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Neural Networks Approach to Remodel Capacity on Urban Road and Street Network

Anton Sysoev[1*], Svetlana Zhikhoreva[1], Vladimir Klyavin[1], Anatoly Pogodaev[1]

[1] Department of Applied Mathematics, Institute of Computer Science, Lipetsk State Technical University, Moskovskaya str. 30., 398055 Lipetsk, Russia
[*] Corresponding author, e-mail: sysoev_as@stu.lipetsk.ru

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Abstract

The growing number of cars and trucks in cities leads to traffic jams and accidents. To solve this problem, cities have to use smart transportation systems powered by artificial intelligence models and machine learning techniques. An important parameter of transportation systems showing the effectiveness of using existing urban infrastructure is the capacity of the planned route. The paper is devoted to the modeling of urban route capacity based on the capacities of its elements, namely stretches and intersections. The approach to create such a model is Mathematical Remodeling, where feed-forward neural network is chosen as a unified class to substitute models of different heterogeneous classes during modeling. It is proposed to use index of route capacity to form data sets for model fitting. The given numerical examples show how the proposed approach can be applied. The capacities of three planned routes are estimated and the best route is chosen, the efficiency criterion is traffic flow volume to capacity ratio. The prospective issue of the presented study is analyzing sensitivity of the created model to identify the parameters of route elements that most capacity and to control them increasing the total efficiency of the system.

Keywords

neural networks, remodeling, capacity estimation

1 Introduction

Nowadays many cities and agglomerations face increasing traffic caused by high level of people mobility as well as cargo routes. The way to deal with such problems is apply intelligent transportation systems (ITS) based on machine learning approaches and artificial intelligence models. Typically, ITSs are designed to work out the following problems: traffic control, accident prevention, parking systems implementation, pollution control, etc. (Schrab et al., 2023). ITS is particularly concerned to provide a system that can manage huge number of vehicles on the road, so that traffic congestions can be reduced and consequently accidents can be avoided. ITS-organizations actively develop and implement projects to forecast traffic volumes and flow-control. These organizations actively work in Japan, America, European Union, Australia, Brazil, China, Canada, Chile, Korea, Malaysia, New Zealand, Singapore, Taiwan, UK. In India, Thailand, and some countries of South Africa such scientific schools and organizations are just beginning to develop the concept of smart roads.

Nowadays, the most advanced technologies in the field of ITS are designed in Japan, USA, Singapore, and South Korea. The main directions of ITS development in these countries are connected vehicle technologies, connected corridors, well-managed and resilient traffic flows, smart roads, and integration of these technologies into smart city systems and Internet of things.

One of the most important questions arising at ITS planning is estimating the capacity of existing infrastructure. The positive reserve of the capacity could provide a higher level of ITS functioning. The capacity of a transportation system is the maximum number of vehicles that can pass through a particular road section per unit of time without causing congestion. In ITS, its estimation is more complicated due to the dynamics of road traffic, the influence of adaptive control and the use of real-time data. The main methods for estimating capacity in intelligent transport systems may include analyzing data from sensors and CCTV cameras. ITSs use data from cameras, radars, induction loops, and GPS to calculate traffic density and speed (Klein

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et al., 2006). Based on the data, machine learning techniques can be used to predict traffic changes and identify system bottlenecks (Lv et al., 2015). Micro and macro models (e.g., SUMO, VISSIM) can be used to simulate traffic scenarios under different conditions (Behrisch et al., 2011). In such applications, neural networks can improve accuracy by training on historical data (Zhang et al., 2020). In the case of adaptive traffic light control applications, AI-based algorithms (e.g., reinforcement learning) dynamically adjust the phases of traffic lights, increasing the capacity of intersections (Li et al., 2016). When considering the influence of connected and autonomous vehicles, cooperative systems (V2X) improve throughput by sharing data between vehicles and infrastructure (Alalewi et al., 2021). Further development of AI and IoT technologies will make these methods even more accurate and efficient (Ghosh et al., 2017).

This study is devoted to constructing a model of urban route capacity based on the estimated capacities of its segments, namely stretches and intersections. Each segment has its own characteristics, and the most important ones are considered. The approach in this modelling is remodeling procedure with feed-forward neural network as a model of unified class.

Entering the urban transportation system, vehicles face many possibilities for passing through the city. The study proposes to create routes based on origin and destination points and to estimate the efficiency of the proposed routes to use the rational one. To achieve this purpose, the following stages are proposed:

1. to create possible routes using the existing street and road network layout and considering organizational constraints;
2. to estimate capacity on stretches using a network estimator fitted on historical data sets (based on the remodeling approach);
3. to use the existing traffic lights settings and predicted degree of saturation to estimate intersection capacity within found routes (with simulation intersections as queuing systems of type D/D/1);
4. to construct the capacity index for routes;
5. to build the neural network model approximating capacity indices for the route including factors affecting capacity on the local levels (applying remodeling scheme);
6. to choose the route with minimal capacity index.

The paper is organized as follows. Section 2 contains the main directions in capacity estimation, giving special attention to the capacity of stretches and urban intersections; Section 3 describes the remodeling approach; Section 4 gives numerical examples and Section 5 concludes the paper and contains the perspective direction of the study.

2 State-of-art in capacity estimation

Each country has its own recommendations to estimate capacity on city road and street networks. Depending on its purpose we can divide elements of such network into two main types: stretches and intersections. It should be noted that this study doesn't take into account roundabouts to serve batches of traffic.

2.1 Approaches to estimate capacity on stretches

The most well-known guideline to estimate road capacity on stretches is Highway Capacity Manual (HCM) with its newest 7th edition published in 2022 (National Academies of Sciences, Engineering, and Medicine, 2022). According to this document the following factors can affect capacity: lane width, median type, free flow speed, access point density, and lateral clearance. In case of special type of street or its non-standard location other additional factors can be considered. For example, the Russian guideline (ODM, 2012) to estimate capacity contains 17 factors among which are type of shoulder, road marking type, effect of pedestrians and others. But in both the HCM and ODM (2012) approaches, these factors must be used as decreasing coefficients to the standard capacity values tabulated in their appendices. The studies of Feng et al. (2021) and Abdel-Aal et al. (2018) indicate that the most valuable factors affecting capacity are width of the lane, type of facility, percentage of heavy vehicles, and traffic flow speed.

It is possible to estimate capacity on stretches using the approach given in Geistefeldt and Brilon (2009) and then add factors affecting drivers' behavior to the joint model of capacity for the chosen route.

Sysoev et al. (2020) describes an approach to remodel the capacity of a freeway segment. Being a stochastic parameter of traffic flow (Brilon et al., 2007) capacity was modeled as the random value related to the Weibull distribution.
With this approach a road segment is treated as a D/D/1 queuing system, where all available data about the capacity rate is divided into two classes of intervals: "uncensored", when the observed traffic flow value causes congestion in the next interval, and "censored" when there is no information on traffic jam in the next interval (free traffic). Intervals of the first type can give the information of "measured" capacity, which is used to construct the distribution function to estimate the capacity within

the intervals of the second type by applying the Kaplan-Meier method. Using this approach and empirically comparing different types of statistical distributions, based on the data obtained from many road sections, it was shown that Weibull distribution fits the studied parameter in the best way. Thus, to estimate the capacity on a stretch the distribution function can be written as:

$$F_c(q) = 1 - \exp\left(1 - \left(\frac{q}{b}\right)^a\right), \quad (1)$$

where $F_c(q)$ is the distribution function of the capacity rate, q is the traffic volume of the vehicles (veh/h), a and b are Weibull distribution parameters, responsible for the capacity rate variation and for the systematic average value of the capacity rate caused by such constant factors as the number of lanes, the slope, the number of drivers, respectively.

Sysoev and Voronin (2019) shows that such approach was successfully applied in predicting capacity in urban freeways with work zone layouts.

2.2 Approaches to estimate capacity at intersections

According to many studies the main factor affecting the capacity of an intersection is the ratio of green time to the cycle length. Wu and Giuliani (2016) gives an approach to estimate the capacity at signalized intersections. The proposed model provides a useful tool for estimating capacity and delay at signalized intersections under unsaturated conditions. Using this model, the capacity and thus the traffic quality of service at existing signalized intersections can directly be estimated using data from detectors at stop lines. This study underlines that there is no way to measure capacity at the signalized intersection directly, but this parameter can be estimated with queuing model. The study defined parameters of the proposed model to be used in simulation. VISSIM simulation tool was used to estimate capacity per cycle numerically.

2.3 Estimating capacity of the route

Capacity of the route is dependent on the capacities of its elements. It is obvious that the capacity can be estimated as the capacity of the busiest element, however, we propose an index considering parameters of all stretches and intersections as follows in Eq. (2):

$$c_{route} = \sum_{i=1}^{n} \alpha_i c_i, \quad (2)$$

where c_{route} is the estimated capacity of the selected route (veh/h), c_i is the capacity of the i^{th} route element (veh/h), α_i is the weight of the i^{th} element.

According to the above described approaches, all capacities are divided into two types:

1. capacity on stretches;
2. capacity of intersections.

To find weights α_i for stretches we use the ratio of number of lanes on the stretch to the total number of lanes within the whole route. Determining weights for capacities of intersections relates to finding ratios of green phase of the intersection to the total green times of all intersections on the route. Then obtained coefficients must be normalized as their sum equals to 1.

3 Remodeling approach

It should be noted that using many heterogeneous factors leads to high labor-intensiveness of the evaluation and can make the real indicators noisy. The model shall also be used in real-time conditions to estimate the capacity on the city road and street network. That is why the model should be of the unified structure delivering acceptable accuracy. The remodeling approach is used for this purpose.

Remodeling is the construction of a new model based on already existing models (Saraev et al., 2018). The specific feature of this approach is that existing models can be structures of different classes when the remodeling models are elements of the same class. The reasons leading to remodeling procedure can be:

1. simplification of the model to make its following analysis and control simpler;
2. simplification of model calculation when solving it numerically;
3. unification of different kinds of models (reduction to models of the same class) for using unified well-known algorithms.

Technically, remodeling is an algorithm, which allows transforming the initial model into the model of preferred class. It is clear, that this problem is not trivial and couldn't be solved for all possible classes of models. Even with its principal potential to construct such an algorithm, the accuracy and time costs are questions to be investigated before applying the proposed concept.

Like remodeling are surrogate modeling (Hou and Behdinan, 2022), metamodeling (Stavropoulos et al., 2023). The remodeling approach was already applied in metallurgical production to build an end-to-end steelmaking process model (Saraev, 2018) and to estimate freeway segment capacity (Sysoev et al., 2020).

In this study classical neural networks are used as models of unified class. A general form of such model is:

$$y = \varphi^{(k)}\left(\begin{array}{l} \boldsymbol{w}_0^{(k)} + \boldsymbol{W}_1^{(k)} \varphi^{(k-1)} \\ \times\left(\ldots \left(\boldsymbol{w}_0^{(2)} + \boldsymbol{W}_1^{(2)} \varphi^{(1)} \left(\boldsymbol{w}_0^{(1)} + \boldsymbol{W}_1^{(1)} \boldsymbol{x} \right) \right) \ldots \right) \end{array} \right), \quad (3)$$

where $y \in \boldsymbol{R}$ is the output scalar (in this study capacity rate on a stretch or intersection line), $\boldsymbol{x} \in \boldsymbol{R}^n$ is the input vector, $\varphi^{(i)}$, $i = 1, \ldots, k$ are vector functions of vector arguments, activation functions, $\boldsymbol{W}_1^{(i)}$ are matrices of weights from layer $(i - 1)$ to i, $\boldsymbol{w}_0^{(i)}$, $i = 1, \ldots, k$ are bias weights.

4 Numerical experiments

4.1 Layout of experiment

In the city of Lipetsk there were selected two points and three routes connecting these points. They are presented in Fig. 1. The 1st route (Fig. 1 (a)) has 4 stretches and 3 intersections, the 1st intersection has only one lane for direct motion; the 4th stretch consists of 1 lane; the 2nd route (Fig. 1 (b)) has 4 stretches and 2 intersections; the 3rd route (Fig. 1 (c)) has 4 stretches and 3 intersections, the 3rd stretch has one lane in direct motion.

Capacities for all stretches and intersections were estimated under different conditions (traffic flow volumes ranged from 350 to 1,000 veh/h per lane; fixed cycle time was used for each intersection equal to 120 sec; durations of green phases were arranged from 10 to 60 sec). The only parameters of transportation system to be controlled within city conditions are green times for the chosen direction on intersections as well as cycle times and the number of lanes on stretches (applying the reverse lanes could provide this scheme of vehicles movement). That is why these mentioned parameters were included in the neural network models delivering predicted capacities for routes 1, 2 and 3. Before the estimated capacities on stretches were obtained (applying the stochastic approach) as well as capacities of the intersections providing the vehicles the path on the route. Then the estimates of the route capacity were calculated. The data sets consisting of green times on the intersections, number of lanes on stretches and estimated capacity for three routes were constructed, then they were split into train and test sets (80% for the train and the rest for the test), the total amount of realization in each train data set is 8,000 cases.

Neural network models for three above described routes were fitted based on created data sets:

- Model 1: 6 inputs, 5 neurons on hidden layer;
- Model 2: 6 inputs, 3 neurons on hidden layer;
- Model 3: 6 inputs, 3 neurons on hidden layer.

Sigmoid activation functions were used in all three models for each neuron:

$$\varphi(net) = \frac{1}{1 + \exp(-net)}. \quad (4)$$

4.2 Obtained results

Fig. 2 demonstrates the boxplots for traffic flow rates on stretches of route 1 as an example and Fig. 3 contains distribution of flow rates of intersections within route 1. It could be seen that the median of the flow rate on all

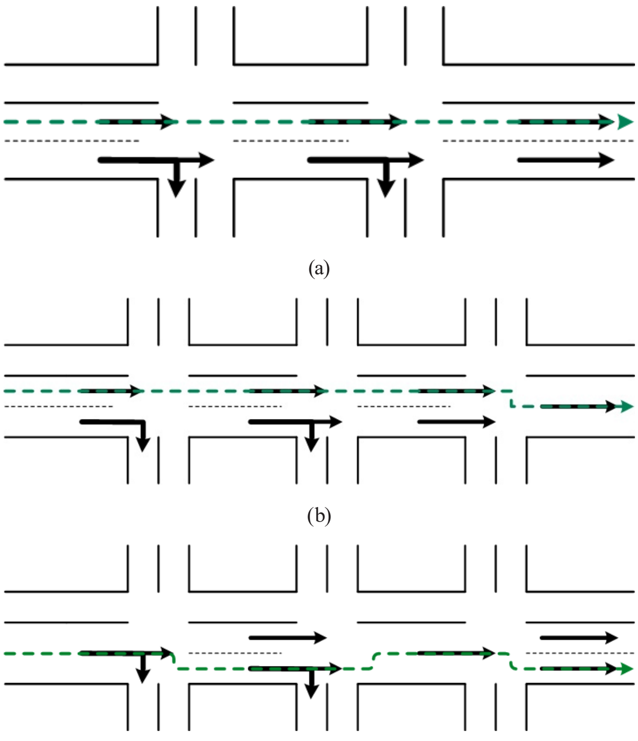

Fig. 1 Layout of routes: (a) the configuration of the 1st route; (b) the configuration of the 2nd route; (c) the configuration of the 3rd route

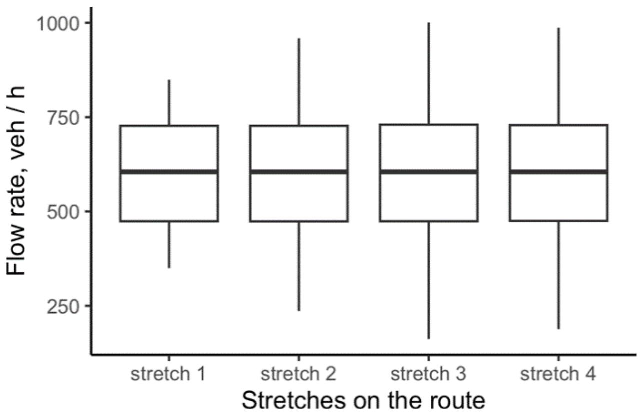

Fig. 2 The distribution of flow rates on stretches of 1st route

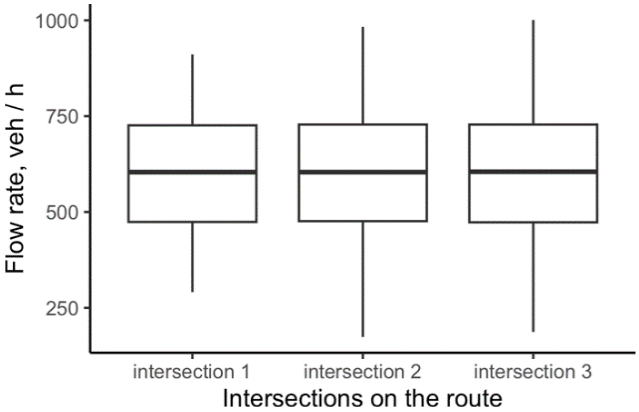

Fig. 3 The distribution of flow rates of intersections of 1st route

stretches is a constant and the flow rate on stretch 3 is higher which can be explained by the geometry of the route. It should be noted that velocities were not considered in the current study.

Table 1 contains information on the quality of the created model. The following metrics were chosen: mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE).

Based on the obtained results we can conclude that the created models have an acceptable quality and can be used in estimating the route capacity.

Fig. 4 represents the histogram of distribution of predicted capacity on the 1st route comparing it with the estimated capacity for the test data set.

Conducted experiment with these three routes demonstrated that under the given conditions 1st route has the highest capacity comparing with the other two routes, which means that this route must be selected for the traffic movement.

Table 1 Quality metrics of the created models

	Model 1	Model 2	Model 3
MAE (veh/h)	13.26	35.49	34.38
MAPE (%)	2.36	4.61	4.45
RMSE (veh/h)	15.27	46.34	43.16

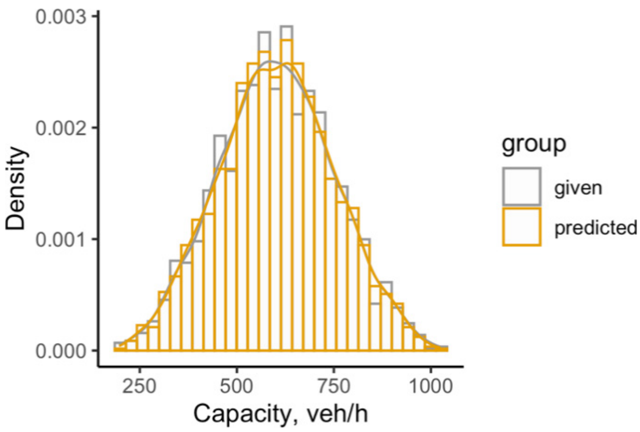

Fig. 4 Comparing predicted capacity (yellow columns) with the estimated measures (grey columns) for 1st route

5 Conclusion and outlook

The study proposes a method to estimate capacity of the chosen routes within the urban road and street network. For this purpose, a remodeling approach was used giving an opportunity to use different types of models for estimations of different parameters of the system and then combining the obtained results to build the model for the system. It was chosen to estimate capacity on stretches applying stochastic approach and direct measuring and simulation to find the capacity of intersections. Neural network structure was chosen as a unified remodeling class and the models for three prospective routes were created. Variable parameters of the system such as number of lanes on stretches and green traffic lights durations were included in the model as inputs. The demonstrated quality metrics help conclude that these models can be used in estimating the capacity of routes within urban road and street network.

Estimating road network capacity using artificial intelligence faces a number of significant limitations. The main problems are related to data quality and completeness: AI models require accurate information on speed, flow density and accidents, but uneven sensor coverage and data transmission delays distort the results. Methodological difficulties also reduce the accuracy of estimates. Transport systems are highly dynamic and depend on many factors – weather, time of day and driver behavior – that are not always accounted for in models. Hardware incompatibility is an additional challenge: existing infrastructure often does not support integration with AI systems, and different data standards across regions complicate analyses. In addition, most algorithms optimize only certain parameters, such as flow rate, ignoring environmental or social aspects. Organizational and social barriers limit the implementation of AI in transport systems. The collection of data from cameras and GPS increases privacy issues, and legal regulations impose further restrictions. The high cost of deploying smart infrastructure makes it unaffordable for many cities, and resistance from drivers and municipalities slows innovation. To overcome these challenges, it is necessary to improve data collection, develop hybrid models, and consider not only technological but also socio-legal aspects.

The prospective question is to define the most valuable inputs of the model within the chosen route. The solution will be based on applying Sensitivity Analysis (Sysoev, 2023) built on Analysis of Finite Fluctuation and will help to create control systems to manage traffic flows (Sysoev et al., 2021) within urban road network.

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References

Abdel-Aal, M. M. M., El-Maaty, A. E. A., Samra, H. A.-R. (2018) "Factors Affecting Road Capacity Under non-Ideal Conditions in Egypt", Nova Journal of Engineering and Applied Sciences, 7(1), pp. 1–13. https://doi.org/10.20286/nova-jeas-070102

Alalewi, A., Dayoub, I., Cherkaoui, S. (2021) "On 5G-V2X Use Cases and Enabling Technologies: A Comprehensive Survey", IEEE Access, 9, pp. 107710–107737. https://doi.org/10.1109/ACCESS.2021.3100472

Behrisch, M., Bieker-Walz, L., Erdmann, J., Krajzewicz, D. (2011) "SUMO – Simulation of Urban Mobility: An Overview", In: Proceedings of the 3rd International Conference on Advances in System Simulation (SIMUL'11), Barcelona, Spain, pp. 63–68. ISBN 978-1-61208-169-4

Brilon, W., Geistefeldt, J., Zurlinden, H. (2007) "Implementing the Concept of Reliability for Highway Capacity Analysis", Transportation Research Record, 2027(1), pp. 1–8. https://doi.org/10.3141/2027-01

Feng, X., Zhang, Y., Qian, S., Sun, L. (2021) "The Traffic Capacity Variation of Urban Road Network due to the Policy of Unblocking Community", Complexity, 2021(1), 9292389. https://doi.org/10.1155/2021/9292389

Geistefeldt, J., Brilon, W. (2009) "A Comparative Assessment of Stochastic Capacity Estimation Methods", In: Lam, W. H. K., Wong, S. C., Lo, H. K. (eds.) Transportation and Traffic Theory 2009: Golden Jubilee: Papers selected for presentation at ISTTT18, a peer reviewed series since 1959, Springer, Boston, MA, pp. 583–602. ISBN 978-1-4419-0819-3 https://doi.org/10.1007/978-1-4419-0820-9_29

Ghosh, R., Pragathi, R., Ullas, S., Borra, S. (2017) "Intelligent transportation systems: A survey", In: 2017 International Conference on Circuits, Controls, and Communications (CCUBE), Bangalore, India, pp. 160–165. ISBN 978-1-5386-0616-2 https://doi.org/10.1109/CCUBE.2017.8394167

Hou, C. K. J., Behdinan, K. (2022) "Dimensionality Reduction in Surrogate Modeling: A Review of Combined Methods", Data Science and Engineering, 7(4), pp. 402–427. https://doi.org/10.1007/s41019-022-00193-5

Klein, L. A., Mills, M. K., Gibson, D. R. P. (2006) "Traffic Detector Handbook: Third Edition – Volume I", Turner-Fairbank Highway Research Center, U.S. Department of Transportation, Federal Highway Administration, Georgetown, VA, USA, Rep. FHWA-HRT-06-108.

Li, L., Lv, Y., Wang, F.-Y. (2016) "Traffic signal timing via deep reinforcement learning", IEEE/CAA Journal of Automatica Sinica, 3(3), pp. 247–254. https://doi.org/10.1109/JAS.2016.7508798

Lv, Y., Duan, Y., Kang, W., Li, Z., Wang, F.-Y. (2015) "Traffic Flow Prediction With Big Data: A Deep Learning Approach", IEEE Transactions on Intelligent Transportation Systems, 16(2), pp. 865–873. https://doi.org/10.1109/TITS.2014.2345663

National Academies of Sciences, Engineering, and Medicine (2022) "Highway Capacity Manual 7th Edition: A Guide for Multimodal Mobility Analysis", The National Academies Press. ISBN 978-0-309-08766-7 https://doi.org/10.17226/26432

ODM (2012) "ODM 218.2.020-2012 Отраслевой дорожный методический документ. Методические рекомендации по оценки пропускной способности автомобильных дорог" (ODM 218.2.020-2012 Industry road methodological document. Russian National Guidelines to detect the capacity of motor roads), Федеральное дорожное агентство (РОСАВТОДОР), Moscow, Russia. (in Russian)

Saraev, P. V. (2018) "Mathematical Remodeling of Technological Processes Using Factor Space Partitioning", In: 2018 International Russian Automation Conference (RusAutoCon), Sochi, Russia, pp. 1–5. ISBN 978-1-5386-4939-8 https://doi.org/10.1109/RUSAUTOCON.2018.8501713

Saraev, P. V., Blyumin, S. L., Galkin, A. V., Sysoev, A. S. (2018) "Neural Remodelling of Objects with Variable Structures", In: Proceedings of the Second International Scientific Conference "Intelligent Information Technologies for Industry" (IITI'17), Varna, Bulgaria, pp. 141–149. ISBN 978-3-319-68320-1 https://doi.org/10.1007/978-3-319-68321-8_15

Schrab, K., Neubauer, M., Protzmann, R., Radusch, I., Manganiaris, S., Lytrivis, P., Amditis, A. J. (2023) "Modeling an ITS Management Solution for Mixed Highway Traffic With Eclipse MOSAIC", IEEE Transactions on Intelligent Transportation Systems, 24(6), pp. 6575–6585. https://doi.org/10.1109/TITS.2022.3204174

Stavropoulos, P., Papacharalampopoulos, A., Sabatakakis, K., Mourtzis, D. (2023) "Metamodelling of Manufacturing Processes and Automation Workflows towards Designing and Operating Digital Twins", Applied Sciences, 13(3), 1945. https://doi.org/10.3390/app13031945

Sysoev, A. (2023) "Sensitivity Analysis of Mathematical Models", Computation, 11(8), 159. https://doi.org/10.3390/computation11080159

Sysoev, A., Anikienko, T., Blyumin, S. (2020) "Highway Capacity Estimation: International Regulation and Neurostructural Remodeling Approach", Periodica Polytechnica Transportation Engineering, 48(2), pp. 180–188. https://doi.org/10.3311/PPtr.12880

Sysoev, A., Galkin, A., Khabibullina, E. (2021) "Hybrid Model of Controlling Traffic Flows Within Regional Intelligent Transportation System", In: Proceedings of the 20th International Conference on Reliability and Statistics in Transportation and Communication (RelStat2020), Riga, Latvia, pp. 528–537. ISBN 978-3-030-68475-4
https://doi.org/10.1007/978-3-030-68476-1_49

Sysoev, A., Voronin, N. (2019) "Approach to Sensitivity Analysis of Stochastic Freeway Capacity Model Based on Applying Analysis of Finite Fluctuations", In: 2019 1st International Conference on Control Systems, Mathematical Modelling, Automation and Energy Efficiency (SUMMA), Lipetsk, Russia, pp. 621–626. ISBN 978-1-7281-4912-7
https://doi.org/10.1109/SUMMA48161.2019.8947493

Wu, N., Giuliani, S. (2016) "Capacity and Delay Estimation at Signalized Intersections Under Unsaturated Flow Condition Based on Cycle Overflow Probability", Transportation Research Procedia, 15, pp. 63–74.
https://doi.org/10.1016/j.trpro.2016.06.006

Zhang, J., Zheng, Y., Sun, J., Qi, D. (2020) "Flow Prediction in Spatio-Temporal Networks Based on Multitask Deep Learning", IEEE Transactions on Knowledge and Data Engineering, 32(3), pp. 468–478.
https://doi.org/10.1109/TKDE.2019.2891537