating behavior is stochastically modeled: if ($v > 0$) and ($rand < p_{noise}$) then $v = v - 1$.

For each link, the transition probability is a function of the capacity of the link. This is useful in order to model multi-lane roads (where a road is seen as a set of paired links). Obviously, the one-lane model is faster and easier to implement and to simulate.

Differentiating the roads in a city, and the corresponding graph links, is achieved by associating probabilities. They help to differentiate the existing links within a city, which vary from high capacity segments such as freeways to low capacity segments such as arterials. If only one-lane links are considered, the probabilistic transition is introduced to control the output flow of a link. A high-capacity link will produce a high output flow, while a low capacity link will produce a low output flow.

4. Simulation of a simple node

In this part, two consecutive links separated by a probabilistic transition p_{trans} are considered (see Fig. 1). Each n iterations, a vehicle is introduced in the first site of the link 1, unless it is already occupied. The iterative model is ran and, when vehicles reach the separation between the two links, they are transferred in the first site of the second link (only if that site is free), with the probability p_{trans} .

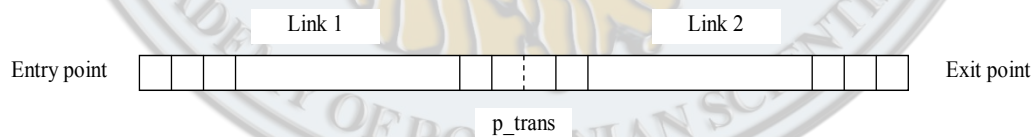


Fig. 1. Two links separated by a transition probability

In the particular case when the p_{trans} equals 0.5, an example of the simulated flow (in vehicles per iteration) at the output of the second link is shown in Fig. 2. In the simulated scenario, a new car is introduced every 3 iterations in the first cell of the first link and a number of 5 speed levels are assumed. If the transition of the vehicle towards the second link is not possible at the current iteration (which happens with the probability $1 - p_{trans}$), then the situation is modeled as the traffic light is red. For the vehicle advancing towards separation, the situation is identical

as if the first site of the second link is occupied. As such, the iteration 2 of the model (i.e. truncating the car's speed at *gap* level) will be applied to the vehicles having red light. One should be aware that the traffic light color is subject to change at every iteration, so the same vehicle may successively accelerate and decelerate as approaching the separation.

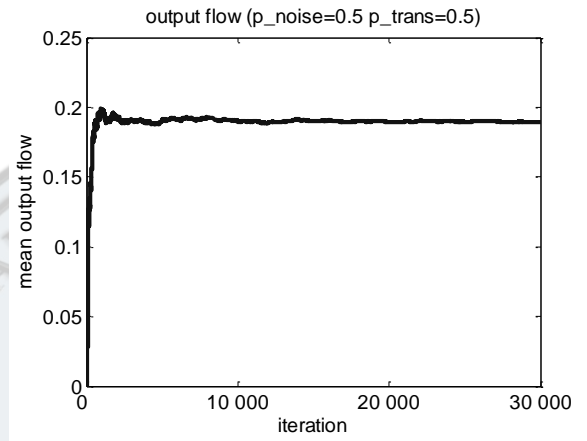


Fig. 2. Flow at the output of the second link

The fact that the transition of the vehicle reaching the intersection is not guaranteed for all iterations means blockages could occur. This is clearly seen with the help of space-time diagrams. These are graphics representing the temporal evolution of the underlying cellular automaton. Black points designate the occupied cells while white areas mean unoccupied cells. A state-space diagram has the spatial information represented by the upwards-oriented vertical axis, while the rightwards-oriented horizontal axis represents the time bins.

Two cases are illustrated: for $p_{trans}=0.5$ (see Fig. 3) and for $p_{trans}=0.9$ (see Fig. 4).

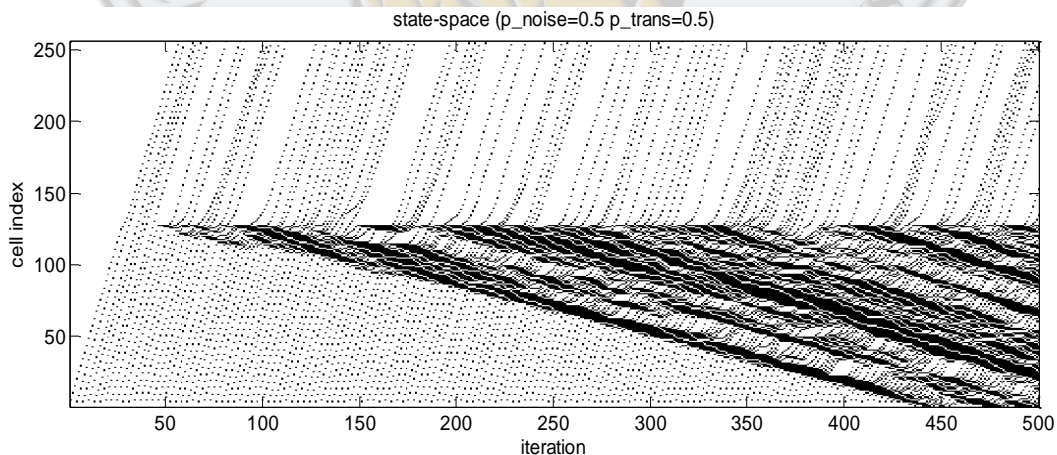


Fig. 3. Space-time diagram ($p_{trans}=0.5$)

Simulations show that the output flow measured at the end of the second link and the probability p_{trans} are not proportional. This is because of the non-linearity of the assumed model, respectively of the cellular automaton.

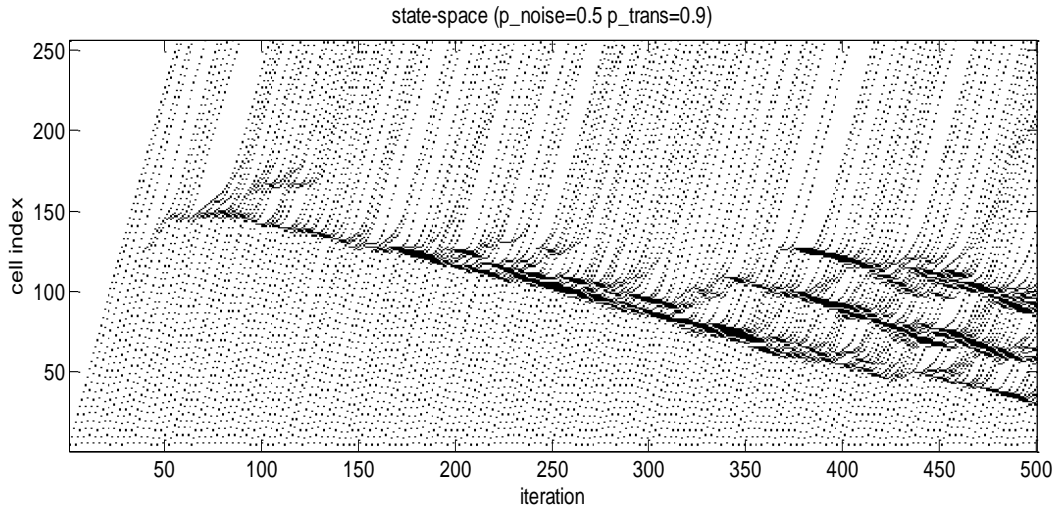


Fig. 4. Space-time diagram ($p_{trans}=0.9$)

The illustration of this phenomenon is given in Fig. 5, where the average flow is depicted versus the values of p_{trans} . The plot may be divided into three areas, analyzed below.

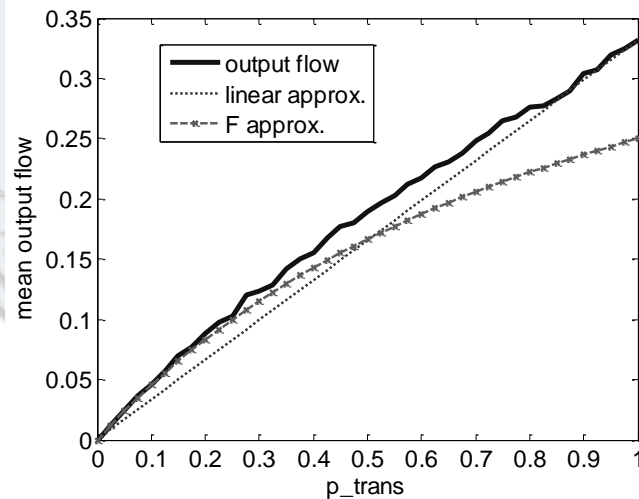


Fig. 5. Average output flow as a function of p_{trans}

The first area corresponds to values of p_{trans} between 0.8 and 1. For such high transition probabilities, the output flow varies linearly with p_{trans} . This is expected since in this case vehicles do not stop at the separation except very rarely. The space-time diagram in Fig. 4 corresponds to this area of the graphic (p_{trans} is 0.9).

The second area is the leftmost one, corresponding to values of p_{trans} between 0 and 0.4. Because of the low transition probability, the vast majority of cars stop at the separation. This generates compact traffic jams, such as the ones shown in Fig. 6 are.

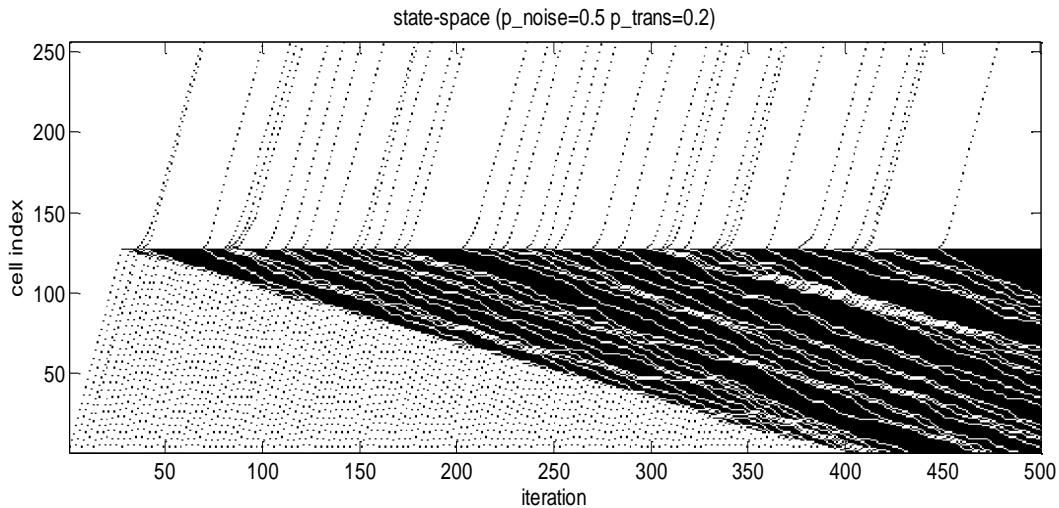


Fig. 6. Space-time diagram ($p_{trans}=0.2$).

It may be shown [15] that, in this area, the corresponding flow is approximately $F \approx \frac{p_{noise} \cdot p_{trans}}{1 + p_{trans}}$. This function (also shown in Fig. 5) fits well the output flow as long as p_{trans} is inferior to 0.4.

Finally, the third area corresponds to values of p_{trans} between 0.4 and 0.8. In this case, an analytical approximation is not as easy to formulate. It is worth noting that the flow may be superior to the analytical approximation of proportionality (which is valid for large p_{trans} values), as shown in Fig. 5.

5. Simulation of a classic traffic light

While the previous results allow one to grasp the underlying concepts, it is unusual in practice to rely on a randomly-changing traffic light, possibly at every iteration. A more realistic situation is to consider a traffic light which keeps the fraction of a green light of the total time of a traffic cycle constant.

From a stochastic point of view, this is analogous with the already-studied case of a random traffic light of transition probability p_{trans} if the approximation $p_{trans} = T_{green} / (T_{green} + T_{red})$ is used. However, in this case the transition is no more probabilistic, but deterministic. Further, the already discussed two-links model is analyzed from this perspective.

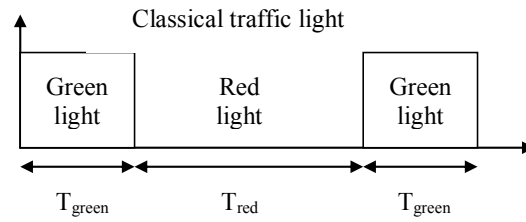


Fig. 7. Transitions of a classical traffic light

The obtained space-time diagrams are illustrated in Fig. 8 (for $p_{trans}=0.5$) and in Fig. 9 (for $p_{trans}=0.9$), respectively.

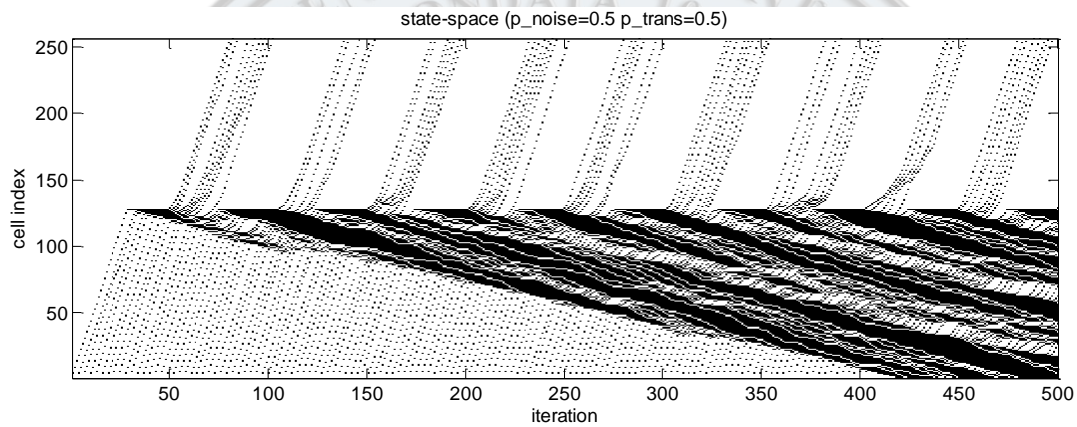


Fig. 8. Space-time diagram for classical traffic light ($p_{trans}=0.5$)

When $p_{trans}=0.5$, the output vehicle flow is quite syncopate and compact traffic jams appear. An easy analytical approximation is unlikely. For high values of the transition probability, such as $p_{trans}=0.9$, vehicles still have to stop occasionally, but the output flow is, as expected, superior to the case $p_{trans}=0.5$.

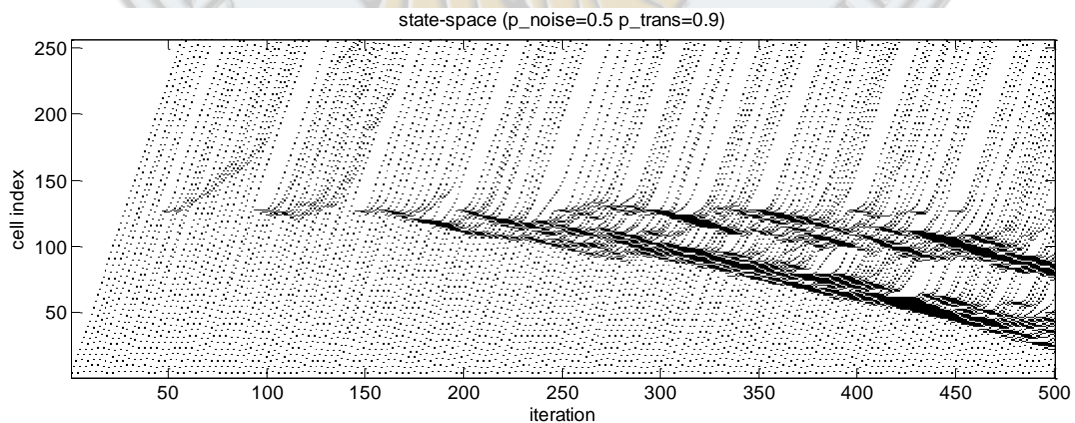


Fig. 9. Space-time diagram for classical traffic light ($p_{trans}=0.9$)

However, because of these stops, the output flow remains inferior to the first-studied, random case, even for large p_{trans} values. The analysis of the output flow with respect to the p_{trans} variable, illustrated in Fig. 10, shows an almost linear behavior. As already remarked, in the rightmost region the values are just under below the linear approximation, while in the random traffic light case, they are a little higher (on the dotted line) – see Fig. 5.

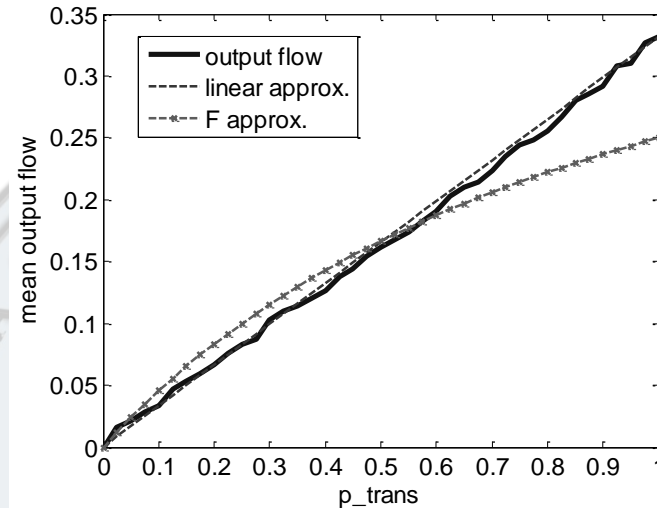


Fig. 10. Average output flow as a function of p_{trans}

Conclusions

Although it represents only a basic tool, the presented approach is useful in that it may be quickly extended to complex city road networks. It provides a realistic modeling tool for the main blockage sites in a city, i.e. the traffic lights. Such model is a valuable tool when it comes to increase fluency of traffic, while minimizing fuel consumption and pollution. The approach allows extracting analytical approximations, which may be used to speed up computations.

The simplicity of the model makes it appropriate for large-scale simulations or when different alternative traffic configurations are tested and evaluated. It can be extended to more complicated roads networks by considering a more elaborate transition procedure.

Also, the proposed model may be used for evaluating the impact on existing structures of the projected modifications (new bridges, roads etc.).

Acknowledgments

This work was supported by the North Atlantic Treaty Organization under the grant EAP.RIG.982933, by the French Ministry of Foreign Affairs/EGIDE under the grant ECO-NET 2007, and by the Office of Naval Research Global under grant number N00014-08-1-1074.

REFERENCES

- [1] H.K. Lee, R. Barlovic, M. Schreckenberg and D. Kim, *Mechanical restriction versus human overreaction triggering congested traffic states*, Physical Review Letters, vol. 92, no; 23, pp. 238702, June 2004.
- [2] J. Matsukidaira and N. Nishinari, *Euler-Lagrange correspondence of cellular automaton for traffic-flow models*, Physical Review Letters, vol. 90, no. 8, pp. 088701, February 2003.
- [3] N. Mitarai and H. Nakanishi, *Spatiotemporal structure of traffic flow in a system with an open boundary*, Physical Review Letters, vol. 85, no. 8, pp. 1766-1769, August 2000.
- [4] K. Nishinari, M. Treiber and D. Helbing, *Interpreting the wide scattering of synchronized traffic data by time gap statistics*, Physical Review Letters E, vol. 68, no. 6, pp. 067101, December 2003.
- [5] D.W. Huang, *Modeling traffic through a sequence of traffic lights*, Physical Review E, vol. 70, no. 1, pp. 016107, July 2004.
- [6] M. Treiber and D. Helbing, *Memory effects in microscopic traffic models and wide scattering in flow-density data*, Physical Review E, vol. 68, no. 4, pp. 046119, October 2003.
- [7] K. Hasebe, A. Nakayama and Y. Sugiyama, *Dynamical model of a cooperative driving system for freeway traffic*, Physical Review E, vol. 68, no. 2, pp. 026102, August 2003.
- [8] T. Nagatani, *Clustering and maximal flow in vehicular traffic through a sequence of traffic lights*, Physica A: Statistical Mechanics and its Applications, vol. 377, no. 2, pp. 651-660, April 2007.
- [9] B.A. Toledo, V. Munoz, J. Rogan and C. Tenreiro, *Modeling traffic through a sequence of traffic lights*, Physical Review E, vol. 70, pp. 016107, 2004.
- [10] B.A. Toledo, E. Cerda, J. Rogan, V. Munoz, C. Tenreiro, R. Zarama and J. A. Valdivia, *Universal and nonuniversal features in a model of city traffic*, Physical Review E, vol. 75, pp. 026108, 2007.
- [11] H. Mahmassani, T. Hu and R. Jayakrishnan, in *Urban traffic networks: dynamic flow modeling and control*, edited by N. Gartner and G. Improta, 1995.
- [12] H.P. Simao and W.B. Powell, *Numerical methods for simulating transient, stochastic, queuing networks – I: methodology*, Transportation Science, vol. 26, no. 4, pp. 296-311, 1992.
- [13] H.P. Simao and W. B. Powell, *Numerical methods for simulating transient, stochastic, queuing networks – II: Experimental results*, Transportation Science, vol. 26, no. 4, pp. 312-329, 1992.
- [14] C. Gawron, *An iterative algorithm to determine the dynamic user equilibrium in a traffic simulation model*, International Journal of Modern Physics C, vol. 9, no. 3, pp. 393-408, 1998.
- [15] P.M. Simon and K. Nagel, *A simplified cellular automaton model for city traffic*, Physical Review E, vol. 58, no. 2, pp. 1286-1295, August 1998.
- [16] K. Nagel and M. Schreckenberg, *A cellular automaton model for freeway traffic*, Journal of Physics I France 2, 2221, 1992.