Forming Production Rules in Intelligent Transportation System to Control Traffic Flow

Elena Khabibullina
Department of Applied Mathematics
Lipetsk State Technical University
Lipetsk, Russia
e.shterenberg@gmail.com

Anton Sysoev
Department of Applied Mathematics
Lipetsk State Technical University
Lipetsk, Russia
sysoev_as@stu.lipetsk.ru

***Abstract*—The paper describes an approach to remodel the capacity of high-speed transportation corridors segments. Tho proposed remodelling scheme is based on applying neural network model combining results of stochastic capacity estimation during congested and free-flow regimes. Based on the obtained model it is proposed to analyze the impact of factors affecting on the estimated capacity with the methods of Analysis of Finite Fluctuations. There is also presented scheme how to form production rules into intelligent transportation system based on the presented approaches.**

***Keywords*—semantic rules, intelligent transportation system, traffic flow, neural network, expert system**

I. INTRODUCTION

Due to the increasing number of personal vehicles and the geographical location of many Russian regions the idea to build the one unified intelligent transportation and logistic system delivering the minimum travel time within it, is now the leading one. Such system could be decomposed into similar items with the identical structural scheme but taking into account specific features of the region.

The organizations developing intelligent transportation systems actively implement projects to forecast traffic volumes and flow-control all over the world. They implement systems in Japan, America, European Union, Australia, Brazil, China, Canada, Chile, Korea, Malaysia, New Zealand, Singapore, Taiwan, the 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 ([1], [2]).

Nowadays, the most advanced technologies in the field of intelligent transportation control are designed in Japan, the USA, Singapore and South Korea. The main directions of developing intelligent systems in these countries are connected vehicle technologies, connected corridors, well-managed and resilient traffic flows, Smart Roads and integration these technologies into Smart City Systems and Internet of Things.

The reported study was supported by the Russian Science Foundation within the project 18-71-10034.

According to the inner policy of the Russian Federation the transportation infrastructure and consequently intelligent transportation systems have to be the priority projects. In 2018 there were determined 7 global economic markets supposed to be the leading world projects in the next 10-15 years [3]. These markets are focused on the person as the main subject of public relations and provide all needs of the person. One of the most important market providing the perspectives of transportation mobility is AutoNet with its road map including the most relevant problems to be solved to reach the main goal, which is to connect Europe and Asia with the high-speed transportation corridors for manned and unmanned vehicles.

The purpose of the presented study is to construct the scheme of forming production rules to control traffic flow parameters in intelligent transportation system.

II. REGIONAL INTELLIGENT TRANSPORTATION SYSTEM: INFORMATION INFRASTRUCTURE AND USED ALGORITHMS

Long-term studies conducted in Lipetsk State Technical University have formed the basis of Lipetsk Regional Centre to Control Traffic Flow being the intelligent transportation system of Lipetsk region. The main task conducted by this centre is to control the traffic situation of manned and unmanned vehicles within the region (cf. Figure 1).

As it could be seen on Figure 1 one of the main tasks of the described centre is to store data on traffic flow and to produce control influences controlling parameters of intelligent transportation system.

A. Methods to Estimate and Analyze Capacity

It is reasonable to model high-speed transportation corridor as a set of freeway segments, each with its capacity. There are two types of ways to estimate freeway capacity. The first strategy is connected with taking it as a constant value defined on empirical results or on simulation series. It is typically used way in many national guidelines like Highway Capacity Manual (HCM) [4], HBS (German HSM) [5] or appropriate Russian guidelines [6]. The

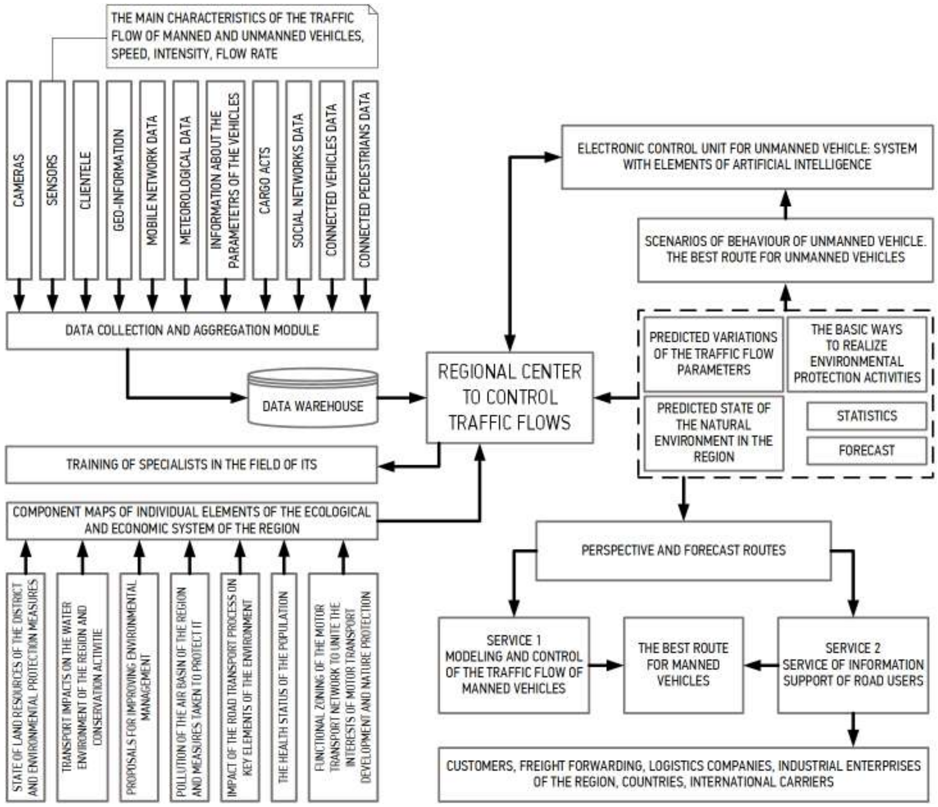

Figure 1. Conceptual scheme of regional intelligent transportation system module

main lack here is that not only each segment has its unique geometrical and physical features, but also each moment of time could have different characteristics, which is explained for example by drivers' behaviour and weather conditions. Such idea has formed the strategy to take freeway segment capacity as a random value specificaly distributed with unique parameters [7]. This strategy is more realistic and could be used in controlling traffic flow via intelligent transportation system.

Based on Mathematical Remodeling approach, involving the substitution of one model by another in complicated system or even mixing models [8], there was build a neural network model to estimate freeway capacity taking into account a set of parameters effecting it [9], [10] (namely they are given in Table II-C). Further it is described the way of constructing such kind of model. Being a stochastic parameter of a transportation system, capacity could be measured only in a time interval prior to the congestion and is precisely equal to the number of vehicles within the survey section during the congestion.

Using the available congested data and statistical assumptions, one can form input-output array dividing all time intervals into two subsets:

- O ("observed"): congested intervals, section capacity is precisely equal to the observed traffic volume;
- E ("estimated"): fluid intervals, section capacity is estimated using the stochastic capacity approach.

These two subsets form an array of initial data to train the chosen structure for further prediction.

B. Algorithm to Remodel Capacity

Step 1. To divide the whole available data into subsets of "observed" and "estimated" intervals. The criteria of this separation must be predefined at this step. Normally it is an average speed threshold, pointing the transition of the traffic flow into a congested regime.

To estimate capacity within congested intervals it has to be applied the Weibull distribution model [11]:

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

where $F_c(q)$ is the distribution function of the capacity rate, q is the traffic volume of the vehicles (veh / h), a, 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.

Step 2. Using the data sample obtained on Step 1, to train neural network model with the predefined structure.

A general form of neural network model to be applied on this step is

$$c = \phi^{(k)}(w_0^{(k)} + W_1^{(k)}\phi^{(k-1)}(...(w_0^{(2)} + \\ +W_1^{(2)}\phi^{(1)}(w_0^{(1)} + W_1^{(1)}x))...)), \tag{2}$$

where $c \in \mathbb{R}$ is the output scalar describing capacity, $x \in \mathbb{R}^n$ is the input vector, $\phi^{(i)}$, $i = 1, ..., k$ are vector functions of vector arguments, activation functions, $W_1^{(i)}$ are matrices of weights from layer $(i\breve{}1)$ to i, $w_0^{(i)}$, $i = 1, ..., k$ are bias weights.

On this step the analysis of the model accuracy must be done and the adjustment (in case of unsatisfied accuracy) should be applied.

Step 3. Using the model obtained on Step 2, to estimate capacity rate within the new data set.

There were conducted numerical experiments data obtained from loop and radar detectors describing the capacity and factors affecting it (cf. paper [10] and study [9]). As an output there was taken nominal capacity for the determination of standardized capacity values in one-hour intervals obtained by applying Kaplan-Meier approach to fit Weibull distribution function. Basis neural network model applied to fit the model of the capacity was:

$$c = \phi(w_0 + W_1 x), \tag{3}$$

where c is the capacity values (veh/h), $x \in \mathbb{R}^8$ is inputs vector (according to study [Nina]), $\phi(net) = \tanh(net)$ is the hyperbolic tangent activation function, w_0 and W_1 are estimated weights for bias and input factors respectively.

Model (3) was fitted in RStudio free software with “nnet” package. Initial data were firstly standardized to obtain weights and then unstandardized to calculate predicted capacity values. It should be noted, that the level of remodeling approximation error was 5.58%, which is acceptable for the described problem.

C. Sensitivity Analysis as a Way of Defining the Most Significant Factors Affecting Capacity

In many applied problems it is very important to find, which input factors are the most significant in order, for example, to control the process or system, ets. Commonly the answer to such kind of question could be obtained after applying approaches of Sensitivity Analysis [12], which is based on statistical and probabilistic techniques and allows to estimate the influence of each model input value (independent variable, argument of the function, factor of the system, etc.) on the output value (dependent variable, function value, index of the system, etc.). Considering the existing mathematical model

$$y = f(X), \tag{4}$$

where $X \in \mathbb{R}^n$ are inputs, $y \in \mathbb{R}$ is output and $f(\cdot)$ can be a function, a system of differential equations, etc., even a program code, the procedure of Sensitivity Analysis is made through the individuation of some indicators, called impact factors, determining quantitatively the influence, that each input has on the output, and consequently, allowing to understand which of them have to be changed the least possible, so that the output of the model does not change too much [12]. Many well-known techniques of Sensitivity Analysis have drawbacks (like stochastic nature or high computational costs, etc.). In contrast to them it is possible to use the approach based on applying Lagrange mean value theorem and called Analysis of Finite Fluctuations [13], [14].

According to the idea of Analysis of Finite Fluctuations let us take the initial instant of time t_0, where the input factors vector is

$$X^{(t_0)} = (x_1^{(t_0)}, ..., x_n^{(t_0)})$$

and respectively the output is

$$y^{(t_0)} = f(X^{(t_0)}) = f(x_1^{(t_0)}), ..., x_n^{(t_0)}).$$

In the next time instance t_1 we have final value of inputs

$$X^{(t_1)} = (x_1^{(t_1)}, ..., x_n^{(t_1)})$$

and output

$$y^{(t_1)} = f(X^{(t_1)}) = f(x_1^{(t_1)}), ..., x_n^{(t_1)}),$$

here $x_i^{(t_1)} = x_i^{(t_0)} + \Delta x_i$, $i = 1, ..., n$.

It follows, that

$$\Delta y = y^{(t_1)} - y^{(t_0)} = f(X^{(t_1)}) - f(X^{(t_0)}) = \\ = f(..., x_i^{(t_0)} + \Delta x_i, ...) - f(..., x_i^{(t_0)}, ...). \tag{5}$$

But according to the Lagrange mean value theorem the same function increment could be estimated as

$$\Delta y = \sum_{i=1}^{n} \left(\frac{\partial f}{\partial x_i} \left(..., x_i^{(t_0)} + \alpha \cdot \Delta x_i, ... \right) \cdot \Delta x_i \right), \tag{6}$$

and, applying notations $A_i = \dfrac{\partial f}{\partial x_i}(..., x_i^{(t_0)} + \alpha \cdot \Delta x_i, ...)$, the formula becomes

$$\Delta y = \sum_{i=1}^{n} (A_i \cdot \Delta x_i) = \\ = A_1\Delta x_1 + A_2\Delta x_2 + ... + A_n\Delta x_n. \tag{7}$$

Equating (5) and (6) and obtaining (7), it is resolved the resultant equation according to the unknown parameter α, finding which and, respectively, estimating impact indexes A_i, determining the influence, that each input factor fluctuation has on the output fluctuation.

Sensitivity Analysis based on applying Analysis of Finite Fluctuations was implemented to Model (3) to gain importance estimates of factors affecting capacity. It should be mentioned, that for this approach there were obtained $N - 1$ estimates (cf. Table II-C) (because of

Table I
COMPARING RESULTS OF SENSITIVITY ANALYSIS FOR MODEL (3) OBTAINED BY DIFFERENT APPROACHES

Affecting factors	**Importance measure, %**	
	Analysis of Finite Fluctuations	***Garson Algorithm***
Speed limit	2,8	1,1
Work zone layout	4,3	2,2
Area	11,1	7,4
Lane widths	5,0	7,7
% of heavy vehicles	9,9	8,1
Grade	11,6	8,5
Lane reduction	12,0	8,5
Number of lanes	43,3	56,5

existing $N-1$ finite fluctuations for N input values realizations in the dataset) and their median values were taken as a sensitivity measure. It is also important, that signs of obtained measures were ignored, so the only degree of sensitivity without its direction was considered. To prove the correctness of the proposed approach the obtained results were compared with Garson algorithm which is common way to estimate the importance of inputs of neural network model.

Analyzing obtained results (cf. Table II-C) we could see, that the number of lanes and the percentage of heavy vehicles are factors which are firstly have the highest impact on the capacity and secondly they are could be controlled to deliver better quality of transportation system functioning. The first parameter (number of lanes) could be varied within the corridor for example by using the hard shoulder as an additional lane or by using reversing traffic lane); the possible way to control the second parameter (the percentage of heavy vehicles) is using ramp metering system to limit access to the corridor from entry-ramps (cf. study [15]).

III. CONCEPTION MODEL OF EXPERT TRAFFIC FLOW CONTROL SYSTEM WITHIN HIGH-SPEED TRANSPORTATION CORRIDORS

According to the results of the study given above, the following factors describing the current and predicted state of the transportation corridor are used in the expert system as input parameters: the estimated capacity (which can be calculated by the proposed neural network model (3)), the average vehicles speed in lanes, the high-speed transportation corridor location, the grade of the highway, the percentage of heavy vehicles, the repair zone layout, the number of lanes in one direction, the lane widths, the lane reduction, the speed limit. The percentage of heavy vehicles, the number of lanes in one direction (shoulders or reverse lanes can be used as additional lanes), the speed limit (using variable traffic signs) are used as the output parameters of the expert system.

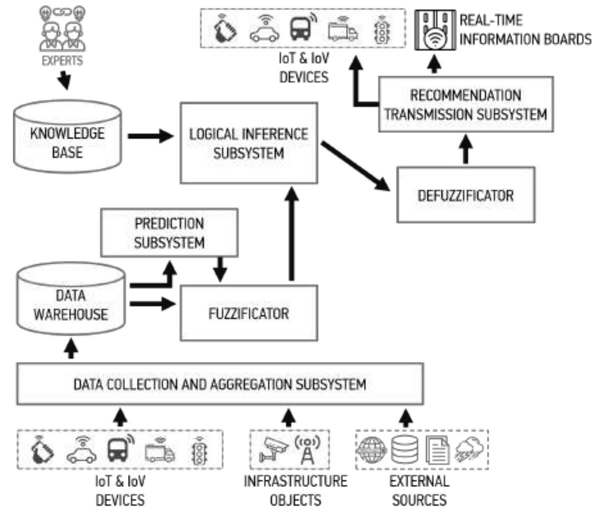

Figure 2. Conceptual model of the Expert Traffic Flow Control System

Task-specific knowledge of experts can be presented as a set of IF-THEN production. Each production rule can include information about one or several input factors in the condition part and in the conclusion part. These parameters can be involved in the production rules in the following forms: linguistic variable, quantitative variable, string variable.

The Figure 2 shows a conceptual model of the Expert Traffic Flow Control System. The values of the input system parameters are calculated and aggregated into Data collecting and aggregating subsystem. Then data is transferred to the data warehouse. In the Prediction subsystem, the estimated capacity is determined using a neural network model. Data coming from the database as a crisp values and corresponding linguistic variables are converted into fuzzy values in the Fuzziffication subsystem. Then, the values of the variable parameters (the percentage of heavy vehicles, the speed limit, the number of lanes) are determined into the Logical inference subsystem using the Mamdani algorithm. In the Defuzziffication subsystem fuzzy values of the output factors are converted to the crisp values. The Recommendation transmission subsystem send recommendations to the devices of road users and road infrastructure objects via wireless interfaces and the Internet.

Due to fuzzy logic algorithms and model describing in a natural language, expert systems have a number of advantages when they are used to solve problems in which information about the system, its parameters, as well as about the inputs, outputs, and system states is unreliable and poorly formalized. However, there is a significant drawback for such systems: the fuzzy rules set is formulated by experts and may be incomplete or contradictory. Therefore, the task of automatically knowledge base construction based on the observable data is urgent.

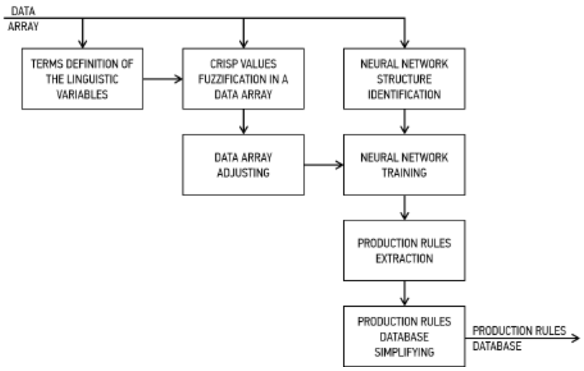

Figure 3. Conceptual scheme of Forming Production Rules in Intelligent Transportation System algorithm

IV. Scheme of Forming Production Rules in Intelligent Transportation System Based on Applying Neural Networks Models

On the 3 is shown a conceptual scheme of the automated knowledge base building process.

Step 1. Terms definition of the linguistic variables based on an experimental data set and sensitivity analysis results. The sensitivity analysis results determine the number of fuzzy values that each linguistic variable can initially accept. Also, the fuzzy membership functions are defined on this step.

At this step, we get the term sets of input parameters $I_i, i = 1, \ldots, N$, where N is the number of input parameters, and output parameters $O_l, l = 1, \ldots, L$, where L is the number of output parameters.

Each input parameter I_i and output parameter O_l can take fuzzy values ("small", "large", etc.) from their term sets (N_i and M_l are the number of corresponding fuzzy values for input and output linguistic variables).

Step 2. Fuzzification of crisp values in an experimental data set.

Step 3. The experimental array pre-processing: normalizing input values that are included in the model as quantitative variables; encoding possible input values that are included in the model as string variables; rows aggregation in the data set which has the same values of the all input parameters and the different values of the output parameters.

Step 4. Determining the structure of a neural network. To solve the task, a neural network can be used without hidden layers [16] or with hidden layers.

To solve the task of expert system knowledge base building for the intelligent transportation system it is considered to use the neural network with one hidden layer (cf. 4).

Input neurons correspond to every possible fuzzy value of input parameters:

$$x_{ij} = \begin{cases} 1 & \text{if } I_i \text{ is } j\text{-fuzzy value from } I_i \text{ term set} \\ 0 & \text{if } I_i \text{ is not } j\text{-fuzzy value from } I_i \text{ term set} \end{cases}$$

where j = 1, …, N_i. If the value of the parameter I1 is "small", then it cannot be any different fuzzy value at the same time. In other words, only one of $x_{11}, x_{12}, \ldots, x_{1N_i}$ can take the value 1 at a given time.

Similarly, output neurons correspond to every possible fuzzy value of output parameters:

$$y_{ls} = \begin{cases} 1 & \text{if } O_l \text{ is } s\text{-fuzzy value from } O_l \text{ term set} \\ 0 & \text{if } O_l \text{ is not } s\text{-fuzzy value from } O_l \text{ term set} \end{cases}$$

where s = 1, …, M_l.

Hidden layer neurons are designated h_k, $k = 1, \ldots, K$, $K \geq L$ – number of hidden layer neurons which shouldn't be less then output neurons.

Step 5. Neural network training.

At this stage, the neural network weights will be calculated:

- V_{ijk} - weights of the trained neural network (input – hidden layer)
- W_{kls} - weights of the trained neural network (hidden layer - output)

Step 6. Production rules extraction from the results of parametric identification of a neural network. The number of rules matches the output neurons number. Extracting production rules can be reduced to selecting the most dominant rule for each neuron.

the hidden layer neuron is selected for every output layer neuron as follows

$$h_s = \max_s (h_k * w_{ksl}) \tag{8}$$

Then, for this hidden layer neuron a combination of input neurons is selected (one for each input parameter) as follows:

$$\forall I_i : \qquad \max_j (x_{ij} * v_{ijk} - b_k), \tag{9}$$

where k is the index of the hidden neuron (8) which is chosen for every output layer neuron.

Step 7. Simplifying the knowledge base: removing duplicate rules, merging rules, etc.

V. Conclusion

The article presents an algorithm and results of sensitivity analysis for the model of estimate capacity, describes an expert system which is designed to control traffic flows in high-speed transportation corridors. The scheme of the algorithm for automated knowledge base building based on a neural network is also proposed. A distinctive feature of the algorithm is the neural network structure with a single hidden layer. The proposed extracting production rules algorithm provides the most dominant rule selecting for each output neuron: selecting a neuron from a hidden layer, and then a combination of fuzzy values selecting for each input parameter included in the rule, based on the analysis of weights obtained as a neural network training result.

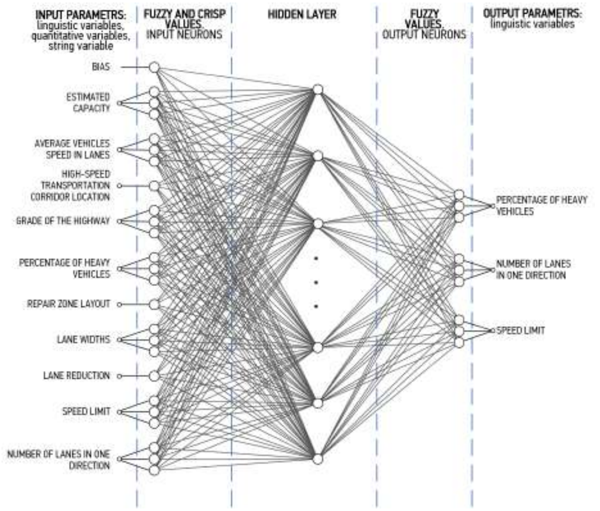

Figure 4. Example of the Neural Network Structure for Forming Semantic Rules Task

In the future, it is planned to study the required neurons number on the hidden layer and build a knowledge base for transport corridors in the research region.

REFERENCES

[1] M. Chowdhury, A. Apon, and K. Dey, “Data Analytics for Intelligent Transportation Systems”. 2017.

[2] ITS-America, “ITS-America. The official website.”, URL: https://www.itsa.org.

[3] “National Technological Initiative”, URL:http://www.nti2035.ru.

[4] TRB, “Highway Capacity Manual — HCM 2010”, 2010.

[5] FGSV, “German Highway Capacity Manual, HBS — 2015” (Handbuch fuer die Bemessung von Strassenverkehrsanlagen), 2015.

[6] Rosavtodor, “Russian National Guidelines to detect the capacity of motor roads ODM 218.2.020–2012”. 2012.

[7] J. A. C. van Toorenburg, “Praktijkwaarden voor de Capaciteit” (Practical Values for Capacity). Transport Research Centre (DKV), Ministry of Transport, Public Works and Water Management, Rotterdam, 1986.

[8] P. V. Saraev, S. L. Blyumin, A. V. Galkin, and A. S. Sysoev, “Neural remodelling of objects with variable structures,” Proceedings of International Conference on Intelligent Information Technologies for Industry, 2017, pp. 141–149.

[9] N. von der Heiden and J. Geistefeldt, “Capacity of freeway work zones in Germany,” Transportation research procedia, No. 15, 2016, pp. 233–244.

[10] A. Sysoev and N. Voronin, "Approach to Sensitivity Analysis of Stochastic Freeway Capacity Model Based on Applying Analysis of Finite Fluctuations," 2019 1st International Conference on Control Systems, Mathematical Modelling, Automation and Energy Efficiency (SUMMA), Lipetsk, Russia, 2019, pp. 621-626.

[11] W. Brilon, J. Geistefeldt, and M. Regler, “Reliability of freeway traffic flow: a stochastic concept of capacity,” Proceedings of the 16th International symposium on transportation and traffic theory. Vol. 125143. Maryland: College Park. 2005.

[12] A. Saltelli, “Sensitivity analysis for importance assessment,” Risk analysis, vol. 22.3, 2002, pp. 579–590.

[13] S.L. Blyumin, G.S. Borovkova, K. V. Serova, and A.S. Sysoev, “Analysis of finite fluctuations for solving big data management problems,” Proceedings of the 9th IEEE International Conference on Application of Information and Communication Technologies (AICT), 2015, pp. 48–51.

[14] A. Sysoev, A. Ciurlia, R. Sheglevatych, and S. Blyumin, “Sensitivity Analysis of Neural Network Models: Applying Methods of Analysis of Finite Fluctuations”, Periodica Polytechnica Electrical Engineering and Computer Science, vol. 63, no. 4, pp. 306-311, 2019.

[15] A. Sysoev, S. Hohmann, and J. Geistefeldt, “Differential Evolution Approach To Calculate Optimal Ramp Metering Rates,” Int. J. Traffic Transp. Eng., 2017.

[16] S.H. Huang, H. Xing, "Extract intelligible and concise fuzzy rules from neural networks", Fuzzy Sets and Systems, vol. 132, no. 2, pp. 233–243, 2002.

Построение семантических правил для управления транспортным потоком в интеллектуальной транспортной системе

Хабибуллина Е.Л., Сысоев А.С.

В статье приводится подход к математическому ремоделированию пропускной способности участков высокоскоростных транспортных коридоров. Предложенный метод основан на применении нейросетевой модели, сочетающий результаты оценки стохастической пропускной способности в период транспортного затора и свободного движения транспортных средств. Основываясь на полученной модели предлагается проводить анализ важности факторов, оказывающих влияние на оцененную пропускную способность с использованием методов анализа конечных изменений. Также на основании предлагаемых подходов представлена схема формирования продукционных правил в интеллектуальной транспортной системе.

Received 30.01.20