URBAN TRAFFIC MODELING AND SIMULATION

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ABSTRACT
The article describes the use of different methods of building both micro- and macro-models of urban traffic. Traffic at intersections can be modeled with a fixed time increment allowing microscopic traffic analysis at the intersection. Attention was drawn to the importance of event-based models, exemplified by solutions based on hybrid and colored Petri nets. One of the newer solutions is a model that uses agent-based technology to take account of the impact of all traffic participants in the city. The article also describes the use of neural networks in the construction and implementation of urban traffic models. Generative model of artificial neural networks can complement data not reachable in actual traffic measurement, deep learning can be used to posses data from video and impute of missing data. A combination of macroscopic intersection models constructed from deep multilayer neural networks can be used to construct a traffic light control system in a network of streets and intersections.

DOI: 10.23762/FSO_VOL5NO4_17_7

KEY WORDS
Artificial neural network, deep learning, modeling, Petri nets, urban traffic.

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Introduction

Congestion of urban traffic is one of the most serious problems of everyday life in metropolitan areas. In order to address this problem, Intelligent Transport Systems (ITS) technologies have concentrated in recent years on problems with urban traffic congestion. Urban communication networks are large, dynamic systems that remain a challenge in control engineering despite all scientific and technological advances. In order to control the urban communication network by means of optimization methods, it is necessary to establish an appropriate model of the urban traffic network. This model should be both accurate in describing network traffic as well as in simple calculation.

In general, model is defined as a representation of a system using necessary rules and concepts. In the era of information and computers techniques, in a situation where there is often no effective analytical model, simulation becomes an effective tool for analyzing of reality. Simulation is considered as a dynamic representation of some part of the real world achieved by building a computer model and calculated its states over time. Computer models and simulation are widely used in traffic and transportation system analysis, but only those with urban traffic analysis are in the focus of this paper.

Paper received: 8 August 2017 • Paper revised: 23 November 2017 • Paper accepted: 14 December 2017

Urban traffic modeling and analysis is part of the advanced traffic intelligent management technologies that has become a crucial sector of Traffic management and control. Its main purpose is to predict congestion states of a specific urban transport network and propose improvements in the traffic network.

At the turn of the 1970s and 1980s, simulation models were primarily used to assess traffic fluctuations at intersections, fuel consumption, and exhaust emissions. Now urban traffic modeling and analysis becomes an element of the nowadays traffic intelligent management technologies that are a important part of traffic management and control. Its main objective is to foresee congestion states of a specific urban transport network and give proposal improvements in the traffic network. There are three different information sources. Historical and recent information data of a traffic network about its density and flow, a data model of the transport network infrastructure and algorithms taking into account spatial and temporal dimensions. The final purpose is to improve optimization of the traffic infrastructure such as traffic organization and traffic lights (Nagui et al. 2000: 1-13).

At the beginning of the development of computer science appeared the possibility of simulation with the minicomputer systems, but their development has inspired the deepening and broadening of such research. Initially, the simulation tests were limited to one area: intersections, intersection sequence, etc.

The needs today are much larger. There are traffic accommodated control systems at the intersection, traffic control coordination in larger areas, as well as traffic control organization. Traffic control, the introducing of new communication solutions, including parking areas, are topics to be considered together. The car can also be "guided" or the driver can be assisted in route selection. Today it is possible to personalize the vehicle-specific control by introducing a GPS-enabled application that allows you to choose the right route for traffic and traffic congestion. At another end, motorists can use Advanced Traveler Information System (ATIS) which bring processed data to the end user to help him choosing the best route. This all makes urban traffic simulators important in the intelligent management of urban traffic.

The first work concerned on traffic simulations was published work (Gerlough 1955). From sixties, computer model simulation has become a widely used tool in transportation engineering with applications both in scientific research to planning, training and demonstration. Research works on various level focus on analysis, by collecting traffic data from different sources, modeling traffic flows and network, and developing algorithms to predict traffic states either in a far or a short-term future (Lippi et al. 2010: *259-273; Su Haowei, Yu Shu 2007: 743-752)*.

Most urban traffic problems are network related. In networks of intersections, one has to combine different signalized and unsignalized intersections and links with arterial roads, motorways, city streets etc.. This makes the simulation model quite complicated, but the number of comprehensive simulation tools for network analysis is quite small. In addition, the development of communications solutions and technologies is causing the current models to become outdated.

1. Classification of method and model simulation

Depending on number of details and detail description which a model provide, models can be classified into several categories:

- *Microscopic models*, in which vehicles and drivers behavior are described with many details and individually on the traffic stream.
- *Submicroscopic models* is like microscopic models; the submicroscopic models go even further by describing the vehicle control behavior and the functioning of specific parts of the vehicle.
- *Mesoscopic models*, in which does not distinguish nor trace individual vehicles, but expresses the probability of having a given vehicle at a given position, time and speed.
- *Macroscopic models*, in which traffic is represented at a high level of aggregation, thus not distinguishing vehicles individually (Badura 1983: 331-336).

Microscopic model is represented mainly by *car-following models*. Such models based on the process of a vehicle following another, and these models appeared in the sixties, being one of the first microscopic modeling approach and consists of three type models:

- *Safe-distance models* Used to determine the distance headway between a vehicle and its predecessor
- *timulus-response car-following models*, in which drivers try to conform to the behavior of the preceding vehicle, this process is based on the following principle: response = sensitivity × stimulus
- *Psycho-spacing models;* car-following models presume that the driver react to small changes in the precedent vehicle velocity even when the headway distances are very large or small.

The second microscopic model type is *Microscopic Simulation models* and it is usually based on the psycho-spacing modeling paradigm.

The third type appeared recently in the domain of microscopic traffic flow theory is the *Cellular automaton models* in which the Cellular automaton describe the traffic system as a lattice of cells of equal size and in which vehicle move from cell to cell.

The fourth type of the micro-model is *particle models,* which distinguish and describe the vehicles individually, but their behavior is described by aggregate equations of motions like in a macroscopic traffic flow model.

2. Simulation mode based on events versus continuous modeling

In dynamic simulation models there are two types of models:

- continuous model and
- event model.

When creating a model, it is important to decide whether the primary phenomena are events or whether the continuity of change is important. The nature of the modeled process is decisive for choosing an event model. If the model maker considers the dynamics of a moving car, how does it change its state: changing position and speed continuously, it would be better a continuous model. However, the process at the intersection is largely event-driven: turning on green light, entering the intersection, leaving the intersection. The vehicles arrives at the intersection, creating queues waiting to enter the intersection, regardless of their owns dynamics.

A good tool for constructing a simulation model of events is the Petri network (Murata 1989: 541-580). They have been used in research by various researchers. In the 1980s, Badura and Wrona (1986) proposed a model of motion at an intersection using models using the basic version of the Petri nets in multiprocessor systems. Di Febbraro et al. (2004) described a model using the hybrid version of the Petri nets and in 2006 a developed version of the so-called colored Petri nets was proposed (Dotoli, Pia Fanti 2006: 1213-1229).

Within a cycle of lights, when there is red light, a queue may be temporarily increased, but the distribution of traffic decides about the traffic congestion rather than the dynamics of motion of a single vehicle. So we have to deal with a stochastic process. It is therefore possible to approach traffic in the street network as a phenomenon of random change with respect to traffic intensity, so whole the urban traffic will be described not by events but by statistical description. It is easy to see that both the event and statistic models look complementary. They can also be a way to link real-time measurements with prediction of phenomena across the network.

3. Petri nets and artificial neural networks as a modern tools for urban traffic modeling

Contemporary researchers have a wide assortment of tools to build models of reality around us. Urban traffic models are expected to reflect its dynamics, take into account the variety of communication solutions, and take into account the impact on urban traffic of modern information-control technologies. Among many tools that meet these requirements, one can distinguish: Petri nets, artificial neural networks, fuzzy logic, cellular automata and multi-agent technologies. These IT measures can be used to create models facilitating the assessment of the impact of the traffic light program on traffic (Barcelos de Oliveira et al. 2010), in which authors used a multi-agent system or traffic flow prediction in the street network using a cellular automata model (Brilon et al. 2010: 111--117) or fuzzy-neural networks in (Hongbin Yin et al. 2002).

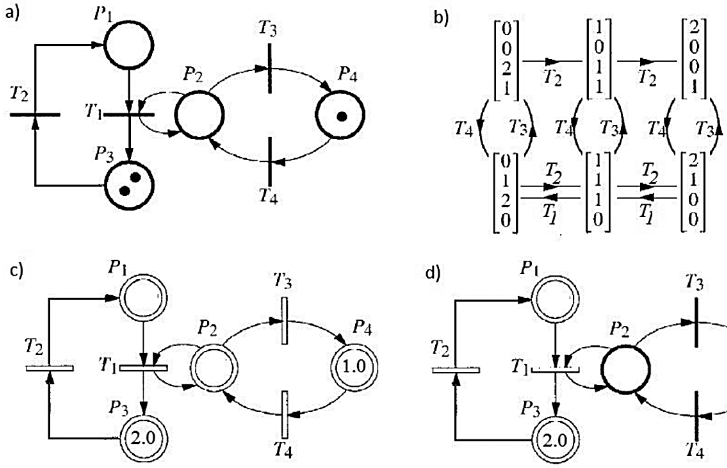
In this chapter we will focus on the first two tools as the most commonly used in urban traffic modeling.

3.1. Petri nets

Petri nets (PNs) are widely used to model discrete systems such as: computer systems, manufacturing systems, communication systems, etc. Petri net is a bipartite graph consisting of places, transitions and arcs. Marked Petri net is a net whose places may contain a arbitrary number of markers. In Coloured PN each marker has own color from defined set of colors. Number of markers in traditional – discrete PN is an integer value but in continuous PN one can be also real value, but in hybrid PN places can contain both type of markers (Figure 1).

In a PN, the marking of a place may correspond either to the Boolean state of an object (for example a device or a resource is available or not), or to an integer (for example the number of vehicles in a queue). A general analysis method is to compute the set of reachable states and deduce the different properties of the system.

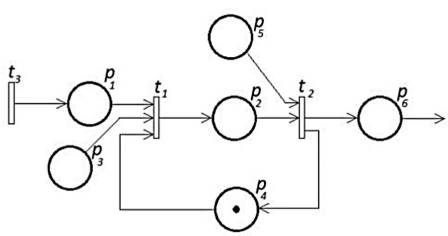
Figure 1. Illustration of Petri nets: a) discrete PN, b) graph transitions in PN, c) continuous PN and d) hybrid PN



Source: Own elaboration based on David, Alla 2001: 32.

To illustrate this point, let's consider the movement of the vehicle through the intersection. The vehicle appears in the queue through the transition t3, treated as a source of vehicles in the queue. The presence of a marker in place P3 symbolizes the green light of the signaling light. Place P4 corresponds to the free space at the intersection, and the P2 place corresponds occupation of the space at the intersection by the vehicle. Removing the marker from the P3 site causes the marker to appear at P4 and vice versa. Similarly, the space at the exit of the intersection corresponds to the places P5 and P6 respectively.

Figure 2. The Petri net model of the movement of the vehicle through the intersection.



Source: Own elaboration.

3.2. Artificial neural networks

Artificial neural networks are a rich set of tools and methods used in artificial intelligence. They represent the most diverse learning methods: from supervised learning through unsupervised and reinforcement learning to mixed learning methods. The same refers to the widely field of application of ANN. The basic, most common, is approximation, that is, to reflect the relationship between input and output data obtained through the learning process under supervision. It may therefore be well suited to reflect the dependence of parameters in the urban traffic model. Then identification of model parameters takes place in the training process of the ANN and does not require tedious analysis of measurement data.

Other uses of neural networks are:
- classifiers,
- patterns recognition systems,
- identification of data groups - clustering,
- control systems,
- prediction of data,
- generalization of knowledge.

Classifiers make it possible to recognize objects by assigning them a class, and pattern recognition systems provide the pattern object nearest to the recognized object or give it a label. Classification capabilities of neural networks can be used in a variety of decision support systems, decision-making or control systems. Traffic data collection systems can classify states of an intersection or city traffic network, identify of danger in traffic conditions, etc.. Especially in the modeling of traffic it can be useful to the ability of prediction: congestion, traffic jams, emergency situations, traffic changes, when at any point of the network will happen accident.

Recent years have brought a number of new developments in neural network technologies. Intensive research into video and audio processing has resulted in the range of training methods for complex, multi-layered structures. There are methods called deep learning, including such solutions as:
- auto encoders,
- convolutional neural networks,
- deep believe network and deep Boltzmann machine.

4. Urban traffic model

In car urban traffic we have to deal with a network of roads and intersections, so the traffic model should take into account both these components. The network can be various and the intersections can have different configurations. One type of intersection in the city may be a traffic circle, on which traffic depends to a large extent on its size. Below we have been presented two traffic models: the model of road traffic and the model of intersection with traffic lights.

4.1. Road model

Many previous proposals (Badura, Wrona 1986; Di Febbraro et. al. 2001: 866-871) presented road models, most of them were macroscopic models. From the point of view of urban traffic in the network of streets and intersections, considering the effectiveness of this traffic, it matters the length of the section between intersections. Just a simple observation to note that short distances between intersections do not have a significant effect on the behavior of vehicles at inflow to the intersections.

The traffic pattern on the road stretch depends on the shape and organization of the road. It is worth saying that the model presented below assumes unidirectional flows. For this reason, any bidirectional road stretch should be split into two separate road stretches. Each unidirectional road stretch can be spatially separated into different length sections. In each section the traffic behavior can be described using a well-known second-order macroscopic model, introduced in (Payne 1971: 51-61), in which the traffic behavior is described by means of the following overall variables:
- the traffic flows *f(t)*, i.e., the volume of vehicles, described by the instantaneous number of vehicles exiting section toward section, at time

– the vehicle density *ρ(t)*, i.e., the number of vehicles per unit length, in section at time;
– the vehicle speed *v(t)* that is quotient of the above mentioned variables.

Due to various factors influencing the variability of these parameters, not only their mean values but also their distributions are important. This is particularly important when the road is an inlet to an intersection. Dynamic motion parameters affect the speed of individual vehicles, number of stopping and braking, fuel consumption, exhaust emissions, etc.

4.2. Intersection modeling

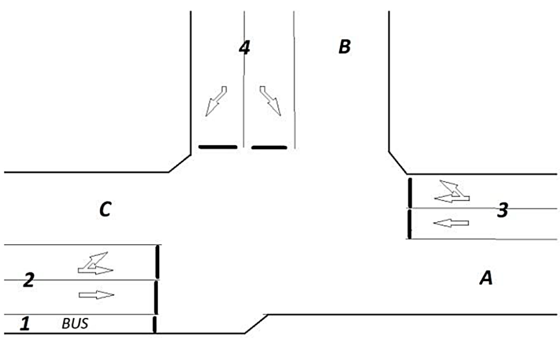
Considering the efficiency of street and intersection traffic as a digital image of fuel consumption, exhaust emissions, driving comfort, average travel speed, a macroscopic model may not be enough. Hence, there are still attempts to microscopically describe the motion of vehicles at the intersection.

A good microscopic approach to traffic modeling at an intersection is an event description using the Petri network (Badura, Wrona 1986; Di Febbraro et. al. 2001; Dotoli et. al. 2006. Parameters of this model should always be determined by measuring vehicle traffic at a particular intersection. Such a model can be used to create a urban traffic network model or to determine macroscopic traffic parameters at an intersection. Traffic measurements are made under limited conditions resulting from the current state at the time of measurement and are not sufficient to determine macroscopic model parameters. Data supplementation can be obtained by simulation based on a microscopic model.

General model

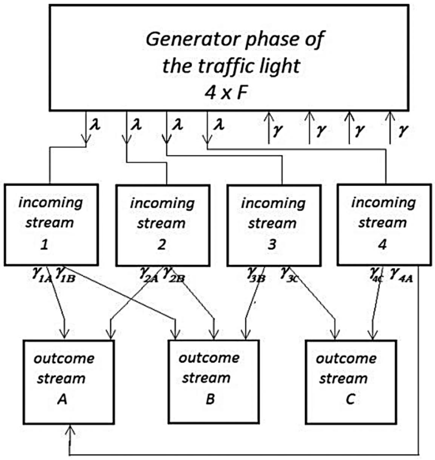
Let's consider the traffic area reported in Figure 3, which consists of a particular intersection with four incoming flow roads, namely, R1, R2, R3 and R4, and three outgoing flow roads, namely RA, RB, and RC, and the adjacent roads. Arabic numerals indicate the input flows of the vehicles, while the uppercase letters indicate the output flows of the intersection. In Figure 1, the input flow represents the input vehicle flow approaching the intersection from the adjacent road and the input flow represents the flow crossing the intersection, entering from the incoming direction, when enabled by the traffic light. The output flow represents the flow leaving the intersection toward direction. Moreover, input flow denotes the queue of vehicles waiting for the green light at an incoming direction.

Figure 3. Exemplary four-phase signalized intersection



Source: Own elaboration.

Figure 4. The block diagram of an intersection model



Source: Own elaboration.

Figure 4 shows a block diagram of an intersection model in which three separate elements are distinguished: the signal generator phase generator block, the input flow handler model, and the output flow handler model. Each of the four input flow model is represented by a separate input module and similarly each output flow model is represented by a separate output module. Scheme of the model diagram can be presented in the form of a coloured Petri net, where the input and output modules represent the color locations corresponding to the directions of entry and departure from the intersection. Arches λ and γ were related to the transits corresponding to vehicles entering the intersection and the vehicles leaving the intersection respectively.

The Petri net models

The following Figures 5, 6 and 7 show a detailed picture of the modules in Figure 4 as a colored Petri net. The implementation of the Petri network for the light-signal generator depends on the signal timing plan of the intersection. Tables 1a and 1b show two different signal timing plans. Table 1a assumes a sequence of four separate phases for four input streams. Table 1b illustrates another sequence of eight phases with amber light phase distinction. According to both tables, Figures 5a and 5b show the Petri network for both signal timing plans. The network fragment marked (F) with a dashed line in Figure 5a represents a module from which other signaling plans can be created. However, when signaling phases have a more complex sequence, creating of network requires an individual approach, as network shown in Figure 5b for the signal timing plan of the Table 1b.

Table 1a The exemplary signal timing phase

Phase		1		2		3		4	
Streem (flow)	1								
	2								
	3								
	4								
Phase duration		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8

Source: Own elaboration.

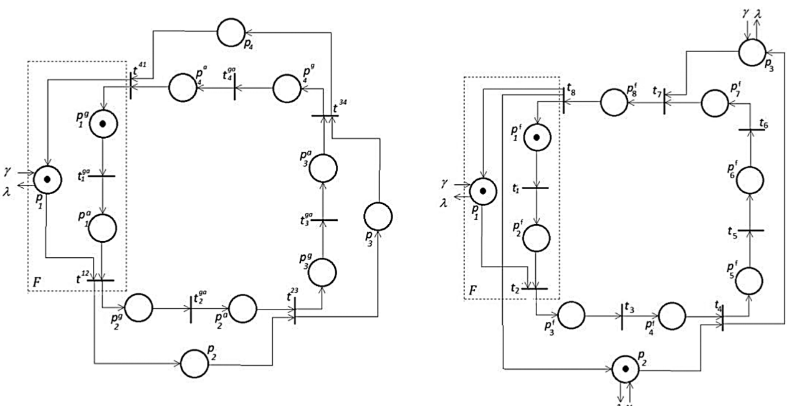
Table 1b. The exemplary signal timing phase

Phase		1		2		3		4	
Streem (flow)	1								
	2,3								
	4								
Phase duration		t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8

Legend green amber red

Source: Own elaboration.

Figure 5. The Petri net model of the phase signal generator:
a) for the phase plan from Table 1a; a) for the phase plan from Table 1b;



Source: Own elaboration.

Table 2. Places and transitions of the Petri net from Figure 5a and 5b.

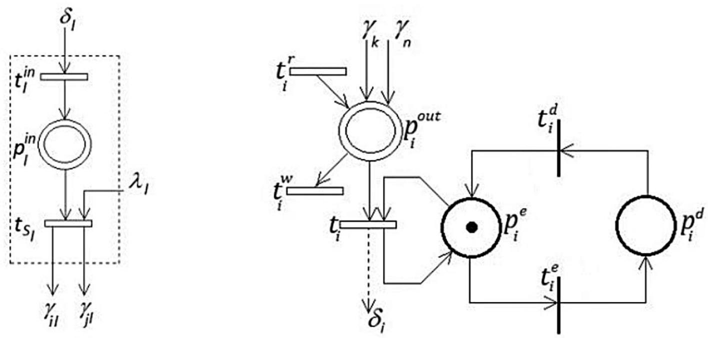
Place	Meaning
p_i^g	green period of the i-th phase
p_i^a	amber period of the i-th phase
p_i	the i-th phase is enabled
Transition	Meaning
t_i^{ga}	the i-th green period ends and the i-th amber period begins
t^{ij}	the i-th phase ends and the j-th phase begins

Source: Own elaboration.

The description of places and transitions in the networks of Figures 5a and 5b are presented in Table 2a and 2b, respectively.

The diagrams of the Petri nets showing events of the vehicle entry the intersection (Figure 6a) and the events of the leaving intersection by any vehicle (Figure 6b) are very straightforward, and the descriptions of the places and the transits these Perti nets can be found in Table 3.

Figure 6. The Petri net models of: a) entry of vehicles; b) leaving the intersection by vehicles.



Source: Own elaboration.

Table 3. Places and transitions of the Petri net from Figure 6a and 6b

Place	Meaning
p_l^{in}	vehicles are in the queue at incoming direction l
p_l^{out}	vehicles are leaving the intersection towards direction l
p_i^d	vehicles cannot flow through the i-th road
p_i^e	vehicles can flow through the i-th road
Transition	Meaning
t_l^{in}	vehicles enter the queue at incoming direction l
t_{Sl}	vehicles leave the queue at incoming direction l
t_i^r	vehicles enter the i-th road stretch from secondary road
t_i^w	vehicles exit from the i-th road stretch towards secondary road
t_i^d	the i-th road streach becomes blocked
t_i^e	the i-th road streach becomes unblocked
t_i	vehicles leave the intersection towards direction i

Source: Own elaboration.

4.3. Urban traffic model and deep learning.

The relationship between the above described traffic and light-signal parameters is complex. The size and structure of traffic at the intersection depend on the time of the year, the time of day and the day of the week, as well as random events such as traffic accidents, social events, etc. The measurement of these dependencies is difficult and does not constitute a complete closed traffic picture at the intersection. Selection of timing traffic light control parameters should take into account the structure of traffic, optimizing traffic not only within one intersection, but in a larger area of the city.

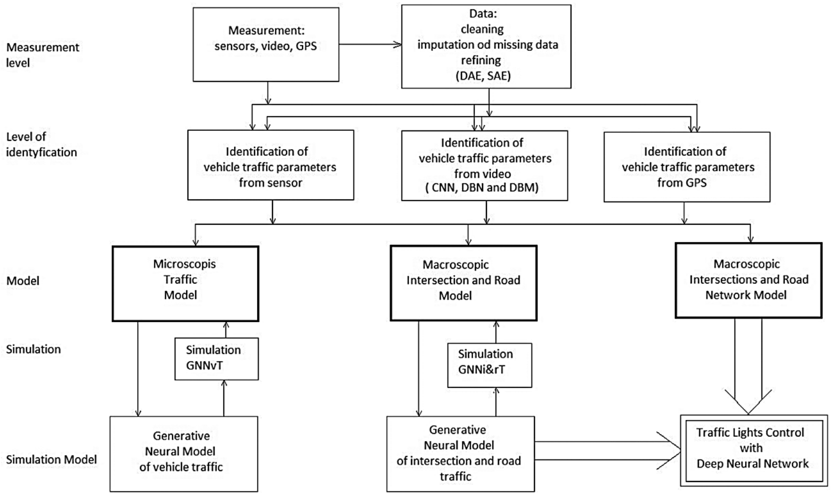
Building a traffic model involves defining the structure and parameters of the model. When designing a microscopic model, the dynamics of the vehicles, the reaction times of the drivers, the speed of the acceleration of the vehicles, the distribution of the flow traffic streams, and the distributions of these quantities should be determined. Today's development of measurement technology is very wide ranging from various motion sensors to video, GPS and gives you a lot of opportunities in determining the characteristics of motion vehicles not only at the intersection. Real traffic data collected from loop detectors or other sensors often include missing data. Incompleteness of data and noise in the measurement image need improvement accuracy by conducting a fine-tuning afterwards. Yanjie et al. (2014: 453-464) presented the deep learning approach, which can discover the correlations contained in the data structure by a layer-wise pre-training and improve the imputation. Vehicle dynamics can be obtained from data obtained from GPS devices and from video cameras. Both techniques require complex processing especially video. An effective tool in processing this data is multi-layer artificial neural networks (Xiaolei, Ma et al. 2017).

Complexity of the traffic at the intersection causes that during the measurement of the macroscopic model parameters, there will not be able to measure all the situations that we are interested in. Then, it will can use the microscope model to complete the data. The network of streets and intersections model can be obtained using a macroscopic model of streets and intersections. True, taking into account the capabilities of today's computer systems, it is possible to use a microscopic model, but experience indicates that this model is not more accurate than a macroscopic model requiring much less computational effort. In addition, using the tools of generative multilayered neural networks to train deep learning technologies, they provide far greater modeling capabilities, as they are much more suited to modeling in changing traffic conditions through continuous adaptation. The process of using neural networks and deep learning technology in identification and exploitation of the traffic model is illustrated in Figure 7. It also presents the proposed scheme for the use of the traffic model for optimal traffic control.

The application of deep learning technology in urban traffic modeling can be divided into the following categories:

- cleaning, refining noisy traffic data and data imputation – Denoising Stacked AutoEncoder (DSAE) (Shu, Yugeng 2008:743-752) which is composed of a Denoising AutoEncoder (DAE) and Stacked AutoEncoders (SAE) (Ledoux 1997).
- traffic video processing - Convolutional Neural Networks (CNN)
- Road Traffic Classification - Deep Believe Network DBN and Boltzmann Deep Machine BDM,
- traffic identification,
- tracking car routes.

Figure 7. The diagram of the urban traffic structure models using in intelligent traffic control.



Source: Own elaboration.

Conclusions

This paper presents a proposal for modular urban traffic modeling, from a microscopic model based on Petri net elements through a macroscopic model describing traffic flows and a generative model based on a multi-layer deep neural network. Item of the presented idea focuses on the event-based models, exemplified by solutions based on hybrid and colored Petri nets and the use of deep neural networks in the construction and implementation of urban traffic models. Generative model of artificial neural networks can complement data not reachable in actual traffic measurement, deep learning can be used to posses data from video and impute of missing data.

The rules for determining parameters of this model are based on various data sources: sensors, video and GPS. The model requires verification through using real data obtained from traffic measurement, intersection, and network of streets and intersections. This is another task in the presented modeling paradigm.

References

Badura, D. (1983), Makroskopowy model ruchu na ciągu ulic i skrzyżowań, Sympozjum nt. Transport pasażerski – energetyczne aspekty transportu zbiorowego w konurbacji Górnośląskiej, Katowice.

Badura D., Wrona W. (1986), Symulacja ruchu drogowego w systemie wieloprocesorowym przy zastosowaniu modelu opartego na sieci Petriego, Zeszyty Naukowe Politechniki Sląskiej, 5: 27-46.

Barcelos de Oliveira, L., Camponogara, E. (2010), Multi-agent model predictive control of signaling split in urban traffic networks, Elsevier Transportation Research Part C: Emerging Technologies, 18(1): 120-139.

Brilon, W., Wu, N. (1998), Evaluation of cellular automata for traffic flow simulation on freeways and urban streets, Tagungsband zum Ergebnis-Workshop: Verkehr und Mobität, (pp. 111-117), Aachen: Rheinisch-Westfälische Technische Hochschule Aachen.

David, R., Alla, H. (2001), On hybrid Petri nets, Discrete Event Dynamic Systems: Theory and Applications, 11: 9-40.

Di Febbraro, A, Giglio, D., Sacco, N. (2004), Urban traffic control structure based on hybrid Petri nets, IEEE Transactions on Intelligent Transportation Systems, 5(4): 224-237.

Di Febbraro, A., Giglio, D., Sacco, N. (2001), Modular representation of urban traffic systems based on hybrid Petri nets, Intelligent Transportation Systems Proceedings: 866-871.

Dotoli, M., Pia Fanti, M. (2006), An urban traffic network model via coloured timed Petri nets, Control Engineering Practice, 14(10): 1213-1229.

Gerlough, D.L. (1955), Simulation of freeway traffic on a general-purpose discrete variable computer, Los Angeles: University of California.

Hongbin Yin, Wong, S.C., Jianmin, Xu, Wong, C.K. (2002), Urban traffic flow prediction using a fuzzy-neural approach, Transportation Research Part C: Emerging Technologies, 10(2): 85-98.

Ledoux, C. (1997), An urban traffic flow model integrating neural networks, Transportation Research Part C: Emerging Technologies, 5(5): 287-300.

Lippi, M., Bertini, M., Frasconi, P. (2010), Collective traffic forecasting, in: J.L. Balcázar, F. Bonchi, A. Gionis, M. Sebag (Eds.), Machine learning and knowledge discovery in databases. ECML PKDD 2010. Lecture Notes in Computer Science, vol. 6322 (pp. 259-273), Berlin-Heidelberg: Springer.

Murata, T. (1989), Petri nets: Properties, analysis, and applications, Proceedings of the IEEE, 77: 541-580.

Nagui, M. R., Byungkyu, B.P., Sacks, J. (2000), Direct signal timing optimization: Strategy development and results, CitySeer'10M, paper presented at the XI Pan American Conference in Traffic and Transportation Engineering, Gramado, Brazil, May 2000, pp. 1-13.

Payne, H.J. (1971), Models of freeway traffic and control, in: G.A. Bekey (Ed.), Mathematical models of public systems, Simulation Council, 1: 51-61.

Su, Haowei, Yu, Shu (2007), Hybrid GA based online support vector machine model for short-term traffic flow forecasting, in: Xu Ming, Zhan Yinwei, Cao Jiannong, Liu Yijun, (Eds.), Advanced Parallel Processing Technologies (pp. 743-752), Berlin- Heidelberg: Springer.

Shu, L., Yugeng, X. (2008), An efficient model for urban traffic network control, Proceedings of the 17th World Congress, The International Federation of Automatic Control, Seoul, Korea, 6-11 July: 743-752.

Xiaolei, Ma, Zhuang, Dai, Zhengbing, He, Jihui, Ma, Yong Wang, Yunpeng, Wang (2017), Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction, Sensors, 17: 818.

Yanjie, D., Yisheng L., Wenwen, K., Yifei, Z. (2014), A deep learning based approach for traffic data imputation, paper presented at the IEEE 17th International Conference on Intelligent Transportation Systems (ITSC), Qingdao, China, 8-11 October.

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