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OPERATIONAL QUALITY MEASURES OF VEHICLES APPLIED FOR THE TRANSPORT SERVICES EVALUATION USING ARTIFICIAL NEURAL NETWORKS

EKSPLOATACYJNE MIARY JAKOŚCI POJAZDÓW W ZASTOSOWANIU DO OCENY USŁUG TRANSPORTOWYCH Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH*

Operational vehicle quality measures are an important element used to evaluate the performance of transport services. In practice, there are many methods involved in the operational evaluation of vehicles. They are characterized in this article. Artificial Intelligence methods, especially artificial neural networks, can also be successfully used for this purpose, and especially when deciding on quality assessment processes for machines, including motor vehicles. The use of methods to support decision-making based on facts is extremely important for the credibility and objectivity of the evaluation. These methods can also be used in relation to the use of vehicles in the assessment of transport services. The article presents the method of using artificial neural networks for the operational evaluation of vehicles used in freight transport services. The basis for the verification of the method was an experimental research carried out at a company making dairy products, cooperating with transport companies, supplying products for the production process. The results obtained from the operation of vehicles from the studied companies have confirmed, at the probability level of 99%, high efficiency of the proposed method in evaluating transport services using operational vehicle quality measures.

Keywords: *vehicles operation, evaluation of transport services, quality measures, artificial neural networks.*

Eksploatacyjne miary jakości pojazdów są istotnym elementem wykorzystywanym do oceny realizacji usług transportowych. W praktyce mamy do czynienia z wieloma metodami związanymi z eksploatacyjną oceną pojazdów. Scharakteryzowano je w artykule. Metody sztucznej inteligencji, a zwłaszcza sztuczne sieci neuronowe, również mogą być z powodzeniem wykorzystane do tego celu, a zwłaszcza przy podejmowaniu decyzji w procesach oceny jakości maszyn, w tym pojazdów samochodowych. Zastosowanie metod, które pozwalają wspomagać proces decyzyjny na podstawie faktów jest niezmiernie istotne z punktu widzenia wiarygodności i obiektywności oceny. Metody te mogą być również wykorzystane w odniesieniu do eksploatacji pojazdów w zastosowaniu do oceny usług transportowych. W artykule przedstawiono metodę wykorzystania sztucznych sieci neuronowych do eksploatacyjnej oceny pojazdów wykorzystywanych w usługach transportowych towarów. Podstawę weryfikacji metody stanowiły badania eksperymentalne przeprowadzone w przedsiębiorstwie produkującym produkty mleczarskie, współpracującym z firmami transportowymi, dostarczającymi wyroby do produkcji. Uzyskane wyniki potwierdziły z 99-procentowym prawdopodobieństwem wysoką skuteczność proponowanej metody w dokonywaniu oceny usług transportowych z wykorzystaniem eksploatacyjnych miar jakości pojazdów.

Słowa kluczowe: *eksploatacja pojazdów, ocena usług transportowych, miary jakości, sztuczne sieci neuronowe.*

1. Introduction

Operational quality measures of motor vehicles are used, among the others, to evaluate the performance of transport services. An important group of problems in making such an assessment is selection of the appropriate method. The operational evaluation of an object requires defining the measures (measurements, indicators) and the determining their values. The appropriate value allocation of the vehicles performance measures is one of the key criteria for the proper functioning of the whole transport system [9]. The numerical evaluation of the efficiency of the equipment is based on the values derived from the observation of the equipment during operation [10]. The variety of operational measures depends, of course, on the type of object (process), and usually these measures have different denominations and orders of scale, making them mutually incomparably [6, 11]. Comparing the measures describing an object (process) is only possible after normalization. Among the groups of technical objects' features relevant for their operational evaluation (determination of their measures and indicators) were distinguished, among the others [8]:

- technical condition of the object, being a measure of the ability to use the object over time,
- reliability in statistical terms,
- quality, understood as the ability of an object to meet specific needs,
- functionality describing the object in the sphere of human contact,
- efficiency characterizing the performance of an object,
- serviceability characterizing the object's suitability to be serviced,

(*) Tekst artykułu w polskiej wersji językowej dostępny w elektronicznym wydaniu kwartalnika na stronie ***www.ein.org.pl***

- ability to be diagnosed characterizing the object's susceptibility to obtaining information on technical condition.

Determining the measures of the above mentioned groups of objects' features requires the use of mathematical models. The most commonly used models include reliability models [8, 14] overall equipment effectiveness models (OEE) and Key Performance Indicators models (KPI) [17].

The reliability model allows statistically determine operational measures. The reliability measure in this model is based on the reliability function defined as the probability of correct operation of the object in the assumed time [14]. In practice, the reliability models allow to define the indicators related to the operational objects in terms of technical and technical-organizational aspect.

The overall equipment effectiveness models focus the operation measures by the use of object's availability, efficiency, and quality of its operation. The Key Performance Indicators model (KPI) includes a collection of key performance and efficiency measures. These measures are specified in EN 15341: 2007 standard (Maintenance - Maintenance Key Performance Indicators). This standard contains 72 indicators, with a detailed interpretation of the components that they contain [15].

Determining the value of the measures of the objects' operational features allows to further evaluate the changes of these values at a certain time. Assessing an objects or processes involves making a decision. Decisions usually have to satisfy the whole set of needs of the decision maker, which makes it necessary to compare possible solutions, variants in terms of many criteria characterizing a given object or process. Hence making complex decisions requires the use of multi-criteria analysis methods (MCDM - Multi Criteria Decision Making). These methods play an important role, among the others, in the diagnosis of existing objects or organizational solutions [22]. Due to the fact that the features of objects or systems are usually expressed in different units of measure, their states can not be directly compared with each other. It is only the division of the set of features characterizing a given object (system), in terms of the desired tendencies of the formation of their values, enables the unification of the partial criteria and the comparing of these characteristics. Multi-criteria decision supporting methods can be divided into those stemming from the usefulness theories (UTA, UTASTAR, AHP, ANP, SMART) and methods based on overriding relationships (e.g. ELECTRE, PROMETHEE, ORESTE, REGIME), which indicate that due to a certain criterion one solution is „at least as good" as the other solution. The UTA (UTilités Additives) method is based on the principle of aggregation/division. It uses linear programming techniques to optimally define additive value/usefulness functions so that these functions are as consistent as possible with the preferences of the decision maker [24]. The development of UTA method is a UTASTAR method. It has additionally two error functions that denote the violation of the lower and upper ends of the usefulness function of the alternatives group by the k-th decision variant [24].

The Analytic Hierarchy Process (AHP) is a generic hierarchical approach to multi-criteria decision making that allows to combine quantified criteria with non-quantified ones and objectively measurable with subjective [11, 17, 18]. Modelling with a hierarchical analysis of the problem AHP is particularly useful where there is no known functional dependence between the elements of the decision making problem, described in form of the hierarchy of the factors, but the effect of the property data occurring and their practical effect, can be estimated. The extension of the AHP method is the ANP method (Analytic Network Process) method [1]. It can be applied to solve more complex decision problems. A system of components relevant to the decision-making problem in the form of a network is constructed. This includes not only the relationships between the groups of elements or within them, but also the feedbacks.

The Simple Multi-Attribute Rating Technique (SMART) method is a multi-stage method that identifies decision makers, opportunities, attributes relevant to a given decision making problem, the values and weights of individual attributes, the decision is made and the analyzes of its sensitivity is made [4].

The ELECTRE methods (Fr. ELimination Et Choix Traduisant la REalité) [3] have a wide range of applications in a variety of decision-making problems. They include a group of methods (e.g. ELECTRE I, Iv, IS, II, III, IV, TRI) designed to solve various problems of multi-criteria decision making support. The choice of a particular method depends on the one hand on the kind of problem we are dealing with and on the other on the type of data we have. The ELECTRE methods assume the axiom of limited comparability of variants, expressed by the recognition of four basic relations: I - equivalence, P - strong preference, Q - weak preference, and R - incomparability. The basic rule used in the ELECTRE methods is comparing each variant with all others. In this way it is checked whether one variant can be regarded as having an advantage over each of the others.

The PROMETHEE method (Preference Ranking Organization METHod for Enrichment Evaluations), like ELECTRE, represent a group of methods [2]. The PROMETHEE methods use information about the degree of preference of the given variant relative to the other variants and the information on the extent to which the other variants are more preferred to the given variant.

The ORESTE method has been developed for the situations where the alternatives are ordered according to each criterion and the criteria themselves are ranked according to their importance [12]. This method uses independent rankings for the criteria and alternatives to each criterion.

The REGIME method [12] is based on an overriding analysis, and can be seen as an orderly generalization of comparison methods in pairs such as compatibility analysis. The REGIME basis is CiL compliance coefficients defined as the sum of weights for criteria for which the alternative *ai* is at least as good as *al*. The purpose of this method is to determine the Cil - Cli difference sign. If the sign of this difference is positive then the alternative *ai* is preferred over the *al* and vice versa (when the sign is negative).

Selection of the method is extremely important from the point of view of the output information following the evaluation. It also depends on the nature of the input information held, the quantity and common dependencies, if any, and the information (purpose) one wants to obtain as the output. Therefore, the indicators and measures used for evaluating of the individual components of the vehicle operational evaluation are not exhaustive because they represent one variable. They do not reflect the relationships between the individual variables and the strength (size) of this relationship.

For the operational evaluation of the vehicles one can also use artificial intelligence methods, and, above all, artificial neural networks.

The purpose of this article is to present the possibility of using artificial neural networks for:

- support making decisions related to the operation of vehicles used in transport services related to the delivery of products for production,
- forecasting the quality and operational efficiency of the motor vehicles in the transport service system.

Applied were the following research methods: analysis (used to identify the area of artificial intelligence), descriptive modelling (used to formulate and describe collected information), mathematical modelling, using artificial neural networks (for operational evaluation of motor vehicles).

2. Aspects of operational evaluation of transport services

Transport services are invariably an essential element of the economy and social life, enabling them to function effectively. Socio-economic development generates the need for the people to move and transport loads. Lack of consistency between transport and manufacturing activity significantly undermines development opportunities. In addition, high competition in this segment has led to the fact that the lowest price has ceased to be a guarantee of market advantage. These considerations are one of many aspects of interest in evaluating transport services in terms of vehicle operation. The problem of quality in the face of dynamic market changes is becoming particularly important for such reasons as: ever-increasing customer expectations, minimizing the duration of the service, guaranteeing the highest efficiency of the service, or the safety of the vehicle and the goods being transported. One of the more important dimensions of the assessment of the transport service is the evaluation from the point of view of vehicle operation. This assessment is a complex problem, due to numerous criteria, described by attributes that are not measurable or difficult to measure. As a rule, the criteria are of heterogeneous character, which further complicates the credible assessment. This problem solves the use of multi-criteria decision-making methods based on, for example, heuristic methods or fuzzy sets theory. Unfortunately, these methods, due to their mathematical construction, are difficult to implement. For this reason, simple, practical tools are being sought for utilitarian benefits. In situations where there is a full knowledge of the rules and a small complexity of the problem, exact algorithms (e.g. linear models) are used. For partial or complete lack of knowledge of the rules and high complexity of the problem, neural networks are used. Because of its complexity and multi-facetedness, operational evaluation belongs to the area of artificial intelligence use.

There are many criteria for the classification of transport services. The relevant areas that influence the evaluation areas include: the subject of the carriage (e.g. passenger transport market, freight transport market), the mode of transport used, the area of operation (e.g. local, national, international market), economic strength of the operators (carrier's market or user's market), etc.

This article attempts to carry out an operational evaluation whose objects are motor vehicles.

The essential features of transport services include:

- complexity - the transport service consists of a very large number of elements and relationships between these elements,
- probability - all states and events can not be predicted,
- dynamics - the implementation of transport service gets constantly intervened in, both in time and space.

The basic conditions for the functioning of transport services include:

- economic and legal aspects – e.g. financial system, transport legislation,
- technical aspects - such as vehicles, infrastructure, transport and handling equipment, along with many operational aspects,
- organizational aspects – e.g. rules of cooperation between the carrier and the customer, carrier's working time.

The quality aspects of providing transport services constitute a separate group of research areas. It is possible to distinguish three quality categories [23]:

- postulated by the user, which sets out their requests and wishes regarding the way the transport service is performed,
- offered by carriers, that is the offered supply of transport services that can be realized with current knowledge, technology and organizational resources,
- implemented by service providers.

The issues of evaluating transport services are dealt with in different ways. Most often, this analysis is done with respect to the delivery time, safety and reliability of the service, and the safety and reliability of the vehicles themselves [5]. On the other hand, Neo and others have analyzed the quality of services provided by logistical operators and have given the accuracy of the information, the accuracy of the assembling process and the timely deliveries as the basic indicators of the evaluation [13].

Taking the above into consideration, the evaluation of the transport service can be made in many other aspects, i.e. costs incurred, risks, resources: human, information, or vehicles used. Depending on the aforementioned conditions and the nature of the service performed, these aspects are differently interpreted. Although for risk estimation, for example, it is recommended to carry out this process in a specific order: defining scope, identifying hazards and predefining consequences, estimating risk, verification, documenting, and updating analysis [16].

In general, the evaluation of a transport service can be presented as a following function:

$$R_n(t)=f(w_{n,1}(t), w_{n,2}(t),\ldots, w_{n,k}(t)) \tag{1}$$

where:

$R_n(t)$ – evaluation of n-th transport service in time t,
$w_{n,k}(t)$ – evaluation of the k-th requirement of the n-th transport service in time t.

The aspects presented above can be described by different measures, depending from which point of view the evaluation is made. But reliable vehicles operated in the course of the transport service are essential. Their quality depends mainly on the proper operation, which is determined by reliability and readiness. In turn, the readiness of the vehicle consists of elements such as: resistance to damage, serviceability and ensuring operating means [15]. Therefore, for the purpose of this work, the operational evaluation of the n-th transport service is defined as a following function:

$$E_n(t) = f\,(w_{n,u}(t), w_{n,o}(t), w_{n,w}(t), w_{n,st}(t)) \tag{2}$$

where:

$E_n(t)$ – operational evaluation of the n-th transport service in time t,
$w_{n,u}(t)$ – evaluation of the resistance to damage requirement of the vehicle performing the n-th transport service in time t,
$w_{n,o}(t)$ – evaluation of the serviceability requirement of the vehicle performing the n-th transport service in time t,
$w_{n,w}(t)$ – evaluation of the age requirement of the vehicle performing the n-th transport service in time t,
$w_{n,st}(t)$ – evaluation of the technical condition of the vehicle performing the n-th transport service in time t.

In order to perform an operational assessment of transport services, due to its multidimensional nature, tools are needed to find the relationships between sets of variables at a high complexity of the problem. This tool can be artificial neural networks. So further in this article the modelling is shown, using this software, of the operational vehicles evaluation applied for assessment of transport services and results of the authors own studies.

3. Neural modelling

Research on the possibility and use of artificial neural networks for the operational evaluation of transport services was carried out based on the services provided by external carriers to a company that produces and markets dairy products. Evaluation concerned transport services carried out on the domestic market using motor vehicles.

Table. 1. Requirements description of the transport service operational assessment E_n

Symbol of the assessment requirement	Requirement description of the transport service operational assessment E_n
$w_{n,u}(t)$	vehicle resilience to defects - number of defects occurring per unit of time (e.g. week, month, etc.),
$w_{n,o}(t)$	vehicle serviceability - the amount of hours the vehicle is in service,
$w_{n,w}(t)$	age of the vehicle - affects other reliability characteristics therefore this requirement is included in vehicle quality measurements,
$w_{n,st}(t)$	technical condition of the vehicle - this characteristics stems, among the others, from the other reliability assessment indicators and is assessed organoleptically by an expert, markings adopted: very good technical condition of the vehicle (vg) satisfactory (sat), not satisfactory (nsat).

Source: author's own compilation.

Table 2. Parameterized assessment of requirement $w_{n,u}$ - vehicle's resilience to defects

No.	Vehicle's resilience to defects [number / month]	Parameterized quality assessment	Descriptive quality assessment
1	0	1	high level of quality
2	1	0,75	very good level of quality
3	2	0,5	good quality level
4	3	0,25	low quality level
5	4	0	unacceptable level of quality

Source: author's own compilation.

Table 3. Parameterized assessment of requirement $w_{n,o}$ - vehicle serviceability

No.	Vehicle serviceability [number of hours]	Parameterized quality assessment	Descriptive quality assessment
1	0	1	high level of quality
2	0-1	0,75	very good level of quality
3	2-5	0,5	good quality level
4	6-10	0,25	low quality level
5	>10	0	unacceptable level of quality

Source: author's own compilation.

Table 4. Parameterized assessment of requirement $w_{n,w}$ – age of the vehicle

No.	Age of the vehicle [in years]	Parameterized quality assessment	Descriptive quality assessment
1	0-5	1	high level of quality
2	6-12	0,5	good quality level
3	>12	0	unacceptable level of quality

Source: author's own compilation.

Table. 5. Parameterized assessment of requirement $w_{n,st}$ – technical condition of the vehicle

No.	Technical condition of the vehicle	Parameterized quality assessment	Descriptive quality assessment
1	very good	1	high level of quality
3	accept	0,5	good quality level
5	not accept	0	unacceptable level of quality

Source: author's own compilation.

Table 6. Sample data for teaching neural network

No.	Vehicle's resistance to defects	Vehicle serviceability	Vehicle's age	Vehicle's technical condition	Evaluation (weighted average)	Decision
	number / month	number of hours / month	years	v.good/accept./not accept.		
1	0	0	1	very good	1,00	Positive
2	1	1	3	very good	0,87	Positive
3	0	0	6	very good	0,88	Positive
4	1	1	6	very good	0,75	Positive
5	1	1	7	accept	0,63	Positive
6	0	0	7	accept	0,76	Positive
7	1	6	8	accept	0,56	Negative
8	0	0	8	accept	0,76	Positive
9	0	0	8	very good	0,88	Positive
10	1	6	11	not accept	0,44	Negative
11	0	0	11	not accept	0,64	Positive
12	2	8	12	accept	0,46	Negative
13	0	0	13	accept	0,64	Positive
14	1	2	13	not accept	0,36	Negative

Source: author's own compilation.

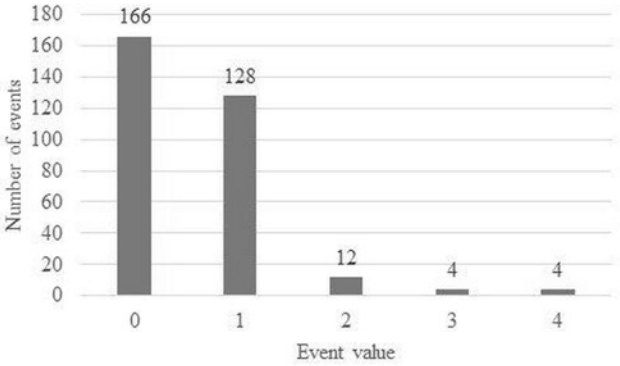

Fig. 1. Results of investigating the requirement $w_{n,u}$ – Vehicle's resistance to defects

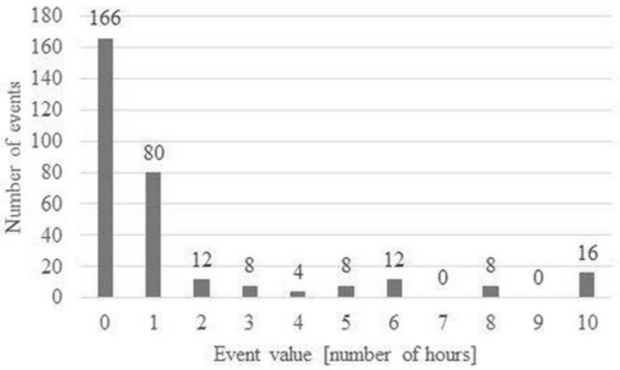

Fig. 2. Results of investigating the requirement $w_{n,o}$ – serviceability of the vehicle

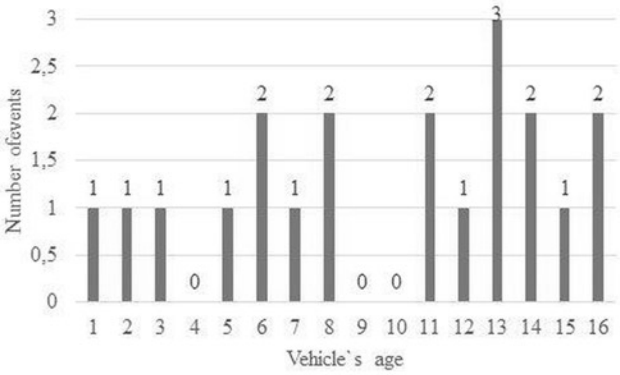

Fig. 3. Results of investigating the requirement $w_{n,w}$ – age of the vehicle

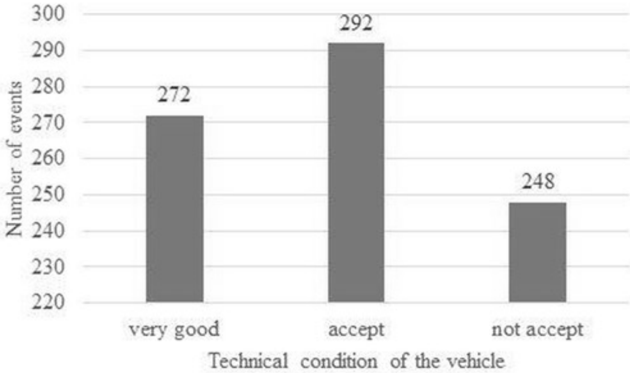

Fig. 4. Results of investigating the requirement $w_{n,st}$ – technical condition of the vehicle
Figures 1-4 source: author's own compilation.

In order to use the neural networks to carry out an in-service evaluation of transport services, a set of input signals, both quantitative (expressed in terms of numbers) and qualitative (expressed in words), was defined. The vehicles quality measurements describing the requirements of the operational evaluation of transport services are presented in the table 1.

For the purpose to assess the quality of the transport service $E_n(t)$ according to the requirements $w_{n,u}(t)$, $w_{n,o}(t)$, $w_{n,w}(t)$, $w_{n,st}(t)$, they have been parameterized as per arrangements given in tables 2-5.

To evaluate individual requirements, the experts assigned weights to the characteristics on the scale (0-10), where 0 is not significant, 10 is very important. The following weight values are assigned:

- $w_{n,u}$ – 8,
- $w_{n,o}$ – 3,
- $w_{n,w}$ – 5,
- $w_{n,st}$ – 5.

With so defined operational assessment requirements, vehicle users and experts assessed the individual requirements. The data collected from the operation was from the implementation of 812 transport services completed in the last 5 years, supplying products for production. This data provided the starting point for the studies (table 6). Based on the weighted average of the individual requirements, the decisions were made on the operational evaluation of the quality of transport services (positive or negative). The quality level considered satisfactory was assumed at 0.6 and above.

Below is a summary of the structure of the results obtained, according to the individual requirements.

Based on the above data, 540 positive and 272 negative evaluations were received.

Of the many types of neural networks and many of their teaching algorithms, further studies have used the Multilayer Perceptron and teaching algorithms: the fastest drop method, the conjugate gradient method; BFGS method (Broyden-Fletcher-Goldfarb-Shanno). The neural network used belongs to the following groups:

- the so-called, supervised networks, where the teaching process takes place under the supervision of the teacher (among the outgoing signals there is a master signal),
- unidirectional networks where the flow of signals (information) takes place in one direction (from the input to the output of the neural network).

Using the Statistica 12 computer program, transportation services have been evaluated using predefined vehicle quality measures.

The following signals were thus identified:

- input quantitative ones : $w_{n,u}(t)$, $w_{n,o}(t)$, $w_{n,w}(t)$,
- input qualitative ones: $w_{n,st}(t)$,
- output quantitative ones: $E_n(t)$.

With the input data indicated, the size of the sets was defined. It was stated that:

- 80 % - of the data will be the teaching set used to modify the weights,
- 10 % - a test set for ongoing monitoring of the teaching process,
- 10 % - validation set for network quality assessment after completing teaching process.

Then the basic parameters of the network were defined, i.e.:

- network type (multi-layer perceptron (MLP)
- minimum number of hidden neurons
- maximum number of hidden neurons
- number of teaching networks,
- the number of networks retained,
- hidden neuron activation function,
- activation function of output neurons,

- weight reduction values for the hidden layer and the output layer.

Once the data and network parameters were defined, neural network teaching was performed using the collected data. The sample results of this process are shown in the table 7.

With such defined requirements and having conducted the teaching process, the structure of the best network became MLP 6-3-1, which means 6 neurons in the input layer, 3 neurons in the hidden layer and 1 neuron in the output layer (figure 5).

The teaching quality of MLP 6-3-1 network was rated at 99,6% probability of indicating a correct (response), while testing quality at a 99,7%, which means that all tests in this set have been properly assigned and the quality of the validation has been determined to be at 99,4%. The best teaching algorithm turned out to be BFGS 148 (number 148 means the number of epochs the network needed to carry out the teaching process and finding the best network, with the smallest error).

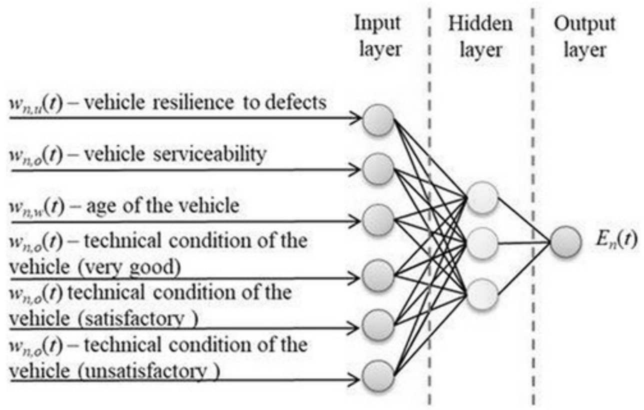

Fig. 5. Structure of the investigated MLP 6-3-1 network
Source: author's own compilation

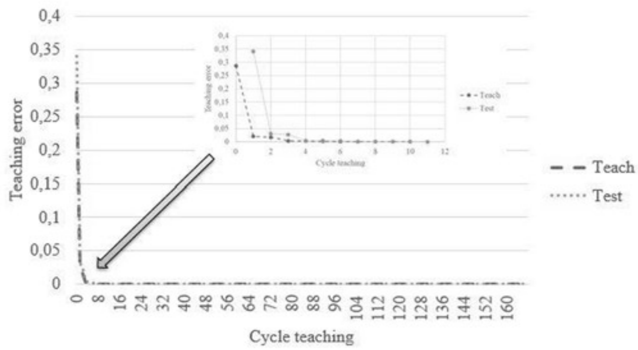

Fig. 6. Neural network MLP 6-3-1 teaching diagram
Source: author's own compilation.

Table 7. Sample results of teaching neural network

No.	Network Name	Teaching Quality	Testing Quality	Validation Quality	Teaching Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 6-5-1	0,988	0,992	0,989	BFGS 55	SOS	Logistic	Logistic
2	MLP 6-4-1	0,988	0,992	0,989	BFGS 98	SOS	Logistic	Tanh
3	MLP 6-6-1	0,984	0,990	0,991	BFGS 10	SOS	Linear	Linear
4	MLP 6-7-1	0,984	0,991	0,990	BFGS 8	SOS	Linear	Linear
5	MLP 6-8-1	0,983	0,991	0,991	BFGS 10	SOS	Linear	Linear
6	MLP 6-4-1	0,983	0,992	0,991	Fastest Drop 30	SOS	Tanh	Linear
7	MLP 6-4-1	0,987	0,993	0,989	BFGS 47	SOS	Logistic	Exponential
8	MLP 6-8-1	0,987	0,992	0,987	BFGS 48	SOS	Logistic	Logistic
9	MLP 6-7-1	0,990	0,993	0,989	BFGS 63	SOS	Logistic	Linear
10	MLP 6-3-1	0,996	0,997	0,994	BFGS 148	SOS	Tanh	Linear
11	MLP 6-8-1	0,983	0,991	0,991	BFGS 9	SOS	Linear	Linear
12	MLP 6-4-1	0,985	0,992	0,988	Conjugate gradients 27	SOS	Tanh	Linear
13	MLP 6-6-1	0,977	0,984	0,990	BFGS 12	SOS	Logistic	Sinus
14	MLP 6-4-1	0,981	0,984	0,990	BFGS 23	SOS	Sinus	Sinus
15	MLP 6-6-1	0,981	0,988	0,990	BFGS 23	SOS	Sinus	Sinus
16	MLP 6-10-1	0,996	0,995	0,997	BFGS 87	SOS	Tanh	Linear
17	MLP 6-5-1	0,991	0,995	0,990	BFGS 86	SOS	Tanh	Tanh
18	MLP 6-8-1	0,985	0,992	0,988	BFGS 16	SOS	Exponential	Logistic
19	MLP 6-14-1	0,991	0,993	0,990	BFGS 47	SOS	Tanh	Exponential
20	MLP 6-1-1	0,976	0,983	0,990	BFGS 16	SOS	Linear	Sinus
21	MLP 6-1-1	0,985	0,992	0,987	BFGS 39	SOS	Exponential	Exponential

Source: author's own compilation.

4. Verification of the selected neural network MLP 6-3-1

The prove of the positive result of teaching neural network is provided by the teaching curve which shows that the best network structure was found in 148 epoch where the share of incorrect answers is below 1%, and the error was estimated at 0,0002.

The errors matrix are shown in the Table 8. It indicates exactly how many cases of evaluation have been qualified by the network as a positive (above 0,6) or negative (below 0,6) evaluation. The table shows that for 432 positive evaluations, the network correctly assigned 408 indications, while correctly indicating all negative evaluations.

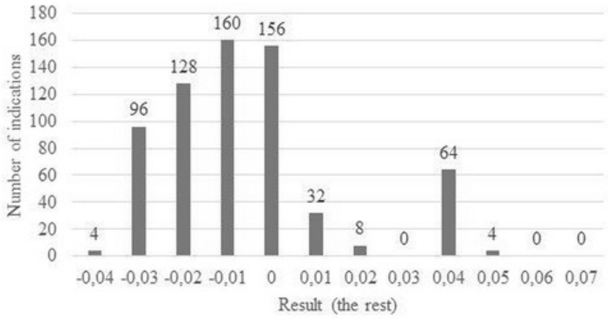

Fig. 7. Distribution of residues neural network MLP 6-3-1
Source: author's own compilation.

Table 8. The errors matrix of the neural network MLP 6-3-1

No.		Negative Decision	Positive Decision	Decision - all
1	Total	220	432	652
2	Correct	220	408	628
3	Incorrect	0	24	24
4	Correct (%)	100%	94%	96%
5	Incorrect (%)	0%	6%	4%

Source: author's own compilation.

Table 9. Predictions for new data based on MLP 6-3-1 neural network

No.	Vehicle resilience to defects	Vehicle serviceability	Age of the vehicle	Technical condition of the vehicle	Evaluation
1	0	0	3	Very good	0,99
2	1	5	3	Very good	0,863
3	1	2	5	Accept.	0,726
4	2	10	7	Accept.	0,552
5	1	5	10	Not accept.	0,458

Another important feature of the study of the neural network is the distribution of residues shown in figure 7, i.e. the differences between the output variable and its prediction.

From the histogram can be seen that the residues are normally distributed around zero with an emphasis on negative values. The vast majority of evaluations were made with an error level -0,03-0.

The last stage of verification of the neural network are the predictions for new inputs (for attempts that have not yet appeared in any collection). In order to obtain new operational evaluations of the quality of transport service the values of all input signals to the neural network were supplemented based on which the output signal (i.e. operational evaluation (quantitative) of transport service) has been generated. After entering data into the network the final results were obtained. Table 9 contains predictions for new data based on MLP 6-3-1 neural network.

The obtained results indicate the possibility of using a single-layer neural network to perform an in-service evaluation of the quality of transport services. Both, the number and type of data (quantitative or qualitative), do not affect high performance at 98% - 99% of efficiency. Based on data from the past, a neural network allows making decisions, generating assessment of the current or future operation.

5. Conclusion

There are many different methods and models (mostly multi-criteria), in the subject literature, for the purpose of evaluating operation of vehicles and technical systems. They are characterized in the introduction to this article. They are commonly used in practice. The authors' experiences and the conducted analysis of the situation indicate that neural networks are not yet widely used for the operational evaluation of vehicles to be used in transport services. Neural networks are used in operation but in other areas [7, 19, 20, 21].

The results of the investigations carried out obtained at the company manufacturing dairy products and at the transport companies co-operating with this company indicate the possibility of using artificial neural networks to evaluate vehicles used in the delivery of transport services, using operational quality measures. In the case of negative assessments, corrective action can be taken without delay. Based on this it is possible to forecast future predictions with the data from current operation.

The proposed operational quality measures resulted from the needs of the surveyed company. In practice, they can be selected in different ways, depending on the purpose of the analysis.

Neural networks have proved to be useful as a tool for:

- supporting the decision making related to the use of vehicles used in transport services for the delivery of goods for production,
- forecasting the quality and efficiency of the operation of motor vehicles in the transport service system.

So the purpose of the research has been achieved.

The use of neural networks in operation can be broader. For example, to assess not only operational risks, but also related to the reliability and safety of vehicles (not just cars) and other machinery and to the safety of the transport services themselves.

The computational example presented in the article thus reflects the essence of using artificial neural networks to evaluate operational issues. This is one possible starting point for further research into the use of neural networks in this area.

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