TRANSPORT TECHNOLOGIES

Vol. 3, No. 2, 2022

Vasyl Mateichyk[1], Miroslaw Śmieszek[1], Nataliia Kostian[2]
1. Rzeszow University of Technology
10, al. Powstancow Warszawy, Rzeszow, 35-959, Poland

2. Cherkasy State Technological University
333, Shevchenko Boulevard, Cherkasy, 18006, Ukraine

https://doi.org/10.23939/tt2022.02.052

EVALUATION OF TRANSPORT SYSTEM CONFIGURATION BY EFFICIENCY INDICATORS

Summary. *The study is devoted to the process of evaluating the efficiency of the transport system in terms of urban mobility. The approach is based on the use of a system of performance indicators using neurocomputer technologies. Generalized models for obtaining a vector of performance indicators and an integral performance indicator in the form of computer neural networks are proposed. It is shown that to record the fact that the indicator values fall to the threshold and below, it is enough to use a neural network built on perceptron neurons. The multi-layered model for determining the integral indicator allows assessing the importance of individual indicators in the system of monitoring the efficiency of a given configuration of the transport system. An experimental study of twenty-five states of the transport system of various configurations in the cities of Poland and Ukraine was carried out. The key indicators of the system's efficiency are determined, namely, the energy efficiency indicator of the vehicle as a system element, the environmental indicator and the traffic safety indicator. Based on the results of the experimental study, a neural network structure is proposed for evaluating the energy efficiency of given configurations of the transport system. For the purpose of training and testing the obtained network, the procedure of adjusting the threshold value of the activation function and normalizing the values of the input parameters array of the transport system was used. The constructed network was implemented using Visual Studio 2019 using the C++ language. The network was adjusted to determine the energy efficiency estimate with a given accuracy by replacing the perceptron neuron with a regular one with a sigmoidal activation function. The random nature of the choice of the configuration and the initial values of the weighting factors made it possible to obtain a model with an accuracy of implementation on the control sample in the range from 90 to 98.7 % at a learning rate of 0.1.*
Keywords: *transport system, efficiency indicators, model, energy efficiency level, perceptron*

1. INTRODUCTION

The insufficient pace of development of urban transport networks and the corresponding infrastructure, the growth of the population's motorization and the need for periodic replacement of the car fleet lead to the setting of research tasks to ensure the necessary level of transport mobility and reduce its negative impact on the urban environment. The solution of this type of problems requires a systematic approach to study the properties of the specified objects and phenomena that form a whole complex structure, as well as to establish new connections and regularities inside the system, analysis of previously unknown effects. The specific values of the characteristics of the functional elements of the transport system determine its current configuration (mode). Thus, the given configuration reflects the properties of the traffic flow moving in the given traffic environment under the given road conditions, and the properties of a discrete object (vehicle) isolated from it. At the same time, the environment of the traffic flow takes into account the type of the given settlement, motorization level, weather conditions and the daily time interval. Modes of operation of the transport system within its morphological capabilities are determined by the level of management, which depends on the quality of current and forecasted data on the state of the system. The need to change the operating mode of the system is due to the unsatisfactory state of the indicators that set the vectors of the possible direction of efficiency improvement. Monitoring of the current operating modes of the transport system and the search for its new design solutions are inextricably linked with the use of modern modeling methods and automation technologies. Graphical and mathematical description of the system allows identifying the indicators of system state assessment and determine criteria for its optimization.

Thus, the availability of adequate functional and mathematical models contributes to solving the urgent tasks of reorganizing the existing transport system following the development strategies of cities and regions, including the development of an information model and the implementation of an intelligent system for managing transport processes.

2. ANALYSIS OF LATEST RESEARCH AND PUBLICATIONS

In the process of making decisions regarding the improvement of the transport system, an important and necessary element is the measurement of indicators of the effective flow of transport processes within the system. The environmental impact indicator can be decisive in making the final decision. Indicators can have different weighting factors for a specific type of system. The methods of determining indicators and evaluating their weighting factors are mostly based on expert evaluations with the involvement of specialists from this area [1, 2]. However, these estimates are subjective and may not be adequate for transport systems in another region or at another level of scaling. Therefore, the issue of developing a mechanism for adjusting the specified coefficients in accordance with the actual values of the system parameters without re-engaging experts remains open.

Taking into account the requirements for modern transport systems and global environmental problems, it is advisable to use assessments of its environmental friendliness, energy efficiency of vehicles in the system, traffic safety and others to determine the current values of system performance indicators. The amount of emissions of harmful substances into the air correlates with fuel consumption. In addition, separate methods of determining the energy efficiency of cars take into account the amount of work performed, so the energy efficiency indicator of transport has a significant weight as part of the integral efficiency indicator.

Methods of evaluating and improving the energy efficiency of vehicles are divided into two groups. The first includes methods and technologies aimed at achieving the goal by improving the structural properties of new cars [3–7]. Thus, the author [3] proposed a complex indicator of car energy efficiency, which is used to justify and implement a complex of technical and technological innovations based on the model of the modular structural and parametric organization of the design of a new car. This indicator takes into account the speed, carrying capacity, curb weight and mileage of the car, road properties for the test route when performing the reference operation. At the same time, the method of mathematical modeling of the processes of energy transformation of technological resources of transport into a physical product is used. But to determine the indicated indicator, it is necessary to additionally calculate coefficients that take into account the specifics of a particular car. In addition, the model operates on the average values of the speed during the execution of the test operation, while different distributions of the speed values in different experimental samples may have the same measures of central statistics. In [4], the effect of aging of materials during the life cycle of vehicles with different types of power plants on their energy efficiency was investigated. The authors determine the generalized car energy efficiency indicator at the state level by calculating the sum of the products of the values of the energy efficiency indicators of individual types of vehicles by the share of their annual sales. The paper [5] presents a model of energy consumption control for use in an intelligent electric vehicle control system. The algorithm that implements this model is designed for a specific model and needs modification for others. The authors [6, 7] proposed technologies for increasing the energy efficiency of vehicles by reducing the weight of individual components and systems of vehicles and optimizing the operation of air conditioning and ventilation systems using the example of a demonstration model of a battery electric vehicle. However, it has been proven that this optimization is appropriate only for electric vehicles with low rolling resistance.

The second group of methods includes methods of increasing the energy efficiency of vehicles by correcting their operational characteristics. The authors offer a number of analytical models as a basis for evaluating the energy efficiency and fuel consumption of transport. A significant part of such models takes into account the instantaneous speed and acceleration of movement [8, 9]. Moreover, a different form of the analytical dependencies themselves can be used. In studies [10, 11], the dependence of the fuel efficiency indicator on the mileage of the car was obtained. In [10], car loading is not taken into account, which is an important characteristic when evaluating the energy efficiency of urban passenger transport. Research [9, 11] is devoted to the evaluation of the efficiency of large-class passenger buses, therefore they contain limitations regarding the scope of application of the obtained models. In [12], a morphological analysis of the city's transport system was carried out and four functional elements were identified: vehicle, transport flow, road and traffic environment. In [12], an adequate linear model was built to evaluate the influence of the characteristics of these elements on the energy efficiency of urban transport. The model takes into account 10 essential system parameters corresponding to the characteristics of its functional elements. Since these parameters have different ranges of values, it is not possible to accurately assess the importance of the influence of a single parameter on the efficiency indicator based on the value of the coefficients of the linear model. The author [13] defines the level of energy efficiency as the ratio of energy consumption of the reference and researched vehicles. After performing equivalent transformations, the final model contains coefficients that take into account the morphological characteristics of the elements of the transport system. The procedure for determining the coefficients is subjective in nature, so it contains an error, the value of which depends on the experience of experts and statistical information of a certain region.

Another indicator of the effective operation of the transport system should be the traffic safety parameter, which belongs to the group of technical efficiency criteria [14]. This indicator is a function of two parameters: the response time of safety systems and acceleration under the condition of sudden fuel supply. Research [14] has a theoretical character. A comprehensive safety indicator can also take into account other factors, including the assessment of the probability of a traffic accident depending on the age group of passengers. The stages of carrying out the specified assessment are modeled in [15] on the basis of the theory of decision trees.

The environmental safety indicator can take into account several criteria of environmental efficiency [14] according to the principles given in [16]. The article [17] solves the problem of optimizing the city's transport system according to the criterion of minimizing the harmful impact on the environment from the use of passenger transport. The problem model takes into account the coefficients of duplication of routes and restrictions on the passenger capacity of transport. However, only urban public transport for general use is investigated. The authors [18] presented mathematical models for determining indicators that can be used as indicators of environmental safety of the transport system. The first model defines the mass of emissions of harmful substances by the transport flow as the sum of the specific emissions of individual vehicles in the flow. The model takes into account the volume and mode of movement, category, environmental standard, type of vehicle fuel, as well as the share of this type of vehicles in the flow. The second model determines the concentration of a given pollutant in the air at a given distance.

According to the results of the analysis of the latest publications, it can be stated that today the question of determining the indicators of the efficiency of the transport system and its individual functional elements, taking into account the operational characteristics of vehicles and external influencing factors, remains relevant. Along with the traditional mathematical apparatus, computer neural networks are a powerful tool for representing object models as part of intelligent transport systems [19-21].

3. FORMULATION OF THE AIM AND OBJECTIVES OF THE ARTICLE

The aim of this study is to develop a model and a mechanism for determining the system of indicators for monitoring the efficiency of the city's transport system.

To achieve the goal, the following tasks must be completed:

- develop a model for determining the system of efficiency indicators using neural networks in general;
- explore the city's transport system at a conceptual level and determine its parameters;
- determine energy efficiency indicators of system configurations;
- to build and implement a neural network for evaluating the energy efficiency of the transport system based on the results of experimental studies.

4. PROBLEM SETUP AND RESEARCH METHODOLOGY

The process of managing the transport system and making a decision on its improvement primarily depends on the current and predicted course of processes in the middle of the system. Measuring the effect of implementing these processes allows evaluating their results and provides an opportunity to determine the starting point for further optimization. The current configuration of the transport system to a certain extent represents the reference plan of the corresponding optimization problem. The next step is to determine the optimization vector (direction) according to a certain criterion. The criterion involves the the evaluation of the values of the measured indicators of the system. This provides an opportunity to provide sound conclusions regarding the evaluation of the effectiveness of the existing configuration and the need to move to a new reference plan. Periodic improvement of transport system processes requires significant financial, labor and other resources. In addition, the very process of implementation of optimization programs may for some time cause obstacles and reduce the level of mobility of the population. Therefore, an important aspect of the optimization of transport systems is the determination of the time of optimization works. The moment and vector of the transition to a new system configuration is determined by the efficiency indicator, the value of which turns out to be greater (less) than the threshold. For this purpose, it is proposed to use models of the transport system in the form of an artificial neural network, in particular, a perceptron. A perceptron with k outputs for monitoring the effectiveness of a given system configuration is presented in Fig. 1. n values xij of the vector of essential parameters X are applied to the network inputs. The index j corresponds to the number of the system parameter. Each element $\sum$ (Fig. 1) is designed to perform the operation of the weighted sum of the values of the parameters of the i-th configuration of the transport system, which are received at its input. At the outputs of these elements, an array Y of the outputs of this network layer with dimension k, is formed, which is transmitted to the inputs of the elements F. Within the specified associative logical elements of the perceptron, the values of k elements of the vector In of the indicators of the efficiency of the transport system are calculated:

$$In_{is} = f(y_s, \theta_s), 1 \le i \le n, 1 \le s \le k, \tag{1}$$

where In_{is} – the value of the s-th system efficiency indicator in the i-th configuration; θ_s – threshold value of the s-th indicator; f – activation function.

Thus, a subtask arises within evaluation task's performance, which consists of justifying the choice of threshold levels. The weighting coefficients of the links of the elements of the perceptron at the initial stage are unknown quantities. Therefore, the perceptron needs to adjust these coefficients (learning) for further use. The learning algorithm is carried out according to the delta rule, which includes a parameter that determines the learning speed.

Usually, the range of indicators is in the range [0, 1]. Therefore, if there is a need for more accurate estimates of the configuration of the transport system, the blocks F of the network can be implemented on the basis of the hyperbolic tangent activation function.

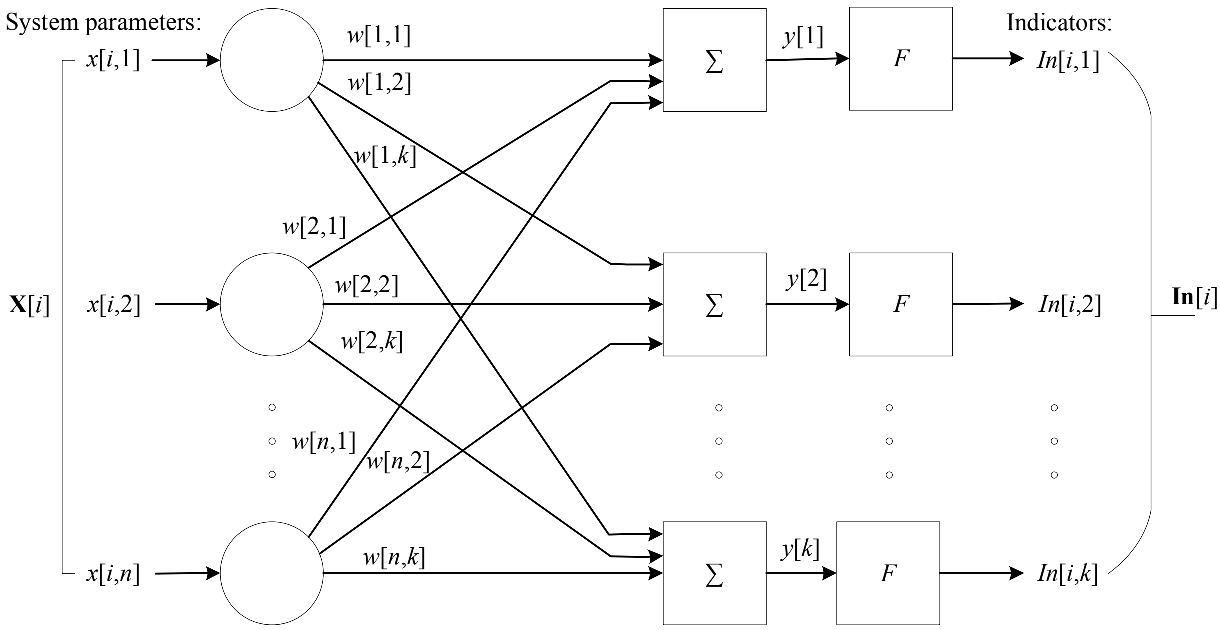

Fig. 1. A generalized neural network model for determining the system of efficiency indicators of the i-th configuration of the transport system

The network (Fig. 1) can be expanded to determine the integral indicator of the efficiency of the transport network In_i according to the given i-th configuration (Fig. 2). The outputs of the first model (Fig. 1) are the system of indicators, and the output of the other (Fig. 2) is the scalar value of the indicator.

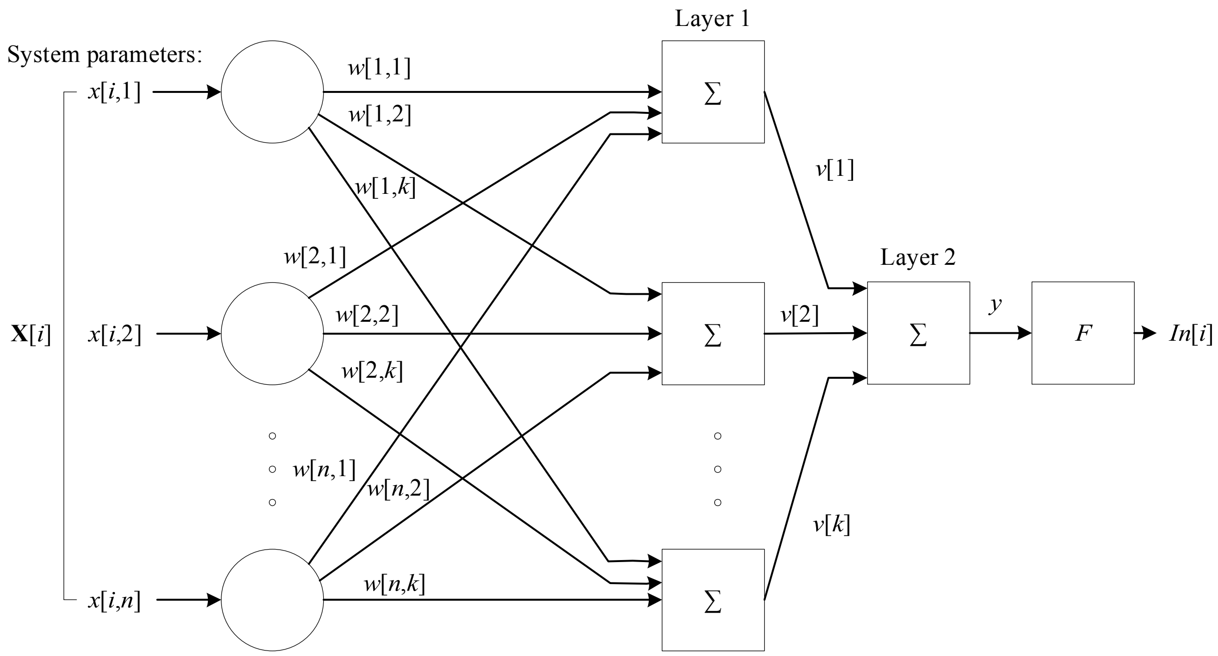

Fig. 2. A two-layer neural network model for determining a complex indicator of the efficiency of the i-th configuration of the transport system

In the block of the second layer of the perceptron (Fig. 2), the weighted sum of outputs from similar blocks of the first layer is calculated. Therefore, it can be assumed that the weight coefficients *vs* determine the importance of the specific values of the transport system efficiency indicators obtained at the output of the first layer.

In general, this neural network can have several internal layers. For the given task, you can use networks with a more complex structure. A backpropagation neural network with layers of Kohonen and Grossberg neurons is suitable. However, the perceptron is simple to implement. Unlike mathematical models, a neural network can have several initial parameters, so it is convenient to use in the process of evaluating several indicators.

5. RESEARCH RESULTS

To build a model of the system for monitoring the efficiency of the transport system, a survey of 25 existing configurations of transport systems in 9 settlements of Poland and Ukraine, belonging to different groups in terms of population size and density, was conducted. In the experimental part of the study, 16 vehicles were used to ensure the completeness of the scope of determining their parameters. Vehicles of different categories and age groups, with different types of power plants and level of controls were presented. In the research process, three main indicators of the system were selected: the energy efficiency indicator $In_{e.e}$, the environmental safety indicator $In_{e.s}$ and the traffic safety indicator $In_{t.s}$, which form an integrated efficiency indicator as a weighted sum of system performance assessments. The $In_{e.e}$ indicator corresponds to the *LEE* energy efficiency indicator of transport in the system. The *LEE* indicator is determined for the studied configurations according to the method described in [13] and is universal for different categories of transport. Basic (independent) parameters were selected from the space of parameters affecting *LEE*. Their structure and methods of determination are proposed by the authors in [12]. The array of input parameters contains both quantitative and qualitative values, which are previously reduced to quantitative analogs according to the scales described in [12]. Transport energy efficiency was assessed within the *TrEECs* transport energy efficiency control subsystem. To check the possibility of using the perceptron in solving problems of monitoring the given state of the transport system, a test network was built to determine the energy efficiency indicator based on the obtained experimental data. The mechanism of determining the energy efficiency indicator $In_{e.e}$ can be explained on the structure of the perceptron neuron shown in Fig. 3. To calculate the values of parameters x_6 – "Road resistance degree" and x_7 – "Carriageway curvature degree" дані, data obtained using Google Earth Pro 7.3.4. The components of the parameter x_{10} – "Complexity of weather conditions" are determined according to the data of the Gismeteo Internet service.

The values of the weighted basic parameters enter the input of the perceptron neuron. The output of this block is used by the activation function to determine an indicator that can have two results: the investigated configuration is energy efficient or inefficient. For training the network, the type of training was used – with a teacher. For this, an experimental sample of monitoring results was formed. When using the method of correction coefficients [12] to determine the *LEE*, its definition range is within the range of 0.5 to 1. Therefore, it is advisable to take the threshold value of the activation function at 0.75. At the same time, the method of accelerating learning by adjusting the threshold value according to Formula (2) was used:

$$\Delta\theta = -\eta \cdot (LEE_i - y), 1 \le i \le n, \tag{2}$$

where $\Delta\theta$ – increase in the threshold value; LEE_i – statistical value of the level of energy efficiency within the ith configuration of the transport system; y – perceptron neuron output; n – number of configurations.

The experimental sample was divided into educational and control samples in a ratio of 20:5, respectively.

The perceptron was implemented in the Visual Studio 2019 application development environment using the C++ programming language. The elements of the vector of basic parameters of each configuration from the training sample are fed to 10 network inputs in random order. The values of each input parameter were previously normalized by dividing it by the length of the input vector:

$$x_j^n = x_j \Big/ \sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}, \tag{3}$$

where x_j – initial value of the parameter obtained as a result of the experiment; x_j^n – normalized value of the parameter.

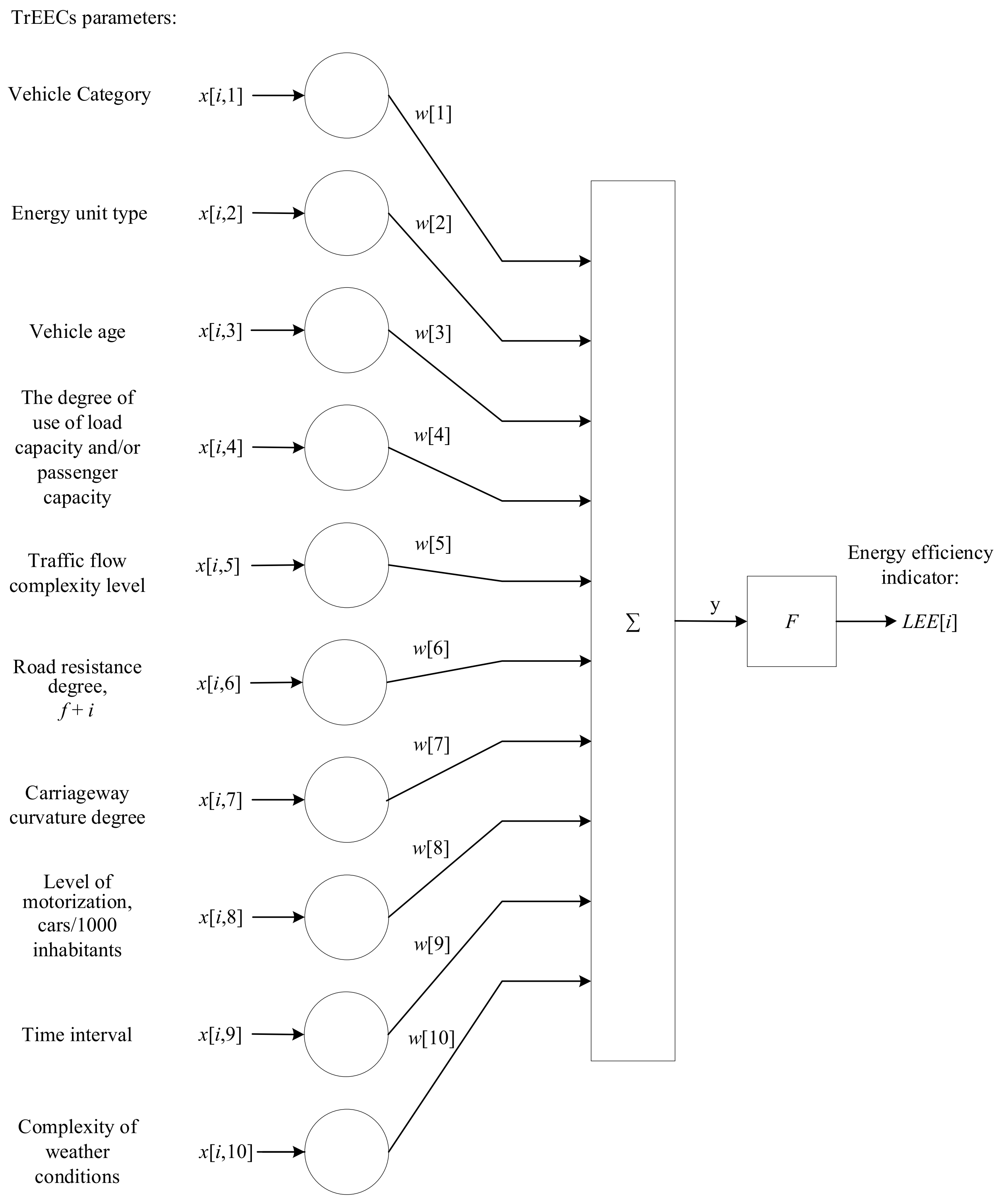

Fig. 3. Structure of the model for determining the transport energy efficiency indicator

The normalized values of the input parameters obtained by expression (3) and the experimental values of the *LEE* energy efficiency level, which is used in the network training process, are shown in Table 1. The results of the network training on the control sample fully confirmed its performance. Learning speed η=0.1.

In addition, a neural network training algorithm was developed to determine more accurate estimates of energy efficiency, in which the activation function was replaced from a threshold to a sigmoidal one.

The value space of the specified function is in the range from 0.5 to 1, as well as the values of the *LEE* energy efficiency level:

$$F = f(y) = 1/(1+e^{-y}), \tag{4}$$

where y – is the output of the corresponding element ∑ of the neural network.

Table 1

The value of the parameters of the neural network, which were used in the process of its training

i	Normalized values of transport system configuration parameters										$In_{e.e}$
	x_1^n	x_2^n	x_3^n	x_4^n	x_5^n	x_6^n	x_7^n	x_8^n	x_9^n	x_{10}^n	
1	0.2053	0.2053	0.6158	0.1540	0.0062	0.0185	0.4106	0.4106	0.4106	0.0821	0
2	0.1454	0.4363	0.7271	0.0713	0.0044	0.0099	0.2908	0.2908	0.2908	0.0291	0
3	0.7257	0.2903	0.2903	0.0929	0.0348	0.0033	0.1451	0.2903	0.4354	0.0000	0
4	0.4545	0.3030	0.6059	0.1091	0.0364	0.0035	0.1515	0.3030	0.4545	0.0000	1
5	0.1584	0.1584	0.6337	0.0903	0.0824	0.0036	0.1584	0.3168	0.6337	0.0792	0
6	0.3730	0.4974	0.2487	0.0995	0.0050	0.0019	0.1243	0.3730	0.6217	0.0249	0
7	0.1279	0.3837	0.6395	0.0384	0.0077	0.0022	0.1279	0.3837	0.5116	0.0256	0
8	0.2648	0.2648	0.2648	0.0953	0.0927	0.0172	0.2648	0.2648	0.7943	0.0265	1
9	0.2208	0.2208	0.6625	0.0287	0.0000	0.0044	0.4416	0.4416	0.2208	0.1546	0
10	0.3398	0.3398	0.5097	0.1308	0.0102	0.0034	0.3398	0.3398	0.5097	0.0340	1
11	0.7131	0.2377	0.3565	0.0844	0.0261	0.0027	0.1188	0.2377	0.4754	0.0594	0
12	0.5017	0.2508	0.5017	0.0865	0.0389	0.0023	0.1254	0.1254	0.6271	0.0000	0
13	0.5549	0.2774	0.2774	0.1193	0.0347	0.0042	0.1387	0.1387	0.6936	0.0555	0
14	0.4500	0.3000	0.7500	0.0750	0.0255	0.0045	0.1500	0.1500	0.3000	0.0600	1
15	0.6624	0.2649	0.5299	0.1206	0.0437	0.0102	0.1325	0.1325	0.3974	0.0265	0
16	0.1559	0.4678	0.7796	0.0312	0.0327	0.0120	0.1559	0.1559	0.3119	0.0312	1
17	0.1288	0.2576	0.6441	0.0193	0.0631	0.0063	0.1288	0.2576	0.6441	0.0000	0
18	0.2224	0.2224	0.6671	0.0934	0.0467	0.0109	0.2224	0.4447	0.4447	0.0000	1
19	0.5338	0.4004	0.6673	0.0494	0.0051	0.0065	0.1335	0.2669	0.1335	0.0133	1
20	0.5606	0.2803	0.5606	0.1023	0.0813	0.0035	0.1402	0.2803	0.4205	0.0280	1
21	0.4509	0.3006	0.4509	0.1233	0.1142	0.0038	0.1503	0.3006	0.6012	0.0150	1
22	0.1739	0.1739	0.5216	0.0469	0.0017	0.0050	0.5216	0.3478	0.5216	0.0000	0
23	0.1619	0.1619	0.1619	0.0502	0.0024	0.0060	0.1619	0.4858	0.8096	0.0324	0
24	0.5837	0.2918	0.2918	0.0948	0.0277	0.0190	0.4378	0.2918	0.4378	0.1021	0
25	0.3109	0.3109	0.3109	0.0824	0.0078	0.0124	0.4664	0.3109	0.6218	0.0466	0

Training and testing were performed at different preset values of learning rate η and accuracy ε. The modeling error was calculated as the relative root mean square error:

$$\bar{S}_r = \frac{1}{10} \cdot \sum_{i=1}^{n_{constl}} \frac{(LEE_i - In_{e.e})^2}{LEE_i^2}, \tag{5}$$

where LEE_i – experimental value of the level of energy efficiency of transport within the configuration; $In_{e.e}$ – model value of the energy efficiency indicator of the given configuration of the transport system; $n_{control}$ – the number of configurations included in the control sample.

The algorithm of the software module is implemented for the following values of learning speed:

η = {0.05, 0.01, 0.1, 0.2, 0.4, 0.8}.

The highest modeling accuracy is achieved by the speed value η = 0.1. The random nature of the selection of weight coefficients of the neural network does not allow obtaining a fixed value of the modeling error. The value of the relative root mean square error of the efficiency indicator on the control sample is in the range from 1.3 to 10 %, according to the chosen speed and the limit level of accuracy on the training sample. The smallest simulation error on the training sample is 0.4 %. Adding an additional parameter with a single value to the input of each neuron did not significantly improve the learning speed or the accuracy of the obtained results.

6. CONCLUSIONS AND RESEARCH PERSPECTIVES

The paper proposes an approach for evaluating multiple configurations of the transport system based on indicators of its effectiveness. It is convenient to present this concept in the form of generalized models of neural networks, the inputs of which are the parameters of the transport system within the given configuration, and the outputs are a single integral indicator or a group of efficiency indicators. For this formulation of the problem, the use of perceptron neurons in the network structure turned out to be sufficient. The advantage of their use is the simplicity of implementing algorithms. At the conceptual modeling level, three key indicators were identified: energy efficiency, environmental friendliness and traffic safety. The proposed structure of a neural network containing 10 inputs. At the output of the system, the value of the indicator is obtained, which shows the level of energy efficiency of the transport system. For a more accurate assessment of the system's efficiency, a neural network with a sigmoidal activation function was implemented, which matched the areas of determination of the outputs of computer neurons and experimentally obtained data. The accuracy of training and testing was improved by normalizing the input parameters values and randomizing the selection of the initial values of the network weights. Adjusting the pair "earning speed – model accuracy" made it possible to obtain adequate models. The results of testing the model on a control sample showed that increasing the learning speed decreases its accuracy. The modeling error was 10 % when training the neural network for 1211 iterations, 2 % for 42736 iterations, and 1.3 % for 258286 iterations.

The results of this study should be used in systems for monitoring the efficiency of urban transport systems. This approach makes it possible to assess the necessity and time of implementation of optimization programs in the direction given by the vector of the most important indicators.

Further research will be aimed at justifying the use of other structures of neural networks in the field of evaluating the results of the functioning of transport systems. Special attention will be focused on computer neural networks, the organization of which is based on the use of fuzzy logic.

References

1. Mateichyk, V., Tarandushka, L., & Kostian, N. (2018). *Optimization of autoservice enterprises activity based on the current state indicators.* In Systemy i srodki transportu samochodowego. Problemy eksploatacji i diagnostyki: wybrane zagadnienia (pp. 91–99). Rzeszow: Transport (in English)

2. Tarandushka, L., & Kostian, N. (2019). Prohramna pidtrymka restrukturyzatsii vyrobnytstva v systemi upravlinnia yakistiu avtoservisnoho pidpryiemstva [Program support for production restructuring in the quality management system of a car service enterprise]. *Naukovyi visnyk Ivano-Frankivskoho natsionalnoho tekhnichnoho universytetu nafty i hazu [Scientific Bulletin of Ivano-Frankivsk National Technical University of Oil and Gas], 2(47),* 48–56. doi: 10.31471/1993-9965-2019-2(47)-48-56 (in Ukrainian).

3. Khabutdinov, R.A. (2020) Systemna kontseptsiia enerhoresursnoi synerhii ta metodolohiia tekhnolohichno-innovatsiinoho upravlinnia na avtotransporti [System concept of energy-resource synergy and methodology of technological-innovative management on motor transport]. *Visnyk Natsionalnoho transportnoho universytetu [Visnyk National Transport University]*, *1(46)*, 365–374. doi: 10.33744/2308-6645-2020-1-46-365-374 (in Ukrainian).

4. Kosai, S., Nakanishi, M. and Yamasue, E. (2018) Vehicle Energy Efficiency Evaluation from well-to-wheel lifecycle perspective. *Transportation Research Part D: Transport and Environment*, *65*, 355–367. doi: 10.1016/j.trd.2018.09.011 (in English).

5. Abulifa, A. A., Soh, A. C., Hassan, M. K., Ahmad, R. M. K. R., & Radzi, M. A. M. (2019). Energy management system in battery electric vehicle based on fuzzy logic control to optimize the energy consumption in HVAC system. *International Journal of Integrated Engineering*, *11*(4), 11-20. doi: 10.30880/ijie.2019.11.04.002 (in English).

6. Lahlou, A., Ossart, F., Boudard, E., Roy, F., & Bakhouya, M. (2020) A real-time approach for thermal comfort management in Electric Vehicles, *Energies*, *13*(15), 4006. doi: 10.3390/en13154006 (in English).

7. Patrone, G. L., Paffumi, E., Otura, M., Centurelli, M., Ferrarese, C., Jahn, S., Brenner, A., & et al (2022). Assessing the Energy Consumption and Driving Range of the QUIET Project Demonstrator Vehicle. *Energies*, *15*(4), 1290. doi: 10.3390/en15041290 (in English).

8. Du, J., Rakha, H. A., Filali, F., & Eldardiry, H. (2021). COVID-19 pandemic impacts on traffic system delay, fuel consumption and emissions. *International Journal of Transportation Science and Technology*, *10*(2), 184–196. doi: 10.1016/j.ijtst.2020.11.003 (in English).

9. Śmieszek, M., & Mateichyk, V. (2021). Determining the fuel consumption of a public city bus in urban traffic. In *Proceedings of the IOP Conference Series: Materials Science and Engineering. 26th International Slovak-Polish Scientific Conference on Machine Modelling and Simulations (MMS 2021), Vol. 1199, (pp. 1–13).* doi: 10.1088/1757-899X/1199/1/012080 (in English).

10. Lim, J., Lee, Y., Kim, K., & Lee, J. (2018). Experimental analysis of calculation of fuel consumption rate by on-road mileage in a 2.0 L gasoline-fueled passenger vehicle. *Applied Sciences*, *8*(12), 2390. doi: 10.3390/app8122390 (in English).

11. Kostian, N., Mateichyk, V., & Śmieszek, M. (2022). Otsiniuvannia enerhovytrat hromadskoho transportu iz vrakhuvanniam potuzhnosti pasazhyropotoku [Estimation of energy consumption of public transport taking into account the capacity of passenger traffic]. *Materialy X-oi mizhnarodnoi naukovo-tekhnichnoi internet-konferentsii "Problemy i perspektyvy rozvytku avtomobilnoho transportu" – Materials of X-th international scientific and technical internet-conference "Problems and prospects of development automobile transport".* (pp. 168–171). Vinnytsia: VNTU (in Ukrainian).

12. Śmieszek, M., Kostian, N., Mateichyk, V., Mościszewski, J., & Tarandushka, L. (2021). Determination of the Model Basis for Assessing the Vehicle Energy Efficiency in Urban Traffic. *Energies*, *14*(24), 8538. doi: 10.3390/en14248538 (in English).

13. Kostian, N. (2022). Pro odyn sposib otsiniuvannia enerhoefektyvnosti funktsionuvannia transportnykh system [About one method of evaluating the energy efficiency of the functioning of transport systems]. In *IV Mizhnarodnoi naukovo-praktychnoi konferentsii "Pidvyshchennia nadiinosti i efektyvnosti mashyn, protsesiv i system" [4th International Scientific and Practical Conference "Improving the reliability and efficiency of machines, processes and systems"]* (pp. 129–130). – Kropyvnytskyi: CUNTU (in Ukrainian).

14. Lukyanchenko, O., & Tykhy, V. (2022). Kompleksna otsinka efektyvnosti ekspluatatsii avtomobiliv [Comprehensive assessment of the efficiency of car operation]. *Materialy X-oi mizhnarodnoi naukovo-tekhnichnoi internet-konferentsii "Problemy i perspektyvy rozvytku avtomobilnoho transportu" [Materials of X-th international scientific and technical internet-conference "Problems and prospects of development automobile transport"].* (pp. 206–209). Vinnytsia: VNTU (in Ukrainian).

15. Islam, M. K., Gazder, U., Akter, R., & Arifuzzaman, M. (2022). Involvement of Road Users from the Productive Age Group in Traffic Crashes in Saudi Arabia: An Investigative Study Using Statistical and Machine Learning Techniques. *Applied Sciences*, *12*(13), 6368. doi: 10.3390/app12136368 (in English).

16. Klimenko, A., Hill, N., & Windisch, E. (2019). Approaches to regulation of CO2 emission and energy consumption indicators of new light duty vehicles in Ukraine. *Visnyk Natsionalnoho transportnoho universytetu [The National Transport University Bulletin]*, *1*(43), 66–75. doi: 10.33744/2308-6645-2019-1-43-006-075 (in English).

17. Bilichenko, V.V., Tarandushka, L.A., Kostian, N.L. & Pylypenko, O.M. (2021). Optymizatsiia merezhi transportu zahalnoho korystuvannia na prykladi m. Cherkasy [Optimization of the transport network by the case of Cherkasy city]. *Visnyk mashynobuduvannia ta transportu [Bulletin of Mechanical Engineering and Transport]*, *1*(13), 13-22. doi: 10.31649/2413-4503-2021-13-1-13-22 (in Ukrainian).

18. Smieszek, M., Mateichyk, V., Dobrzanska, M., Dobrzanski, P., & Weigang, G. (2021). The Impact of the Pandemic on Vehicle Traffic and Roadside Environmental Pollution: Rzeszow City as a Case Study. *Energies*, *14*(14), 4299. doi:10.3390/en14144299 (in English).

19. Brzozowski, K., Ryguła, A., & Maczyński, A. (2021). An Integrated System for Simultaneous Monitoring of Traffic and Pollution Concentration – Lessons Learned for Bielsko-Biała, Poland. *Energies*, *14*(23), 8028. doi: 10.3390/en14238028 (in English).

20. Olayode, I. O., Severino, A., Tartibu, L. K., Arena, F., & Cakici, Z. (2021). Performance Evaluation of a Hybrid PSO Enhanced ANFIS Model in Prediction of Traffic Flow of Vehicles on Freeways: Traffic Data Evidence from South Africa. *Infrastructures*, *7*(1), 1–29. doi: 10.3390/infrastructures7010002 (in English).

21. Katreddi, S., & Thiruvengadam, A. (2021). Trip Based Modeling of Fuel Consumption in Modern Heavy-Duty Vehicles Using Artificial Intelligence. *Energies*, *14*(24), 8592. doi: 10.3390/en14248592 (in English).

Received 04.10.2022; Accepted in revised form 17.10.2022.

ОЦІНЮВАННЯ КОНФІГУРАЦІЙ ТРАНСПОРТНОЇ СИСТЕМИ ЗА ІНДИКАТОРАМИ ЕФЕКТИВНОСТІ

Анотація. *Робота присвячена процесу оцінювання ефективності транспортної системи в умовах міської мобільності. Підхід базується на використанні системи індикаторів ефективності із застосуванням нейрокомп'ютерних технологій. Запропоновано узагальнені моделі для отримання вектору індикаторів ефективності та інтегрального індикатору ефективності у вигляді комп'ютерних нейронних мереж. Показано, що для фіксації факту падіння значень індикаторів до порогового та нижче достатньо застосовувати нейронну мережу, побудовану на перцептронних нейронах. Багатошарова модель для визначення інтегрального індикатора дозволяє оцінити важливість окремо взятих індикаторів у складі системи моніторингу ефективності заданої конфігурації транспортної системи. Проведено експериментальне дослідження двадцяти п'яти станів транспортної системи різних конфігурацій в містах Польщі та України. Визначено ключові індикатори ефективності системи, а саме, індикатор енергоефективності транспортного засобу як елементу системи, індикатор екологічності та індикатор безпеки руху. Виходячи з результатів експериментального дослідження запропоновано структуру нейронної мережі для оцінювання енергоефективності заданих конфігурацій транспортної системи. З метою навчання та тестування отриманої мережі було використано процедуру коригування порогового значення функції активації та нормалізацію значень масиву вхідних параметрів транспортної системи. Реалізацію побудованої мережі здійснено із використанням Visual Studio 2019 із застосуванням мови C++. Виконано налаштування мережі на визначення оцінки енергоефективності з заданою точністю шляхом заміни перцептронного нейрону на звичайний з сигмоїдальною функцією активації. Випадковий характер вибору конфігурації та початкових значень вагових коефіцієнтів дозволив отримати модель з точністю реалізації на контрольній вибірці в діапазоні від 90 до 98.7 % при швидкості навчання 0.1.*

Ключові слова: *транспортна система, індикатори ефективності, модель, рівень енергоефективності, перцептрон.*